Fisheries and Oceans Canada / Pêches et Océans Canada
Ecosystems and Oceans Science / Sciences des écosystèmes et des océans

Canadian Science Advisory Secretariat (CSAS)

Research Document 2017/021

Pacific Region

Evaluating Models to Forecast Return Timing and Diversion Rate of Fraser Sockeye Salmon

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March 2018

Canada

Foreword

This series documents the scientific basis for the evaluation of aquatic resources and ecosystems in Canada. As such, it addresses the issues of the day in the time frames required and the documents it contains are not intended as definitive statements on the subjects addressed but rather as progress reports on ongoing investigations.

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Published by:

Fisheries and Oceans Canada
Canadian Science Advisory Secretariat
200 Kent Street
Ottawa ON K1A 0E6

http://www.dfo-mpo.gc.ca/csas-sccs/
csas-sccs@dfo-mpo.gc.ca

ISSN 1919-5044

Correct citation for this publication:

Folkes, M.J.P., Thomson, R.E., and Hourston, R.A.S. 2018. Evaluating Models to Forecast Return Timing and Diversion Rate of Fraser Sockeye Salmon. DFO Can. Sci. Advis. Sec. Res. Doc. 2017/021. vi + 220 p.

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ABSTRACT

Management of the Fraser River sockeye fishery includes a pre-season planning component that relies on the forecast of three variables that represent characteristics of the returning adult run: recruitment, migration timing to local waters, and migration entry route relative to Vancouver Island (as defined by the Northern Diversion Rate). In this paper, we evaluate the two components related to forecasting the homing migration of adult Fraser sockeye. These forecasts are based on statistical relationships between observed and modeled environmental variables and the known migratory patterns that they are assumed to influence. We present the results from several software tools developed by the authors to identify a suite of North Pacific oceanic time series that have biologically relevant relations to both return timing of two Fraser sockeye stocks and northern diversion rate. In addition to the models that are founded on assumed mechanistic connections, we evaluate a series of naïve models based on the statistics of the dependent time series. Separate from the forecast model evaluation, we also explore the potential influence of major El Niño events on stock migratory behaviour. All forecast models are evaluated by performance analyses that appraise the forecast precision, accuracy, and robustness in relation to seasonal and interannual changes in the time series. We introduce a new method of ranking performance metrics that provides a better indication of a model's relative rank. The final stage of model selection is based on tolerance curves, which are isopleths depicting the number of models that fulfil a desired forecast uncertainty at a given level of likelihood. These tolerance curves serve as an objective tool that will help bridge the science of statistical model development to the subjective requirements of fisheries management.

Évaluation des modèles de prévision de la période de montaison et du taux de déviation du saumon rouge du fleuve Fraser

RÉSUMÉ

La gestion de la pêche au saumon rouge du fleuve Fraser comprend un volet de planification d'avant-saison fondé sur les prévisions de trois variables qui représentent les caractéristiques de la montaison de retour des adultes : recrutement, période de migration vers les cours d'eau locaux et voie d'entrée de migration par rapport à l'île de Vancouver (telle que définie par le taux de déviation par le nord). Dans le présent document, nous évaluons les deux composantes liées à la prévision de la migration de retour des saumons rouges adultes du fleuve Fraser. Ces prévisions sont fondées sur les relations statistiques entre des variables environnementales observées et modélisées et les profils de migration connus sur lesquels on suppose qu'elles ont une influence. Nous présentons les résultats de plusieurs outils logiciels créés par les auteurs afin de déterminer les séries chronologiques dans le nord de l'océan Pacifique qui ont des liens pertinents sur le plan biologique avec la période de montaison de retour de deux stocks de saumon rouge du fleuve Fraser et le taux de déviation par le nord. En plus des modèles fondés sur les liens mécaniques supposés, nous évaluons une série de modèles naïfs basés sur les statistiques de la série chronologique dépendante. Mis à part l'évaluation du modèle de prévision, nous explorons aussi l'influence possible des variations majeures provoquées par El Niño sur le comportement de migration des stocks. Tous les modèles de prévision sont évalués à l'aide d'analyses du rendement qui permettent d'évaluer la précision, l'exactitude et la solidité des prévisions par rapport aux changements saisonniers et interannuels de la série chronologique. Nous présentons une nouvelle méthode de cotation du rendement qui fournit une meilleure indication du rang relatif d'un modèle. La dernière étape de la sélection de modèles est fondée sur les courbes de tolérance, soit des isoplèthes qui démontrent le nombre de modèles qui atteignent un niveau d'incertitude voulu des prévisions à un niveau de probabilité donné. Ces courbes de tolérance servent d'outil objectif qui aide à établir un pont entre la science des modèles statistiques et les exigences subjectives de la gestion des pêches.

1 INTRODUCTION

The Challenge: Management of the fishery on Fraser River sockeye includes a pre-season planning component that relies on the forecast of three variables representing the returning adult run: recruitment, migration timing to local waters, and migration route around Vancouver Island. Recruitment forecasting is presented independently of the latter two variables (DFO, 2015) and will not be discussed in this paper. However, the three variables are strongly linked so that the utility of the recruitment forecast is aided by an understanding of the most probable date and the marine route of returning fish (Royal and Tully, 1961). Walters (1997) describes clearly the fishery manager's dilemma:

> *The key limiting factor today for updating in-season run size estimates is not in gathering precise index information, but rather in using that information in conjunction with estimates of run timing. The basic problem is as follows. Suppose there is a weak showing of fish in the index data early in a season. Even if the index is very precise, should the manager infer a weak run, or instead that the fish are arriving late? Suppose there is a strong showing early. Should the manager conclude that a strong run is coming, or instead that there is about to be the salmon manager's worst nightmare, a "little run coming early"? These questions emphasize that the in-season salmon manager's worst data problem arises from run-timing anomalies. Runs can arrive in fishing areas as much as 2*[1] *wk* [sic] *earlier or later than expected, which would be an extreme variation considering that most single-stock runs only last 4–6 wk.*

Ruggerone (2004) validates the comments of Walters by describing several examples of Alaskan sockeye fisheries that hadn't historically utilized timing forecasts—and the ramifications (including overfishing or missed catch opportunities). Forecasts of marine timing and migration route thus play a role both in pre-season fishery planning and in-season run size adjustment. Post-season estimates of return timing have been produced by the International Pacific Salmon Fisheries Commission (IPSFC) and it's successor the Pacific Salmon Commission (PSC) since the early 1950s. Pre-season forecasts of timing (Chilko stock) likely began no later than 1980 (IPSFC, 1939–1986). In ensuing years, the statistical models considered and the environmental variables utilized were refined (Blackbourn, 1987, and Blackbourn, D. J. 1992[2]).

For at least two decades Canadian Department of Fisheries and Oceans (DFO) Science staff have provided the PSC with pre-season forecasts of Fraser sockeye migratory patterns that are to be used in pre-season fishery planning.[3] The forecasts are based on statistical relationships between these migratory patterns and environmental variables that we have assumed to play a role on the migratory behaviour of returning adult Fraser sockeye.

In the early period, the return timing forecasts for Early Stuart sockeye were moderately accurate, but their effectiveness has substantially declined in recent years. The Chilko timing forecast error

[1] Except for cases of direct quotation, we treat numbers in text using the "zero through nine rule" from the *Chicago Manual of Style* (University of Chicago Press, 2010).

[2] Blackbourn, D. J. 1992. Two examples of methods used in forecasting stock abundance and adult migration behaviour in some stocks of southern Pink, Chum and Sockeye salmon. DFO. Pacific Stock Assessment Review Committee, Unpublished manuscript S92.

[3] "Forecasts of migration patterns . . . shall be provided to the Fraser River Panel by Canada as they become available in order to accommodate the management needs of the Panel in a timely manner." (Anonymous, 2014, Article XV, Annex IV, Chapter 4, Paragraph 4)

has varied greatly throughout it's history. It is now common to have forecasts that differ markedly from the post-season estimates (Figure 1). This is not surprising as statistical predictors, which can be based on a mechanistic link between environmental change and fish behaviour—or just a proxy for that link—eventually become decoupled from the variables they are attempting to forecast. By nature of their construction, some statistical models may be robust to time series outliers but none can be robust to changes in the relations among model variables. It is possible that the marine environmental variables recently used to forecast timing are no longer linked to the fish stocks in the way they were twenty five years ago. Furthermore, one of the variables utilized in the forecasts, a post-processed version of the Ocean Surface Current Simulator (OSCURS) (an index of current velocity), is not in the public domain.[4] Access to annual updates of these data and failures in the forecasting success of several different models has motivated a review of this annual forecasting task.

Purpose of This Research Document: This paper serves to explore new statistical models that relate migratory patterns of returning adult Fraser sockeye to potential environmental correlates. Since 1981 there have been substantial improvements in the resolution of directly measured environmental variables that are published and publicly accessible (Bonjean and Lagerloef, 2002; Reynolds et al., 2002). Satellite technology has allowed for better spatial and temporal resolution of oceanic variables, and near-real time access to these data is possible. Models to estimate both off shore and coastal current velocity have substantially improved during the last two decades, resulting in a much better representation of marine conditions during critical, seasonal transition periods. Finally, the software tools to search these large data sets for robust statistical models has become freely available within the last decade. These changes inspired a review of potential statistical models and variables to forecast return timing, which is formalized in the present document.

We present the results from several software tools, developed by the authors, to search a collection of North Pacific oceanic time series for biologically relevant relationships to the migratory patterns of Fraser sockeye salmon. The relationships (estimated as statistical models) are evaluated by performance testing to appraise forecast precision, accuracy, and robustness to changes in the time series. Statistical models with high performance rankings will likely be suitable candidates to produce annual forecasts of Fraser sockeye migratory patterns that can be applied to both pre-season fishery planning models and (as Bayesian priors) to in-season run size estimation models.

2 FORECASTING METHODOLOGY—THE BACKGROUND

2.1 THE HISTORICAL APPROACH

This sub-section serves as a review of prior research on forecasting of Fraser sockeye adult migratory behaviour, focussing on the successes and eventual failures of these forecasting models. Perusal of this review is not necessary to grasp the analysis within later sections.

[4] While OSCURS is publicly accessible, the historic timing forecast models relied on a contractor to run additional "black box" post-processing such that we have had no independent capability to reproduce the current velocity results.

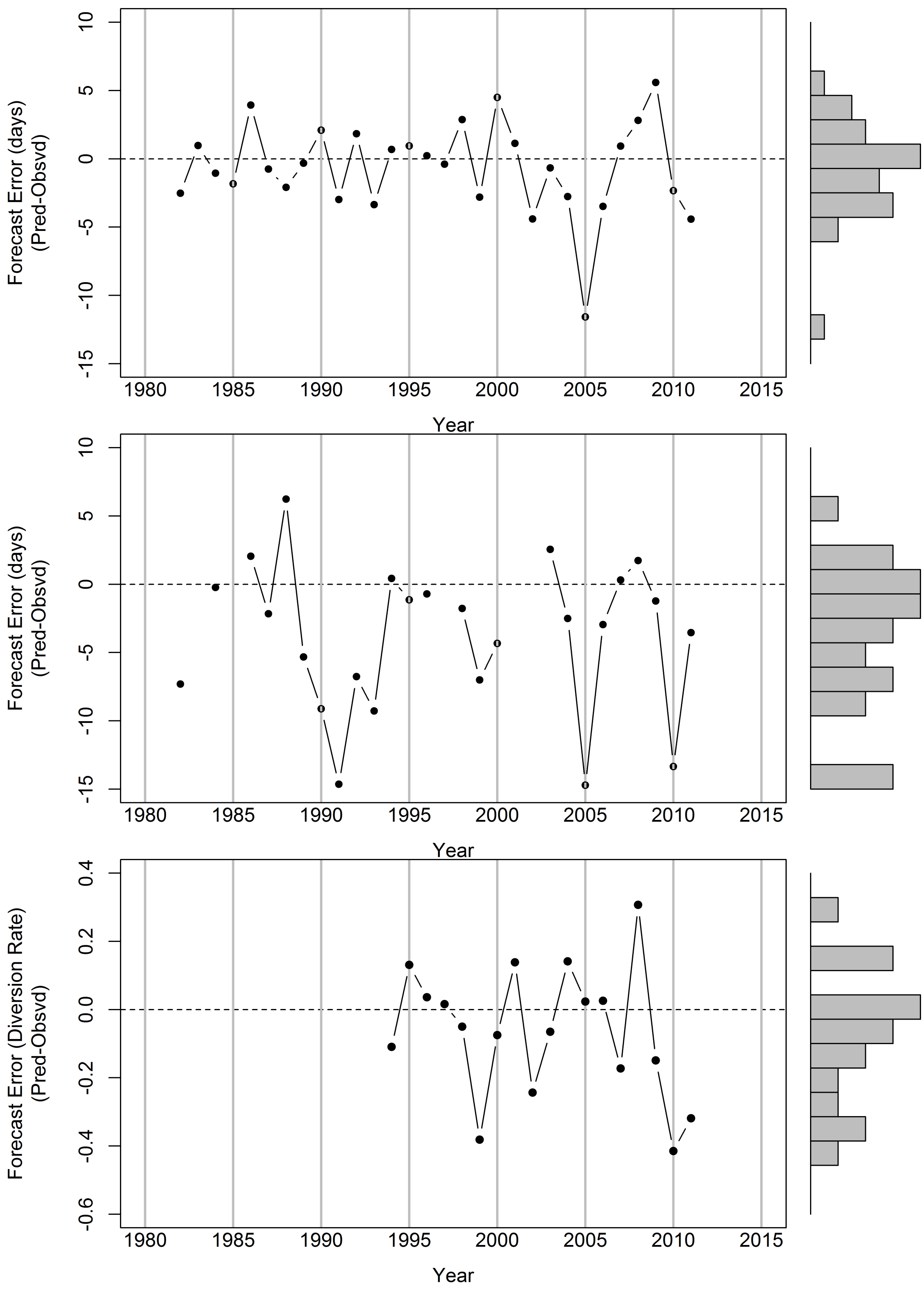


Figure 1. Timing forecast error (in days) for Early Stuart (top panel) and Chilko (middle panel) sockeye and ND forecast error (bottom panel) based on retrospective analysis of forecasting from the previously used models. Note that due to updates of timing and ND values and environmental data, these forecasts may not match those in original DFO memos. The model would have been fitted using data from approximately 1950–1980, and refitted with each additional year. The histogram along the right y-axis indicates the distribution of error values and is scaled to density.

2.1.1 Timing

The homing migration of adult salmon from their marine rearing locations to coastal waters has been heavily explored during the last sixty years and is well summarized in Quinn (2005), who proposed four main patterns of migratory behaviour for anadromous Pacific salmon. The first of these patterns is believed to be shared by sockeye, chum, and pink salmon. These three species likely move off the continental shelf to the open North Pacific by the fall of their first year at sea (Tucker et al., 2009). Tagging programs between 1958 and 1985, including French et al. (1976), that were summarized in the work of Myers et al. (1996) strongly indicate there is mixing of stocks across the species-range. Figure 2 represents locations in the North Pacific, by month, of tagged, maturing sockeye that returned to the Fraser River. All recoveries were made the same year as tagging. Data points for April and May show well dispersed Fraser stocks, which during June and July begin to aggregate in a relatively narrow band perpendicular to the British Columbia (B.C.) north coast. These data are not stock specific so we have no knowledge on the possibility of stock specific aggregation. However, based on the dispersed and mixed distribution of all sockeye from other regions (Alaska, northern B.C., Washington), there is evidence of mixing among stocks. The high sea distribution of stocks would suggest any environmental driver that could influence migration behaviour must either have a geographically broad range comparable to that of the stocks during their late winter/early spring distribution, or be limited to a time and location where stocks are more aggregated along their migratory path.

Roos (1991) indicated that the IPSFC, in their 1959 annual report, first considered ocean temperature as a potential factor affecting adult salmon marine return timing. Analysis for statistical correlation between timing and sea surface temperature (SST) at Ocean Station P (50°N; 145°W) (Freeland, 2007) was mentioned in the 1978 IPSFC annual report. It appears that the first published pre-season forecasts of timing (for Chilko only) were in 1980 (IPSFC, 1939–1986), although Blackbourn (1987) refers to forecasting beginning in 1978. The forecast model was based on both mid-ocean SST and “summer coastal temperatures”, which may refer to West Coast Vancouver Island (WCVI) shore station data. The first year a timing forecast was released for Early Stuart was 1981, which was a dominant year for its recruitment cycles. It wasn’t until Blackbourn (1987) put forward the temperature-displacement model of sockeye distribution (Figure 3) and associated statistical fit between North Pacific SST and timing that a published model could be referenced and reproduced. In subsequent years, Blackbourn produced an improvement on the published model (for Chilko timing only) considering several additional variables:

- Standard length of Chilko sockeye females in prior year;
- Total abundance of Chilko sockeye in return year;
- Total abundance of Fraser sockeye in return year;
- Coastal SST (Kains Island B.C. shore station data);
- Gulf of Alaska SST;
- Coastal SST “Queen Charlotte Islands” (now Haida Gwaii);
- Wind-induced eastward movement of surface water in the north-central Gulf of Alaska.

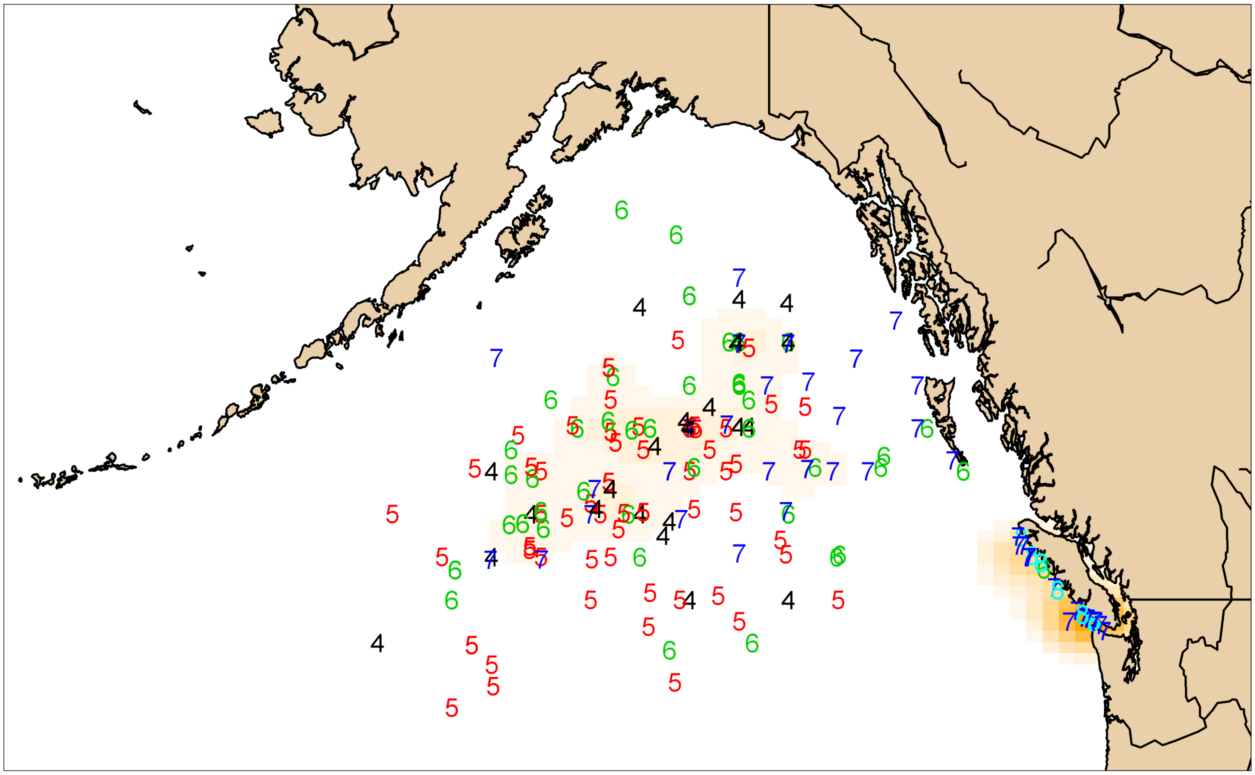


Figure 2. Distribution of Fraser sockeye in spring of return year. The number of each data point corresponds to the month when the fish was tagged, and they have a common colour. The information is based on sockeye tagging of fish (1958–1985) later recovered in the Fraser River, derived from Myers et al. (1996).

For his evaluation of timing forecast models, Blackbourn (1987) defined return timing as the *"peak day of numerical abundance . . . in outer Juan de Fuca Strait"*, i.e. the mode of the run estimated in DFO statistical area 20. Because some years of the data set have multiple peaks, Blackbourn opted to apply the median date estimate, which is when 50% of the run is determined to have passed through an area. In an unpublished analysis (see footnote 2), Blackbourn redefined his use of the term "peak date" as the *"estimated cumulative date of passage of 50% . . . through Area 20"* (i.e., the median date). Marine timing of Fraser sockeye is now defined as the date when 50% of the run has been estimated to have passed through DFO statistical area 20.

Blackbourn's new work on Chilko timing models was reviewed (but not published) in 1992 by DFO's Pacific Stock Assessment Review Committee (PSARC), which was the precursor to the Committee on Scientific Advice - Pacific (CSAP). The single variable with greatest ability to explain timing variation was female length (R^2=0.46). Adding either Chilko or Fraser total abundance (of that same returning year) improved the R^2 to 0.54 and 0.64, respectively. With this approach, the annual timing forecast would rely on the pre-season recruitment forecast from which the annual returns could be forecasted and used as input to the regression model. The logic of using pre-season return forecast as input could be circular and the author recognized these limitations, describing the methods as *"conceptually unsatisfactory"*. Despite these limitations, it is possible to explore the data for any potential linkages between migratory behaviour and the biology of these stocks by examining the relationships between marine timing (Early Stuart and Chilko) and log-transformed annual returns by stock and Fraser sockeye total.

As indicated by Figures 4 and 5, no adjusted R^2 values for Early Stuart timing exceeded 0.22, while Chilko timing was significantly related to both Chilko and Fraser total returns but with much lower adjusted R^2 values (0.27 and 0.43) than noted by Blackbourn in 1992. We will not re-evaluate this approach as a forecasting tool.

Additionally Blackbourn demonstrated that residuals in several of his regressions (including covariates: length and abundance) had a positive trend with time. This suggested another factor, which was not captured with the variables considered, could be significantly affecting return timing. Further, that factor was also trending with time. Blackbourn summarized the problem as follows:

> *Chilko sockeye timing has, on average, become three to four days later per decade, and this has become particularly noticeable since 1988. . . A change in the identification and partitioning of the Chilko stock and sub-stocks, is likely to have had only a minor effect on apparent timing and none before 1980 . . . Apart from the latter, I know of no data from the population itself to account for this trend over time, and presume it to have been driven by biological or physical mechanisms related to the actual migration process . . . It is clear that the factors which account for most of the variation in timing are those which are most strongly correlated with time . . . However, plots of residuals from regression of these factors on A20 peak dates versus time show that any model incorporating one or more of these factors still does not completely account for that part of the variance in A20 timing related to time . . .*

This same challenge has been discussed in the annual Fraser sockeye timing forecast memos (see 2009) from Michael Folkes (DFO, Pacific Biological Station) to the chair of PSC Fraser River Panel (FRP).

Around the year 1998, new timing forecast models were presented to the FRP. A new source of modelled current velocity[5], OSCURS, was available from National Oceanic and Atmospheric Administration (NOAA) (see Ingraham and Miyahara, 1988). It was found that using current velocity estimates from the southern Gulf of Alaska in March, combined with winter SST (similar to that presented in Blackbourn (1987)), yielded an improvement on prior Chilko forecasting models. No documents other than the annual DFO timing forecast memos have been published to detail this work. The locations of these variables are shown in Figure 6.

The forecasting performance of the Chilko and Early Stuart models has been highly variable during recent years. An evaluation of the models using retrospective analysis showed that the Chilko forecasting model tended to predict 2 to 2.5 days too early (see Figure 7). This tendency may be partly due to unaccounted-for environmental forces that may be driving the change in timing. Further, as demonstrated by Blackbourn (see footnote 2), these relationships might not be stationary and therefore could be changing with time.

El Niño Events: In their 1983 annual report, the IPSFC acknowledged the influence that El Niño events could have on Fraser sockeye ND rates via Johnstone Strait (IPSFC, 1939–1986). But at that time, there was no indication of El Niño events impacting timing. To the best of our knowledge, no research has been published that evaluates the role of El Niño/La Niña events on Fraser sockeye marine migration timing—nor that of other Pacific salmon stocks. New research,

[5]Throughout the document we represent the term *sea currents* with the term *current velocity*.

developed in conjunction with the current manuscript, will attempt to fill that gap.[6]

2.1.2 Northern Diversion

In a short note of the annual report from Pacific Biological Station (PBS), Tully (1937) described records of warmer marine water temperatures in 1936 versus 1934 and 1935, and that fishing in 1936 was *"very different from previous years"*. Tully recognized that coastal SST was not the sole source of variation in fishing, but that it served as an index of broader oceanic conditions that could *"affect the number and range of fish on our coast"*. Later, Tully et al. (1960), fostered by early estimates of catch indices at Area 12 versus WCVI, was able to associate migration route to anomalous SST conditions during the year of return migration.

From the time of initial estimates in the early 1950s to 1977, the majority of annual returning adult Fraser River sockeye migrated via Juan de Fuca Strait. After 1977 this proportion changed whereby the majority tended to return via Johnstone Strait (Figure 8). Thus, the stocks were diverting from their previous migratory route. The proportion of the total annual return of Fraser sockeye migrating via Johnstone Strait is referred to as the annual northern diversion (ND) rate. This variable is estimated by staff of the PSC.

Roos (1991) indicated that at least as far back as 1959 the IPSFC staff first speculated on the role of the North Pacific SST as an environmental factor affecting ND through Johnstone Strait. The 1978 IPSFC annual report (IPSFC, 1939–1986) notes that the unprecedented (to that year) ND rate *"was not predicted by any of the near-coastal environmental factors and models that had been used in recent years"*. While not well documented, it appears that the first attempts to forecast ND rate with statistical models began in the mid-1970s. Wickett (1977) explored four hypotheses for oceanic factors affecting ND:

1. SST: an avoidance of warm water (or a northern transport of adults as indicated by surface water temperatures at a shore station on the west coast of Vancouver Island);
2. Juvenile migration represented by Ekman transport: variations in the southward displacement of young fish by equatorward flowing boundary currents as the fish were moving offshore in the surface wind-forced Ekman layer, subsequently resulting in a corresponding displacement of the adults when the return several years later,
3. Sea level: increasing convergence of coastal waters off northern Vancouver Island due to enhanced flow of Fraser River discharge to the north through the Strait of Georgia where it could act as a releaser to the adults,
   a: as indicated by increased mean sea level along the west coast of Vancouver Island,
   b: as indicated by varying north-south sea level differences along the east coast of Vancouver Island,
4. Fraser discharge: greater total amounts of Fraser River water diluting the offshore waters to the northwest of Vancouver Island.

The series Wickett considered for statistical fitting ranged from 1953–1973, which he then used to predict 1974–1977. Based on the statistical significance and high R^2 (ranging to 0.70), Wickett came to the conclusion that Fraser River discharge rate (represented by spring discharge and spring sea level at Tofino) had the greatest influence on the returning adult migration route (i.e.,

[6]Folkes, M.J. and Thomson, R.E. In Prep. El Niño events and marine migratory behaviour of adult Fraser river sockeye salmon.

ND). The IPSFC annual reports do not give any indication that these results were implemented in their annual forecasting exercise. The relationship breaks down when years after 1977 are added to the model. This was demonstrated by Hamilton (1985), and will be discussed later in this assessment.

In their 1983 annual report staff of the IPSFC demonstrated that a strong correlation exists between ND and spring time SST at Kains Island shore station. Thus the mechanism driving ND appeared to be linked to ocean conditions during the final months of the adult marine migratory period. Annual pre-season forecasts of ND based on on Kains SST appear to have begun in 1984 and since then have continuously relied on this indicator, albeit with a modified model structure (see "Kains Island SST Model" below).

Groot et al. (1984) hypothesized there may be a link between the seaward migration route by juveniles and the homing route taken by Fraser sockeye. The assumption was that a sequence of environmental cues would be imprinted on the emigrating juveniles, and that those cues could be retraced. However, later research (Groot and Cooke, 1987) failed to substantiate the hypothesis. Hamilton (1985) explored correlations between ND rate and marine environmental variables, run size, and run duration. While he found minimal differences in ND rate by cycle line (results replicated here using updated series in Figure 23), he did find a moderate, positive correlation between ND rate and "spawning run" [sic] duration (correlation coefficient =0.52, based on 1953–1977 data). More recent unpublished research from the PSC indicates that the ND rate of early run stocks is substantially lower than that for late run stocks (Mike Lapointe, Pacific Salmon Commission, Vancouver Canada, Pers. Comm.). Thus, years with large returns of late run stocks (likely leading to protracted run timing) would shift ND to higher than average rates (see the annual reports of both the PSC and FRP).

El Niño Events: Additionally, Hamilton (1985) showed a significant correlation between ND rate and the change in SST (based on shore station data) during the final 18 months at sea. The author concluded that *"Strong, persistent warming trends in these coastal waters are known to accompany most large tropical El Niño events; thus it often happens that large northern diversions of the Fraser sockeye occur after major El Niños"*. Groot and Quinn (1987) supports the results of Hamilton (1985) and confirmed the IPSFC research that after 1977 the ND rate was significantly correlated to monthly values (April through June) of SST at the Kains Island shore station. Both Hamilton (1985) and Groot and Quinn (1987) argued that Kains Island SST was not likely guiding Fraser sockeye migration, but that the SST was likely a reasonable surrogate for oceanographic conditions and variables at some larger scale, which in turn are affecting open ocean sockeye migration.

Consistent with earlier studies, McKinnell et al. (1999) also acknowledged that there is no obvious reason to believe why Fraser sockeye would be uniquely responding to SST off northwest Vancouver Island, but that these temperatures are more likely an indicator of larger marine processes that are affecting sockeye migratory behaviour. McKinnell et al. (1999) hypothesized that May SST at Kains Island tends to represent May SST in the Gulf of Alaska and North Pacific in general, which in turn could be influencing sockeye migration.

While surface water temperatures at Kains are representative of more open ocean temperatures in winter, this relationship does not always hold following the coast-wide spring transition affecting the boundary regions of the northeast Pacific. The spring transition generally occurs sometime after mid April (Thomson et al., 2014) and marks the transition from predominantly downwelling favourable southerly winds in winter to predominantly upwelling favourable northerly winds in summer. These upwelling favourable winds often give rise to strong equatorward flowing “jets” and associated filaments of cold surface water that flow southward from southern Queen Charlotte Sound to the northwest coast of Vancouver Island (see Figure 9). The cold filaments can have a profound influence on water temperatures in the vicinity of Kains Island, causing them to be distinctly lower than in the open ocean.

The changes in the coastal wind and runoff that follow the spring transition also affect the ability of the buoyancy-driven Vancouver Island Coastal Current to transport relatively low salinity water from Juan de Fuca Strait poleward along the inner continental shelf off the outer coast of Vancouver Island (Thomson et al., 1989). The coastal current (which originates primarily with Fraser River discharge into the Strait of Georgia) typically flows northward past Brooks Peninsula before being lost to tidal mixing and other dispersive mechanisms in the Triangle Island region off northwestern Vancouver Island. However, during periods of wind-generated upwelling, the current can leave the coast around Brooks Peninsula, leading to a possible reduction in surface ocean stratification and mixed layer depth in the vicinity of Kains Island. This process could decouple the SST at Kains Island from that in the offshore ocean. It is further possible that the link between ND rate and Kains Island SST is actually a response to olfactory clues present in the Fraser River water being advected poleward by the coastal current. Years when the coastal current continues past Kains Island at the time stocks are returning from the ocean (a condition that likely leads to relatively high SST in the vicinity of Kains Island) could cause stocks making landfall off Queen Charlotte Sound to favour the Johnstone Strait route. Returning stocks would also avoid swimming against the poleward flowing coastal current, which has a mean poleward velocity of around one knot or more within roughly 15 to 25 km of the coast. In contrast, years when the coastal current is not flowing past Brooks Peninsula at the time that fish are returning from the ocean (a condition likely to lead to relatively low SST at Kains Island) could cause the stocks to continue further south along the outer coast until they encounter a stronger Fraser River signal. Stocks would then favour the Juan de Fuca route to the Fraser River. The weaker Vancouver Island Coastal Current, combined with a surface intensified, wind-generated equatorward flow over the outer shelf and slope, would assist the southward migration of the fish toward the entrance to Juan de Fuca Strait. In this scenario, SST at Kains Island serves as a surrogate variable for the olfactory signal carried by the Vancouver Island Coastal Current.

Thomson et al. (1989) provide a more thorough description of the physical oceanography associated with the WCVI coastal current and the transition periods, which are likely to play an important role in salmon migratory behaviour and possibly survival. Additionally, Thomson et al. (1989); Thomson and Hourston (2011); Thomson et al. (2013) suggested that homeward migration could be temporarily disrupted by short term changes to the coastal current, leading to atypical migration timing, which may then affect ND rate (see Figure 10).

Kains Island SST Model: For the past decade, the annual ND forecast has been based on a statistical least squares fit using a generalized additive model (GAM) relating ND to the combined May to June average SST (Figure 11). While there is a substantial amount of scatter in the data, they appear to be distributed in two distinct modes (Figure 12, right panel), which the GAM model could fit reasonably well. Several recent years (2010, 2011, 2013) displayed lower than average SST and unexpectedly high ND. Other statistical models were evaluated, while retaining the same SST data series (2013 memo from Michael Folkes, DFO Science to the FRP chair.). Models considered in that memo included: step function, linear, logistic, and piecewise regression. None demonstrated superior performance to the GAM.

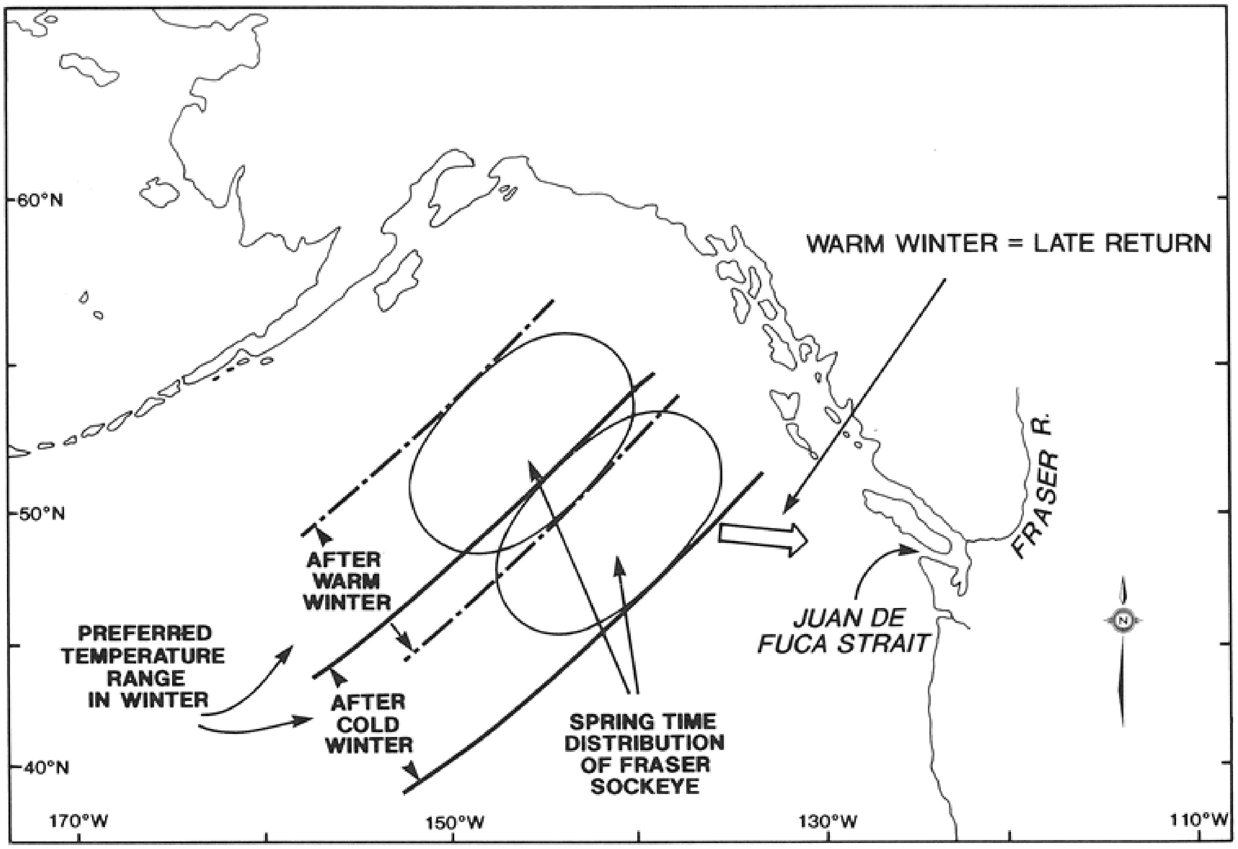


Figure 3. Diagrammatic representation of the temperature-displacement model believed to influence return timing of Fraser sockeye. Figure taken from Blackbourn (1987).

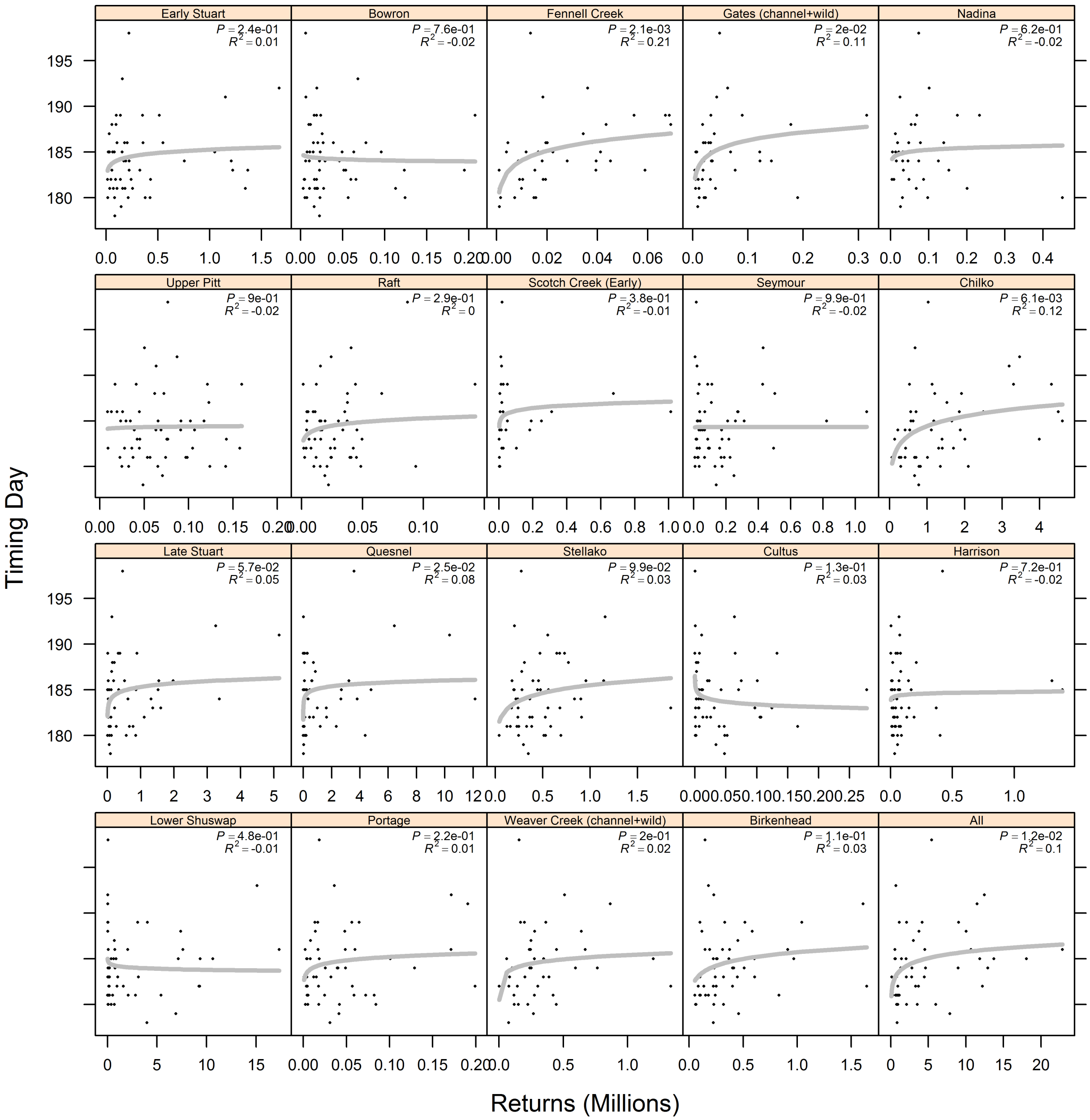


Figure 4. Relationship between Early Stuart timing and the logarithm of stock specific and Fraser total returns. The x-axis represents returns in millions of fish. The y-axis is ordinal date, which is number of days since December 31 of prior year. The grey, fitted lines are calculated from a linear regression between timing and $log(\text{returns})$. The statistical significance (P-value) and adjusted R^2 are included in each panel. This relationship was explored by Blackbourn (see footnote 2).

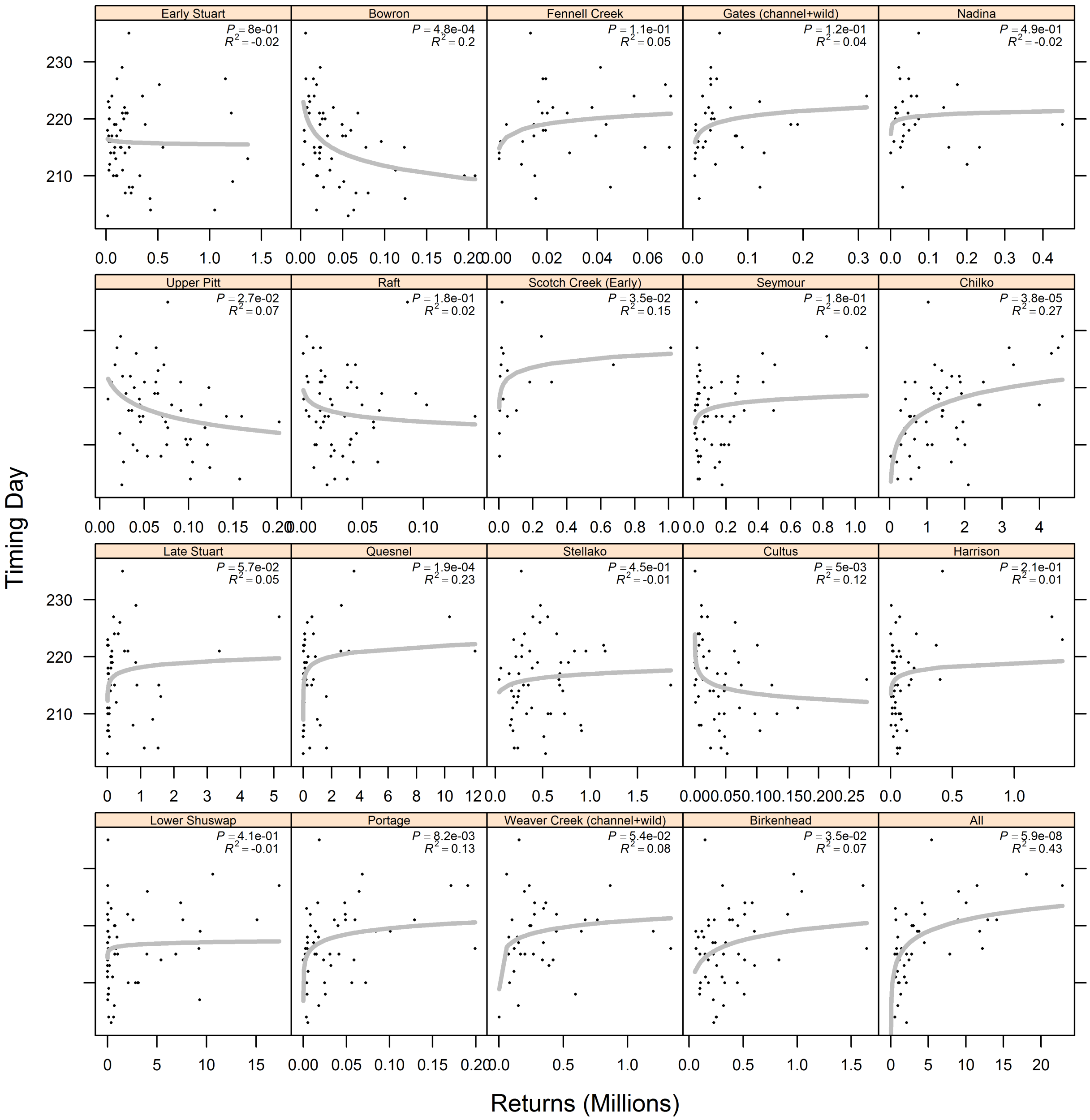


Figure 5. Relationship between Chilko timing and the logarithm of stock specific and Fraser total returns. The x-axis represents returns in millions of fish. The y-axis is ordinal date, which is number of days since December 31 of prior year. The grey, fitted lines are calculated from a linear regression between timing and $log($returns$)$. The statistical significance (P-value) and adjusted R^2 are included in each panel. This relationship was explored by Blackbourn (see footnote 2).

Fraser Sockeye

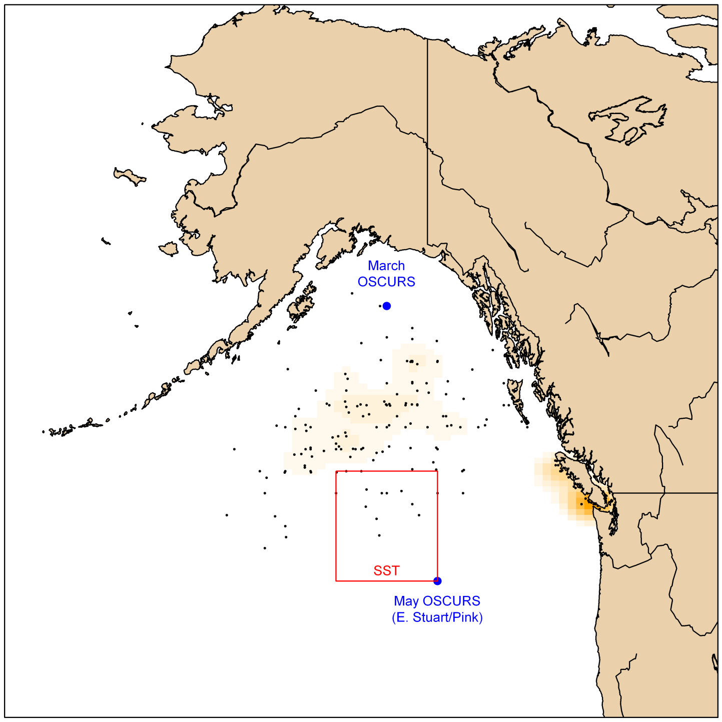


Figure 6. Mapped locations of environmental data (OSCURS current velocity and SST) used in both the Chilko and Early Stuart timing forecast models between approximately 1998–2011. Points are a generalized representation of Fraser sockeye distribution during spring of their return year. The information is based on sockeye tagging of fish later recovered in the Fraser River, derived from Myers et al. (1996). The darker density zone off Vancouver Island indicates that a substantial number of fish were tagged in that area and points are likely overlapping.

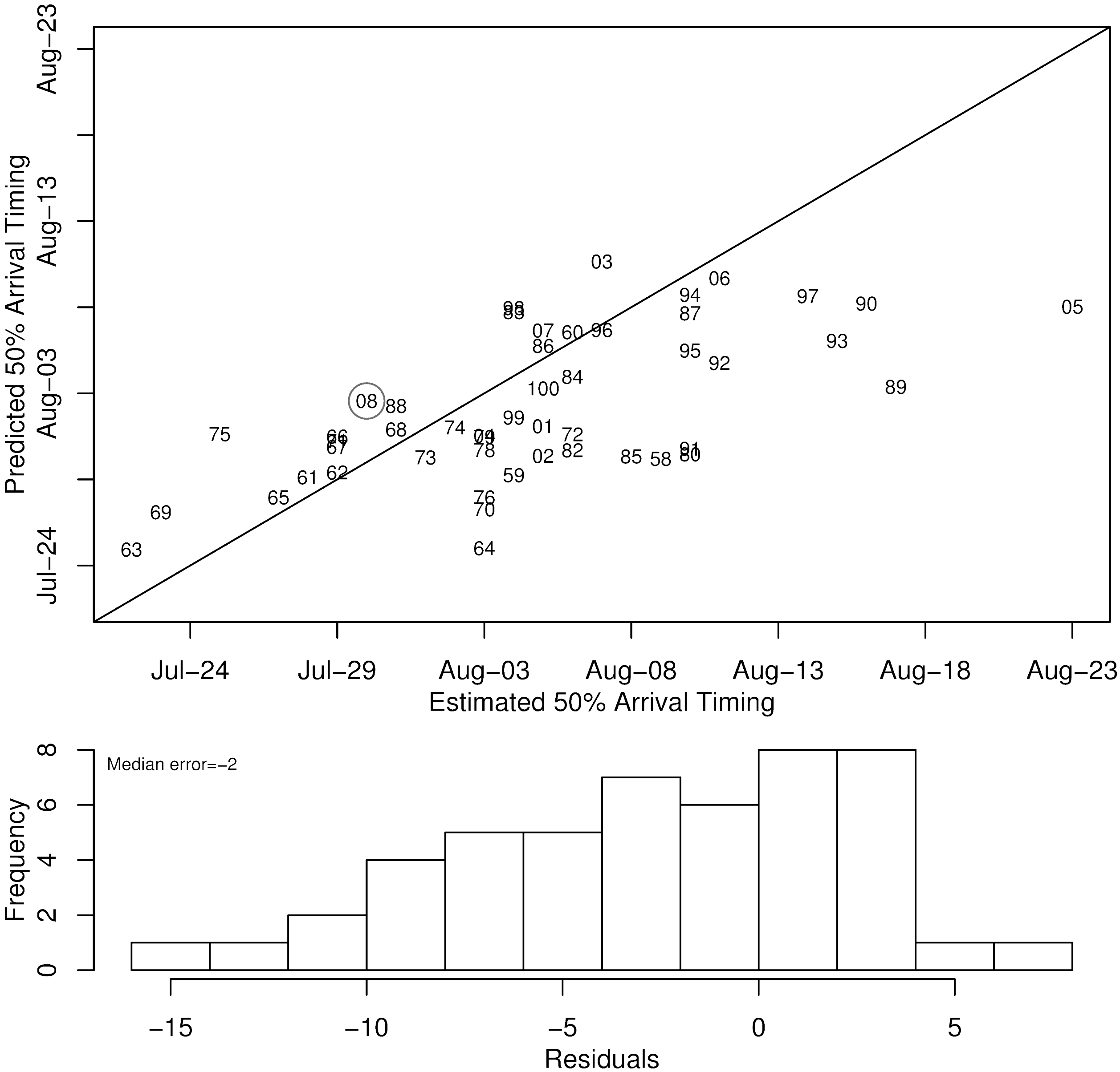


Figure 7. Retrospective evaluation of Chilko timing forecast using the recent OSCURS/SST model developed by Dave Blackbourn. The upper panel shows model forecast timing dates on the y-axis and post-season estimates of true timing dates on the x-axis. The diagonal line represents 1:1 slope. Values falling close to the line would suggest a year that was accurately forecasted. Values above the line are years with forecasts later than the true timing and values below the line are years that forecasted earlier. The two digit value of each data point corresponds to the return year. The lower plot, a histogram, shows residuals taken from the upper plot (i.e., post season date subtracted from forecast date). The x-axis (residuals) is in days. The median value of these residuals is -2 days, suggesting this model tends to forecast timing 2 days earlier than the true value. More precisely, if a line were fitted to the upper panel data, the slope would suggest the model fails to predict later timing.

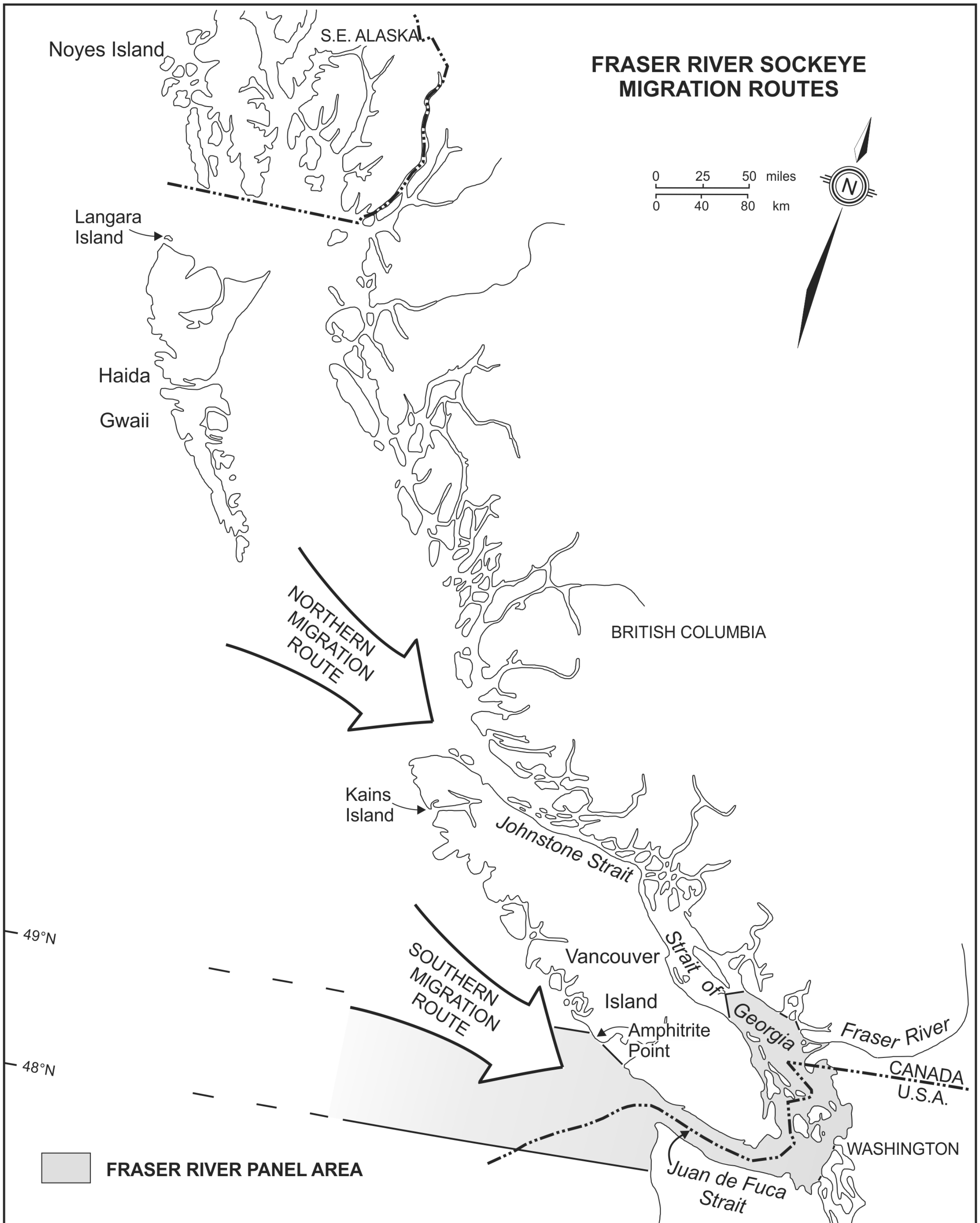


Figure 8. B.C. coast map depicting the two routes taken by adult Fraser sockeye when returning to the Fraser River. The proportion of total returns via the northern route is considered the ND rate. Image courtesy of the PSC.

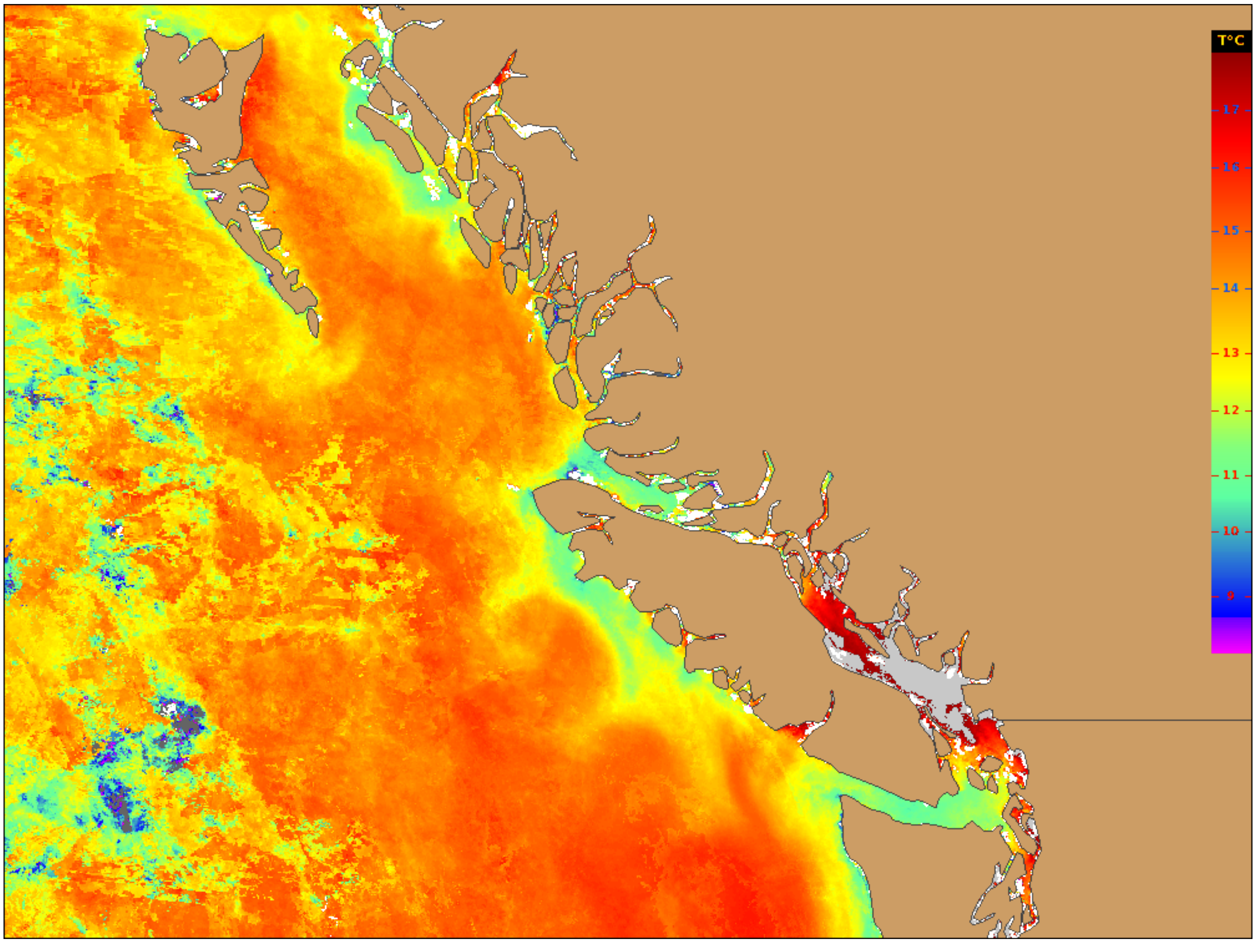


Figure 9. Average sea surface temperature (SST) seaward of British Columbia for 1-15 July 1994 from the NOAA Pathfinder satellite. Image shows the cold water jet off northern Vancouver Island. Courtesy of Gary Borstad of ASL Environmental Sciences, Ltd. (Sidney, B.C.).

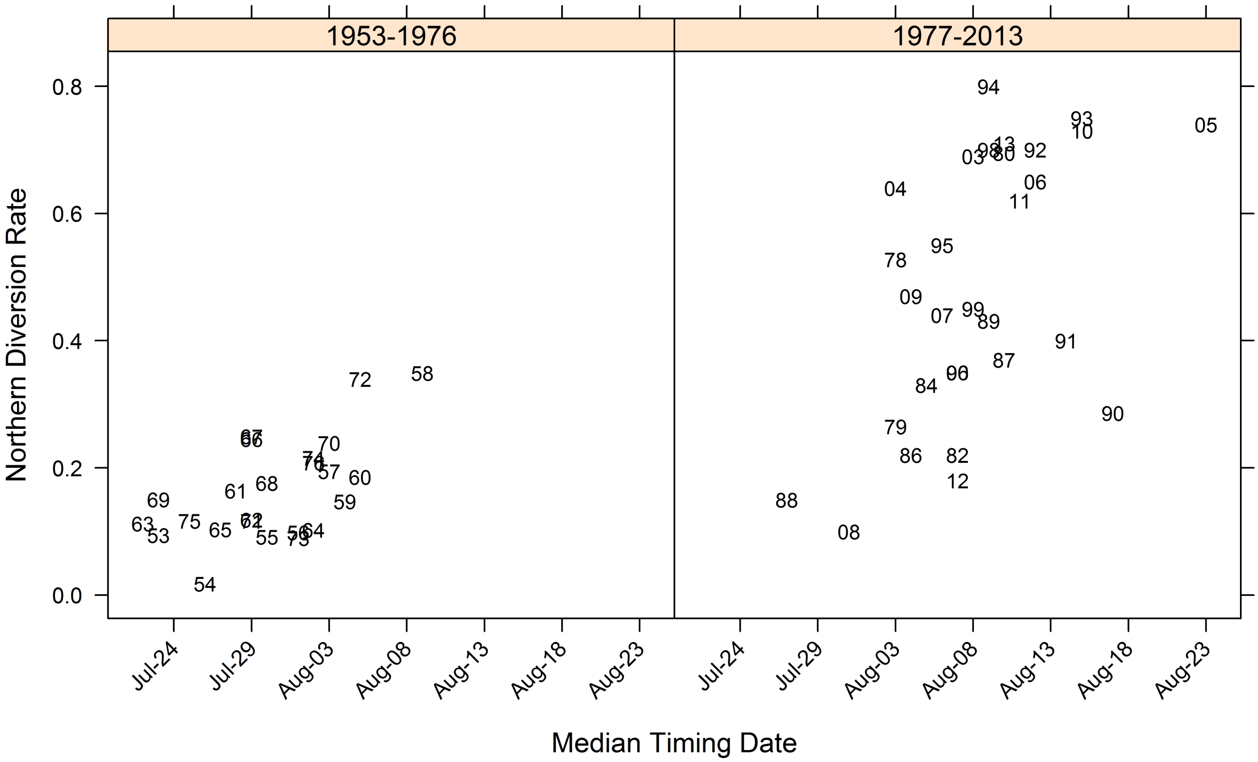


Figure 10. Scatterplots showing positive association between the ND rate and Chilko return timing. ND is the estimated proportion of total returns for all enumerated Fraser sockeye stocks that migrate from offshore to the Fraser river via Johnstone Strait. Data are parsed into two sets: 1953–1976 and 1977–2013. The number of each data point corresponds to return year.

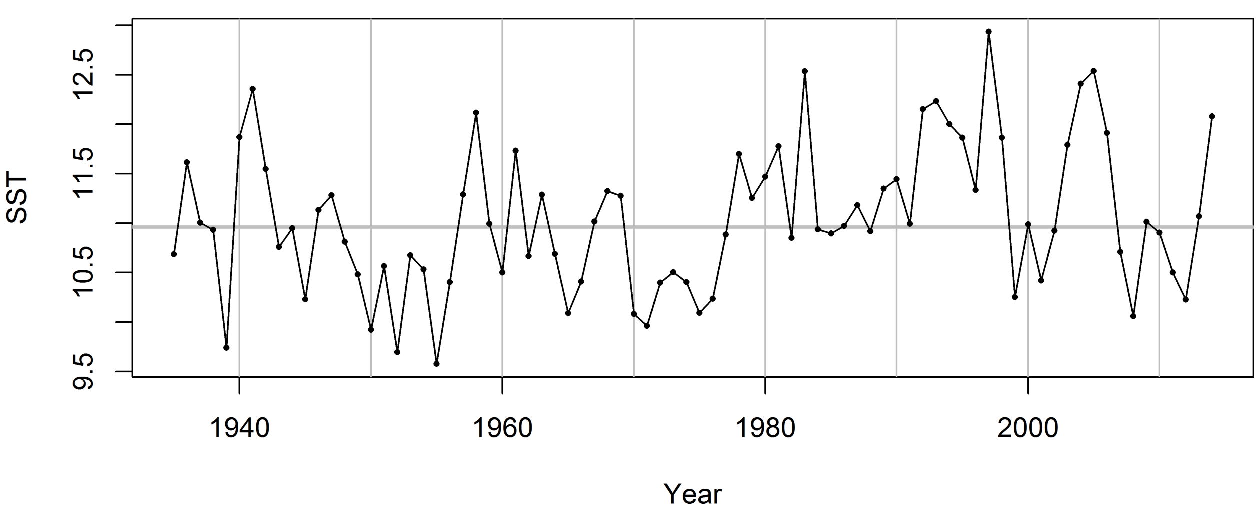


Figure 11. Time series of May to June average SST at Kains Island. Horizontal line is the time series median.

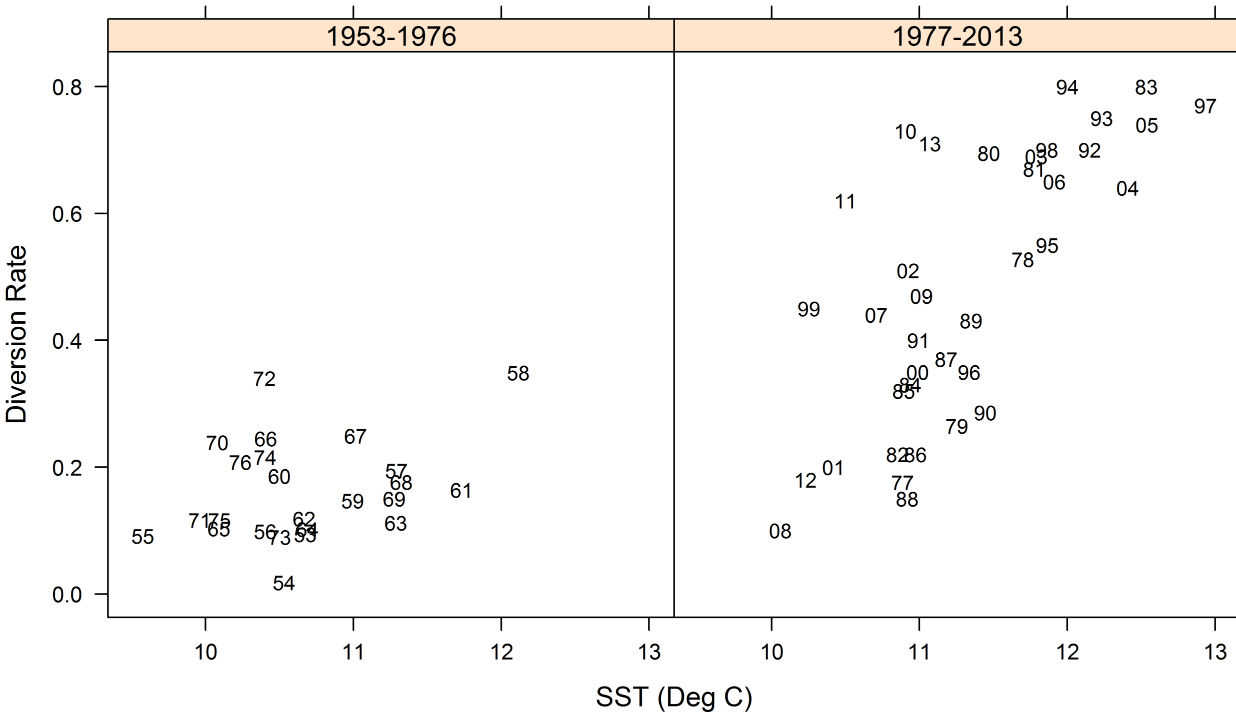


Figure 12. Scatterplots showing positive association between Fraser sockeye ND and Kains Island average SST during May and June of the return year. ND is the estimated proportion of total returns for all enumerated Fraser sockeye stocks that migrate from offshore to the Fraser river via Johnstone Strait. Data are parsed into two sets: 1953–1976 and 1977–2013. The number of each data point corresponds to return year.

2.2 A NEW APPROACH

2.2.1 Timing Forecasts

The accuracy and precision of the prevailing timing forecast model are limited by the influence of current velocity data estimated for a place and time that may no longer play a significant role in the ensuing Fraser sockeye migratory behaviour. Recognizing this, during 2010-2013 the PSC Southern Endowment Fund (SEF) funded the authors (led by R.E.T.) to develop a new, physical oceanographic model (North East Pacific Salmon Tracking And Research (NEPSTAR)) to provide near real-time estimates of current velocity that could then be used in new timing forecast models. The term NEPSTAR is used interchangeably in this paper to represent two aspects of the research. First, ocean modelling of current velocity (what the NEPSTAR/Princeton Ocean Model (POM) model does), and second, NEPSTAR-regression model analysis, which uses both NEPSTAR-derived current velocity and other variables to predict timing. In addition to the NEPSTAR approach, we explored other oceanographic data sets that are freely available from both the Canadian and U.S. governments.

As with previous models, forecasts of Fraser River sockeye salmon marine arrival times of cumulative 50% abundance in Juan de Fuca Strait/Area 20 (for individual stocks) and ND through Johnstone Strait (for an aggregate of stocks) are based on historical observations (of timing and ND) provided by the PSC.

The observations of marine timing data are first fitted (by single variable statistical models) to more recently available series of predictor variables. This allows us to determine which variables, geographical regions, time lags, and time-averaging periods yield statistically significant relationships. These single variable models then form the basis of multiple linear regression (MLR) models for forecasting both marine arrival times and ND (Table 1). The model selection process is described in subsection 4.3.

Oceanic variables considered for inclusion in the MLR models are those that characterize near surface conditions where salmon reside during their period of ocean residency, both near the coast and in the offshore northeast Pacific Ocean. Ocean residency spans three calendar years up to and including the year that the salmon stocks return to their river. Since marine arrival timing is resolved to the day, environmental variables at daily resolution are examined. These include both observed and modelled variables[7] (Table 2). The core variables used include SST and sea surface salinity (SSS), near-surface ocean currents, and surface wind stress (as a proxy for near-surface ocean currents and vertical mixing).

In exploring timing forecasts of Bristol Bay sockeye, Ruggerone (2004) evaluated numerous environmental variables including North Pacific SST at varying locations and times, land and river temperature, barometric pressure, tide levels, and an index of lunar apogee. Single variable linear regressions were applied to find the best statistical fits, and additional covariates were added in steps to search for improved R^2. Ruggerone demonstrated that while SST was a significant indicator of migration timing, Bristol Bay sockeye were most strongly correlated to the winter to spring SST difference. As such, we include winter to spring SST difference as a variable in our evaluation.

[7] See Section 3.2.7 for their description.

Table 1. The statistical models evaluated to forecast return timing or diversion rate.

Forecast	Model Type	Statistical Model
Timing or Diversion	Naive	Series mean
Timing or Diversion	Naive	Four year mean
Timing or Diversion	Naive	Eight year mean
Timing or Diversion	Naive	Series median
Timing or Diversion	Naive	Four year median
Timing or Diversion	Naive	Eight year median
Timing or Diversion	Naive	Like last year
Timing or Diversion	Fitted	Single variable linear regression
Timing or Diversion	Fitted	Single variable GAM
Timing or Diversion	Fitted	Single variable shape constrained generalized additive model (SCAM)
Timing or Diversion	Fitted	Nepstar MLR
Timing or Diversion	Fitted	non-Nepstar MLR
Diversion	Fitted	MLR (Wickett model)

2.2.2 Diversion Forecasts

There are numerous oceanographic and geophysical variables that may affect the ND. It has been assumed that the latitude of landfall for returning adult Fraser sockeye determines whether their entrance into the Strait of Georgia is predominantly via Juan de Fuca Strait or Johnstone Strait[8]. We assume that the migration pattern of adult Fraser sockeye is influenced by environmental factors during the marine period of their life history. As such, we evaluate ND forecast models using the same approach applied to the timing forecast model evaluation. All the same oceanic variables and model structures were considered. Additionally, we re-evaluate the model developed in Wickett (1977) using the same variables described in his paper, but now extended to 2011.

The possible influence of earth's geomagnetic field on Fraser sockeye ND has recently been explored (Putman et al., 2013, 2014*a*,*b*). The first evidence that earth's magnetic field influences animal (specifically bird) migration and homing behaviour was published five decades ago (Merkel and Wiltschko, 1965). Since then a substantial foundation of work has been published regarding its effects on insects and birds (Papi, 1992; Guerra et al., 2014), fishes (Smith, 1985; Quinn, 2005), reptiles (Lohmann et al., 2008), and mammals (Baker, 1978). The biological base of geomagnetic influence on animal perception of location and direction of movement are outlined in Wiltschko and Wiltschko (2001) and Wiltschko and Wiltschko (2006). Putman et al. (2013) suggest properties of earth's geomagnetic field can be correlated to ND, and we find it can explain up to 43%[9] of the variation in the ND series. Thus, the correlation is moderate but does not account for the majority of variation in the ND series. We include in our appraisal of statistical models the same geomagnetic variables considered in the papers of Putman *et al.*. but unlike Putman *et al.* we have not limited the models to linear regression.

[8] There has been suggestion that unusual events do occur such that high ND does not follow from a more northern landfall, as occured in during at least one year in the 1990s (Dave Blackbourn, Retired DFO, Nanaimo, B.C., Pers. Comm. October 23, 2015).

[9] Putman et al. (2014*a*) indicate that *"geomagnetic imprinting accounted for up to 45.0% of the variation in sockeye ND rate ($p <$0.000001, $n =$60)"*, which we could not exactly replicate using their data.

2.2.3 The Influence of El Niño Events

Some climate models indicate the frequency of extreme El Niño events may double during the 21st century (Cai et al., 2014). The relationship between El Niño events and either migration timing or ND is explored. Results from these analyses are not applied to forecasting model evaluation, but serve as an exploratory exercise to inform decision makers regarding the need for future research into the impact of El Niño/Southern Oscillation (ENSO) events on Fraser sockeye migratory behaviour.

3 DATA SOURCES

3.1 THE DEPENDENT VARIABLES

3.1.1 Return Timing

Marine return timing of Fraser river sockeye salmon is now defined as the date when 50% of a stock has passed through a common point along the migration route en-route to their natal freshwater system for spawning. Data series of marine return timing estimates commence in 1951 (Chilko) and 1953 (Early Stuart) and are generated by staff of the PSC. The timing data have undergone revision several times during recent decades (Blackbourn, 1987, Blackbourn (1992) (see footnote 2) and Jim Cave, PSC, 2011 Pers. Comm). However, estimates were always intended to reflect the date of peak timing referenced to outer Juan de Fuca Strait (see Gilhousen (1960)).

Current estimates for the time series beginning in 1982 are based on daily reconstructions of the migratory abundance profiles. The “run-reconstruction” methods use the combination of (1) catch estimates by stock, area and date, (2) escapement estimates by stock and date and (3) fixed migration rates between areas to generate the daily migration profiles for each stock. Catch estimates by stock ,area, and date come from the combination of various catch monitoring programs, fish sales tickets, and the application of stock identification techniques applied to sub-samples taken from catches. A very high fraction of the catch data used in marine reconstruction comes from commercial fisheries (see DFO (2009) for a review of catch estimates). Daily escapement information comes from the hydroacoustics program that has operated at Mission since 1979, coupled with daily samples taken from test fisheries conducted in the lower Fraser River that are used for stock identification. Migration rate information comes from a variety of sources (e.g. historical tagging studies; Verhoeven and Davidoff (1962)) and the consistency in migration rates over time was first documented by Killick (1955). More recently this consistency in migration rates between areas and across years has been validated by large scale acoustic tagging programs (English et al. (2005); Robichaud and English (2007); Robichaud et al. (2011)). The detailed algorithms used in run-reconstruction were first described by Starr and Hilborn (1988) and later refined by Cave and Gazey (1994). The consistency in migration rate information across years and stocks permits the daily escapement and catch estimates by area to be aligned to a common reference point. The common reference point used by the Pacific Salmon Commission in these reconstructions is outer Juan de Fuca Strait, referenced as DFO statistical area 20 (see Figure 14).

In 2011, the timing data for 1980–2010 were revised based on a re-interpretation of what defines the 50% date (Jim Cave, PSC, 2011 Pers. Comm). Prior to this revision, the 50% date was the date falling closest to the 50% level of cumulative daily abundance. For example, if the cumulative run estimate for July 6 was 49.5% and July 7 was 55%, the 50% date was historically defined as July 6. In the revised approach 50% of the run would have been reached on July 7 so that date is the new estimate.

Marine timing is then defined as the date when 50% of a stock's total reconstructed abundance to the area 20 reference point is exceeded (Figure 13). Note that the reconstructed abundance includes catches on all migration routes including both Juan de Fuca and Johnstone Strait. The use of the Juan de Fuca reference point is largely a historical artefact introduced by the IPSFC because of the magnitude and historical consistency of catch data from the southern approach areas in earlier years (e.g., Gilhousen (1960)). Thus, despite the fact that Johnstone Strait has been the predominant migration route taken in recent years (Figure 22), the Juan de Fuca reference date has been retained to describe timing. In practice, given the average two-day offset between timing to outer Juan de Fuca and the middle of upper Johnstone Strait (Robson Bight), a Juan de Fuca date (DFO statistical area 20) can be easily translated to a date for Johnstone Strait (middle of DFO statistical Area 12; e.g., Aug 4th in Juan de Fuca would translate to Aug 2nd in Johnstone Strait).

The sensitivity of marine timing estimates to variation in the three principle input data sources has not been formerly quantified. That said, PSC staff involved in estimating these components have not expressed concerns about time trends or systematic changes in methods that could lead to significant biases in the estimates. However, there are periods in which the methods used to generate the input data have varied and these are outlined below.

The potential influence of catch and escapement data varies both intra and inter-annually. The impact of this factor on estimates of Early Stuart timing is likely small, because there has been very little marine harvest of Early Stuart sockeye since 1980 (average post-1980 exploitation rate of 10%; Mike Lapointe 2015, PSC, Pers. Comm.). Thus, Early Stuart timing estimates are largely based on daily escapement data. Conversely, the annual exploitation rates for Chilko sockeye have been much higher (average post-1980 exploitation rate of 46%; Mike Lapointe 2015, PSC, Pers. Comm.) and timing estimates for that stock is more dependent on catch data.

The methods used to generate daily abundance estimates for hydroacoustics data collected at Mission changed in 2004. Prior to 2004, estimates were generated from single beam acoustics equipment deployed on a vessel that transected the Fraser River between 150–200 times per day, seven days per week each summer during periods of sockeye and pink salmon upstream migration. Late in the season when either acoustic abundance declined to low levels or Fraser River pink salmon abundance predominated, the acoustic program was terminated and estimates were derived from in-river test fishery catch per unit effort (CPUE).

The accuracy of acoustics methods has been the topic of a number of post-season reviews (e.g., Pearse and Larkin (1992); Fraser River Sockeye Public Review Board (1995); Williams (2005)). However, plots comparing upstream spawning ground estimates with acoustic estimates obtained from from the single beam program (1977–1992) do not suggest issues with systematic bias (PSC, 1996, Appendix A p. 23–25). Nevertheless, concerns about potential inaccuracies of the single beam estimates at Mission led to a period of research and development at Mission with the goal of improving the accuracy of estimates (e.g., Mission Hydroacoustic Facility Working Group (1994); Xie et al. (1997, 2002); Xie (2002)). Beginning in 2004, the split beam acoustics system deployed on the vessel and the sideward looking split beam system deployed on the south bank of the Fraser River were used to generate estimates of escapement. Beginning in 2011, data from a DIDSON sonar system deployed on the north bank of the Fraser River was incorporated into the estimates. Favourable comparisons in 1996, 1997, 1998 and most of the years spanning the period 2008–2015 with acoustics estimates from a second site (Qualark) located approximately 80km upstream of Mission, suggest these changes have largely been successful in addressing the principle biases associated with the single beam methodology (Lapointe, M. PSC 2015 Pers. Comm.). But these comparisons have also suggested that some concerns remain (e.g., deviations in late September 2014, have raised concerns about potential bias late in the season during years with abundant late-timed sockeye runs; Lapointe, M. PSC 2015 Pers. Comm.). Estimates of Chilko escapement in past years have been generated almost entirely by the combination of acoustics and stock identification. However, because Early Stuart sockeye enter the Fraser river in late June, daily abundance estimates earlier in their upstream migration are estimated from the CPUE obtained from in-river test fisheries in some years. Small test fishery catches, resulting from low overall abundance and/or high river discharge will result in increased imprecision and potentially bias in portions of daily abundance time series in some years.

Stock identification techniques were based primarily on scale pattern analysis through 2001 (Gable and Cox-Rogers, 1993) and DNA based genetic techniques since 2002 (Beacham et al., 2004). The accuracy and precision of estimates from both methods depends on two primary factors (1) the distinctness of the markers used to distinguish populations and (2) the relative abundance of the population; both factors are relative to co-migrating populations. The transition to genetic markers has greatly improved the distinctness of the markers used for all Fraser sockeye including Early Stuart and Chilko populations. The marine timing of Early Stuart sockeye migrations was thought to be very distinct from all other Fraser sockeye populations; with the greatest overlap occurring with Lake Washington sockeye, a non-Fraser population that co-migrates with Early Stuart sockeye in Juan de Fuca Strait. More recently, genetic stock identification results have indicated that sockeye bound for the Chilliwack lake watershed also co-occur with Early Stuart sockeye in samples taken during much of their migration. Thus, it is possible that the reconstructed abundances of Early Stuart sockeye could contain small abundances of Chilliwack sockeye during the years prior to 2002, when scale patterns were the primary stock identification method. Chilko scale patterns were distinct enough and relative abundances large enough to permit accurate identification in most years, except for a few years when scale patterns overlapped substantially with those of Quesnel sockeye when Quesnel sockeye were very abundant (late 1990s to mid-2000s). The prevalence of a parasite, *Myxobolus articus*, was used in a number of these years to help distinguish Quesnel from Chilko (PSC, 1999, see p. 29).

The migration rates of Fraser sockeye are unlikely to be fixed between areas, stocks and years. Intra and interannual variation in these migration speeds introduces sources of variation in timing estimates that have not been quantified. However, the tagging studies cited above have not detected systematic changes in migration rates, despite the fact these studies provide snapshots of migration rate data that span a period of over 50 years. This gives us confidence that intra-annual variation in the marine timing index does reflect variations in arrival timing of sockeye salmon to the coast and thus can be used to identify potential environmental correlates.

Lastly, concerning the described revisions for estimation of the return timing data, while the full time series is used in the descriptive plots below, a shorter time series (1992–2012) was used in the evaluation of models used to predict timing.

Historically, Early Stuart timing estimates have been calculated based on their cumulative passage past the Patullo Bridge near New Westminster on the main arm of the Fraser River. This

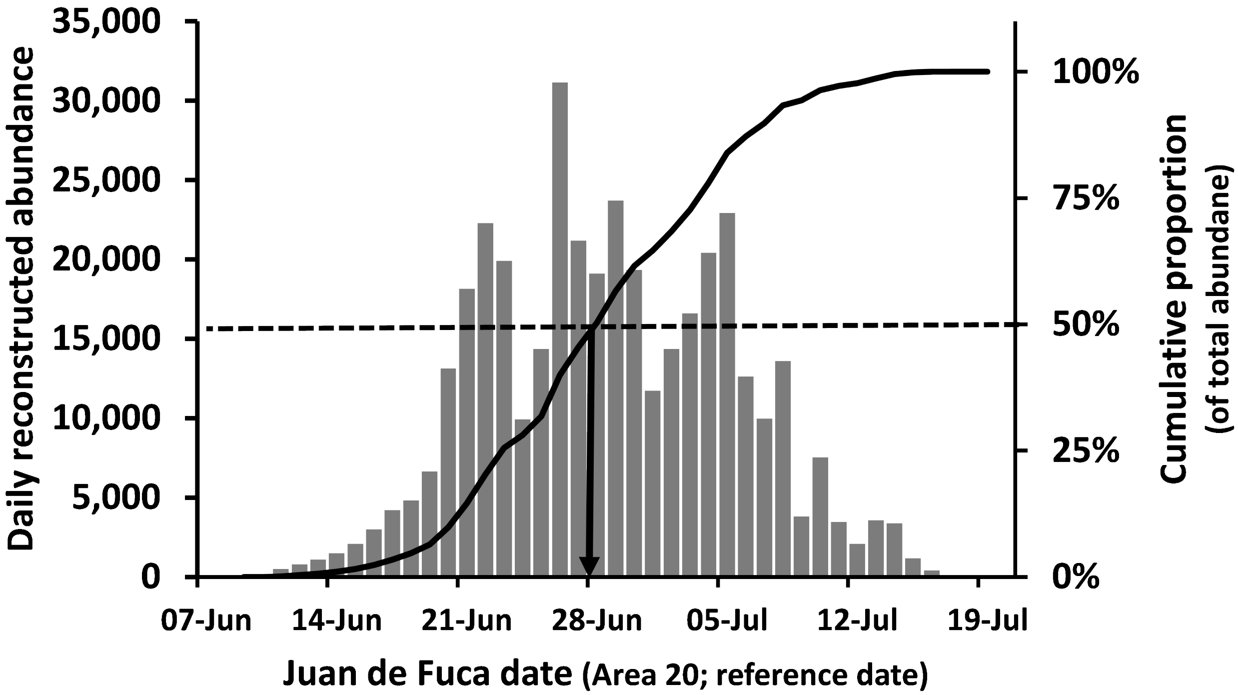


Figure 13. Example of the method used to estimate marine timing. Histogram of daily reconstructed abundance, defined by the left hand y-axis (number of fish). The cumulative proportion of the total abundance is plotted on the right hand y-axis (number of fish). The x-axis represents the calendar data, fixed to Juan de Fuca Strait. The marine timing date is defined at the date when the cumulative daily abundance exceeds 50% (horizontal dashed line) and is denoted by the vertical arrow (June 28). Data are for Early Stuart sockeye in 2000.

site was chosen because historical densities in marine areas were too low to estimate a marine timing date. The historically estimated migration delay between Area 20 and Patullo Bridge is five days. Thus, converting the Early Stuart timing to an Area 20 equivalent requires subtraction of five days. Due to a change in practice within the last five years, the PSC now references Early Stuart timing estimates to Area 20. We maintain that Area 20 reference in this analysis. In the interest of simplicity and clarity all data are represented here by their Gregorian calendar date. Prior to analysis these dates are converted to ordinal date (Wilimovsky, 1990). Leap years are respected such that August 1 on a non leap year has an ordinal day value of 213, while on a leap year the value is 214.

Exploratory Evaluation: Since the 1970s Early Stuart run timing has appeared to trend toward later dates (Figure 15), but this change is not statistically significant. The variance in the timing signal was relatively low during the 1970s and 1980s, but has become much greater since the 1990s. To match the period of the environmental data series used as covariates, the marine timing series was limited to 1983–2012. During this period, there was no significant trend in timing. To determine if there are any cycle specific differences in timing statistics, both box-whisker and time series plots of timing data, by cycle, were produced (Figures 16 and 17). These plots reveal no significant difference in median timing date nor any trend differences between cycles.

Chilko timing since the 1960s shows a statistically significant trend in timing to later dates (Figure 18). The slope averages 2.4 days later per decade. However, there is no significant trend in timing when considering just the years to be used in the present evaluation (1983–2012). As for Early Stuart, analysis of variance indicates that there is no cycle specific difference in median timing date nor difference in slope and intercept of the cycle specific timing trend for the Chilko stock (Figures 19 and 20).

The time series of median timing date for each stock during 1983-2012 was used in the timing forecast models and was tested for partial autocorrelation (Figure 21). While Chilko shows no autocorrelation, there is a minor, but statistically significant lag one (i.e., one year) autocorrelation in the Early Stuart timing series. That is, there appears to be some residual "memory" in the series such that the timing of Early Stuart sockeye for the present year is partially correlated with return timing during the previous year. The practice of removing autocorrelation from time series is described in Hare (1996) and Pyper and Peterman (1998). However, the latter paper also discusses the downside of pre-whitening time series to remove low-frequency variability when considering its role in long-term biological processes. Thomson and Emery (2014) discuss the importance of considering autocorrelation when determining the effective number of truly independent degrees of freedom in a time series. As the Early Stuart lag-one autocorrelation is at the edge of the 95% confidence interval, it was not adjusted.

3.1.2 Northern Diversion Rate

The ND rate is estimated by staff of the PSC. Similar to methods used for timing, run-reconstruction techniques were also used historically to estimate ND. Annual estimates of the ND were estimated by the ratio of the annual total abundance of Fraser sockeye migrating via Johnstone Strait (N_j) divided by the annual total abundance of Fraser sockeye migrating via both approaches (N), where the reconstructed daily abundances are summed along all days (n) in each year:

$$\text{ND} = N_j/N = \frac{\displaystyle\sum_{i=1}^{n} N_{ji}}{\displaystyle\sum_{i=1}^{n} N_i}$$

See Putman et al. (2014*a*) for test fishery based equations.

Errors in stock identification are moot, since Fraser sockeye predominate on both routes and the estimate of ND is for the aggregate Fraser sockeye population. Fraser sockeye were subject to relatively large exploitation rates in most of the years during the period 1953–1994 (average marine area exploitation rate 1952–1994 72% of the total return M. Lapointe, 2015, PSC Pers. Comm.). Consequently, the ND estimates in those years were heavily dependent on the catch data associated with areas located along each migration route. This dependency was confirmed by McKinnell et al. (1999) when they found that a regression relating the PSC reconstruction based estimates of ND to the ratio of approach route catches for the years had an R^2 of 0.93, intersected the origin and had a slope that was not statistically significantly different from 1.0. McKinnell et al. (1999) also conducted Monte Carlo trials to explore the sensitivity of ND estimates to variation in the harvest rates associated with fisheries on each migration route. They found that the ND estimates obtained only from the ratios of approach route catches were reasonable estimates of the underlying (simulated "true" ND values) for approach route harvest rates varying from 40–80%. However, the range in the potential bias of the estimates increased if approach route harvest rates were estimated with error and was largest for intermediate ND

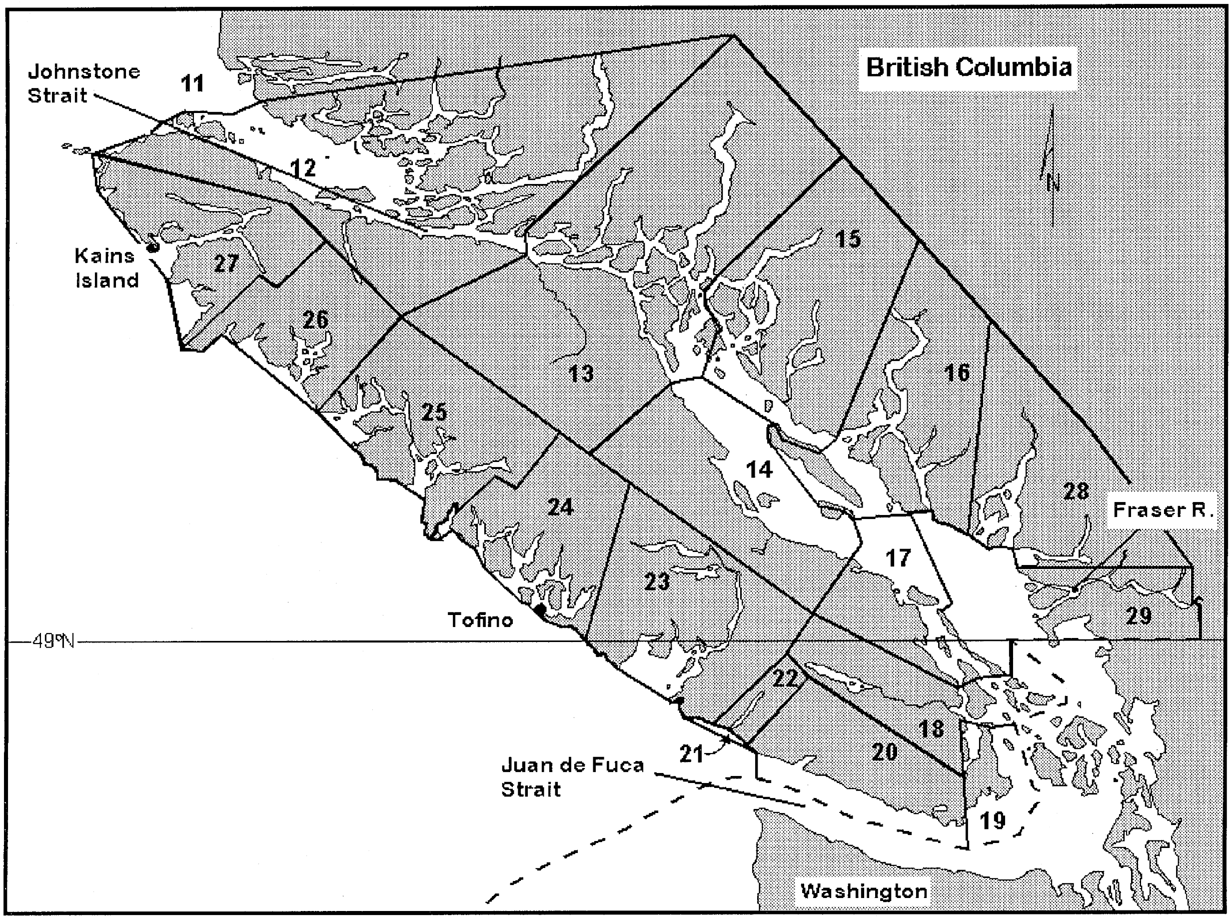


Figure 14. Vancouver Island showing Johnstone Strait in the north and Juan de Fuca Strait in the south. DFO statistical area 20 is within the area of Juan de Fuca and is the geographic area connected to Fraser sockeye timing. Image taken from McKinnell et al. (1999). Fraser sockeye return via both Johnstone Strait and Juan de Fuca Strait. Kains Island shore station, the source for SST data, is identified on the northwest corner of the island.

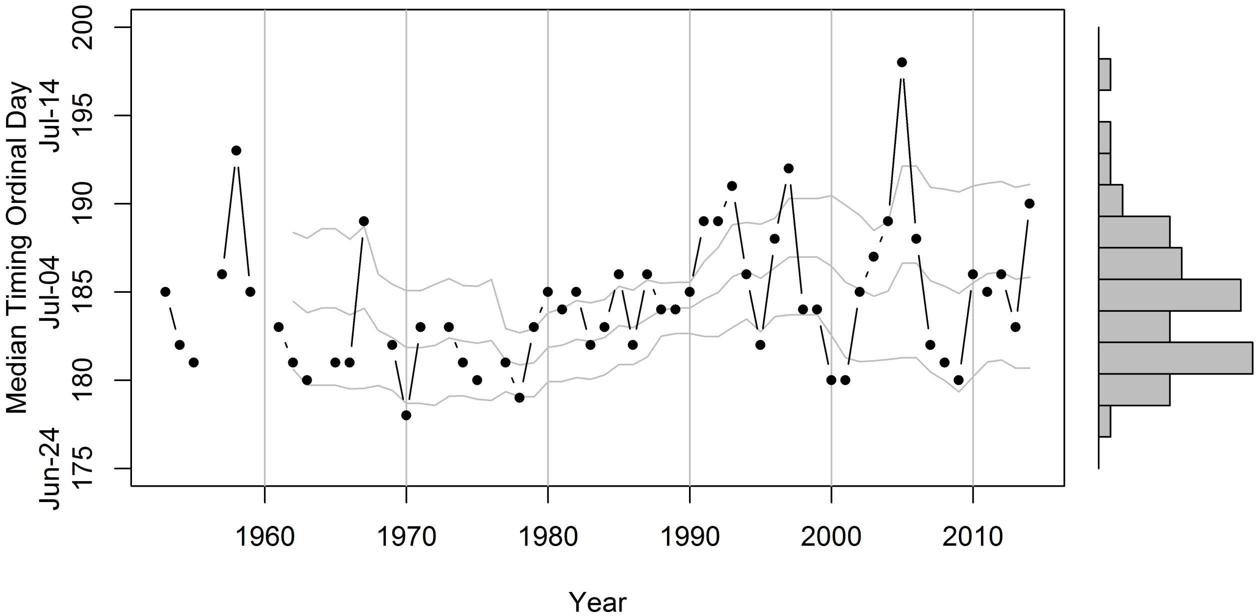


Figure 15. Time series of post-season estimated Early Stuart median arrival date to DFO statistical area 20. The y-axis has both calendar and ordinal date for comparison with other data and plots. The grey lines are the ten year running averages of median and standard deviation (SD), which were calculated in log-space. The histogram is scaled to density (fraction of the total numbers of occurrences).

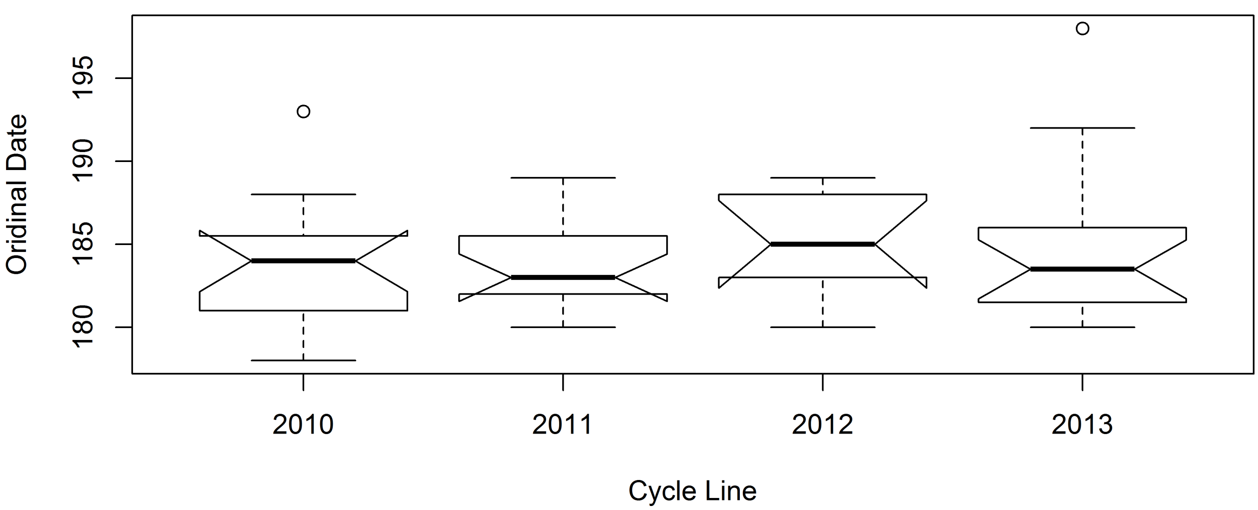


Figure 16. Box and whisker plots of Early Stuart timing dates by cycle line. A cycle line represents shared intergenerational lineage. For example Early Stuart sockeye returns in 2014, 2010, 2006, . . . represent a common cycle line. Overlap of box notches suggests there is no cycle specific differences in Early Stuart return timing dates.

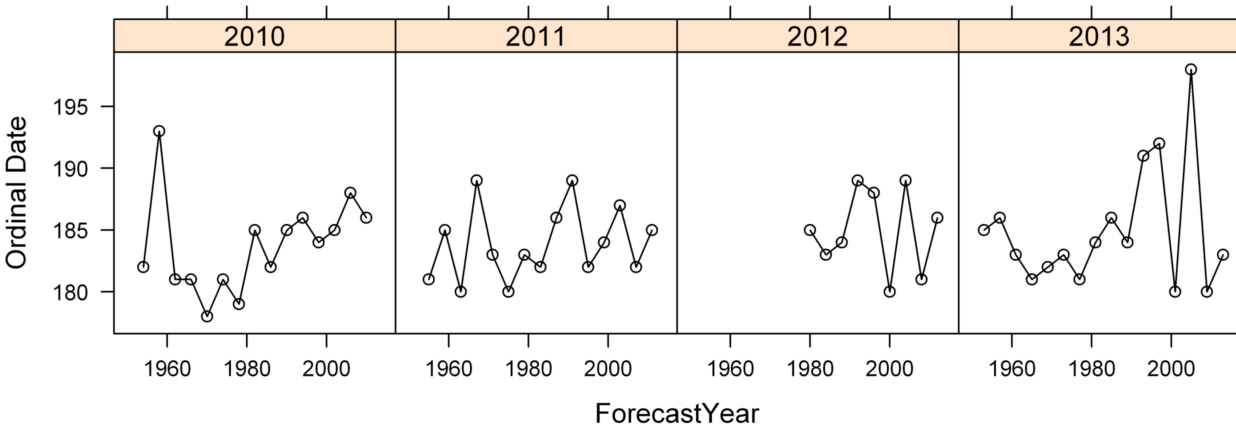


Figure 17. Time series of Early Stuart median arrival date to DFO statistical area 20, by cycle line. These plots were created to explore for cycle specific trends in return timing date. No differences appear to exist.

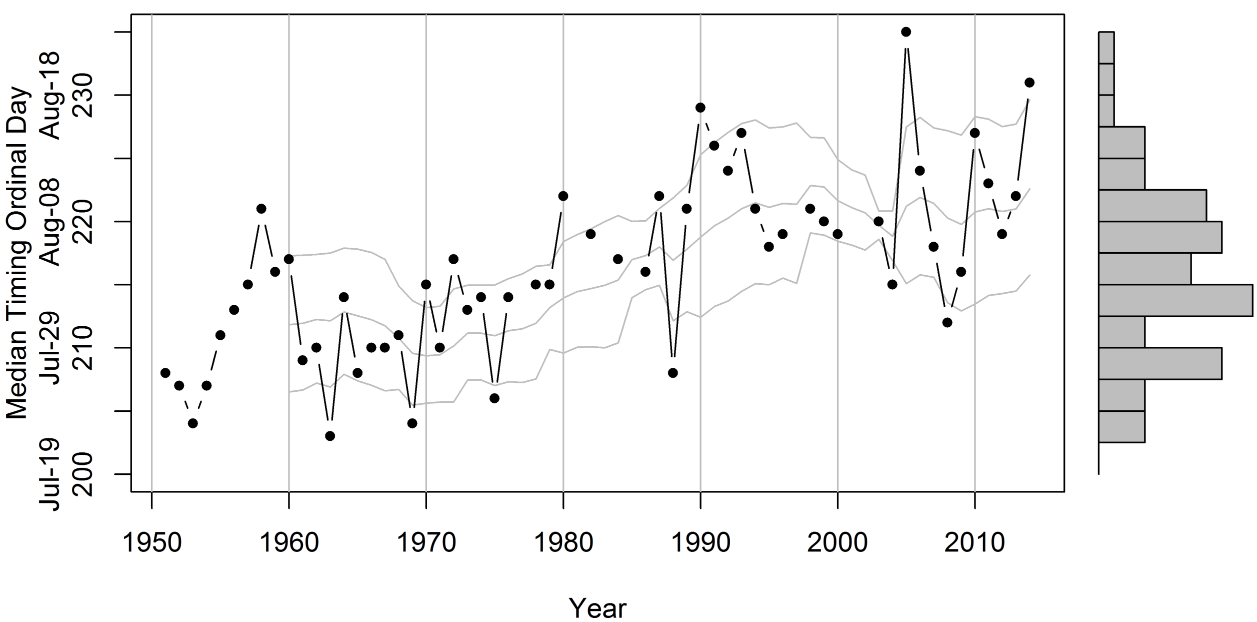


Figure 18. Time series of post-season estimated Chilko median arrival date to DFO statistical area 20. The y-axis has both calendar and ordinal date for comparison with other data and plots. The grey lines are the ten year running averages of median and SD, which were calculated in log-space. The histogram is scaled to density (fraction of the total numbers of occurrences).

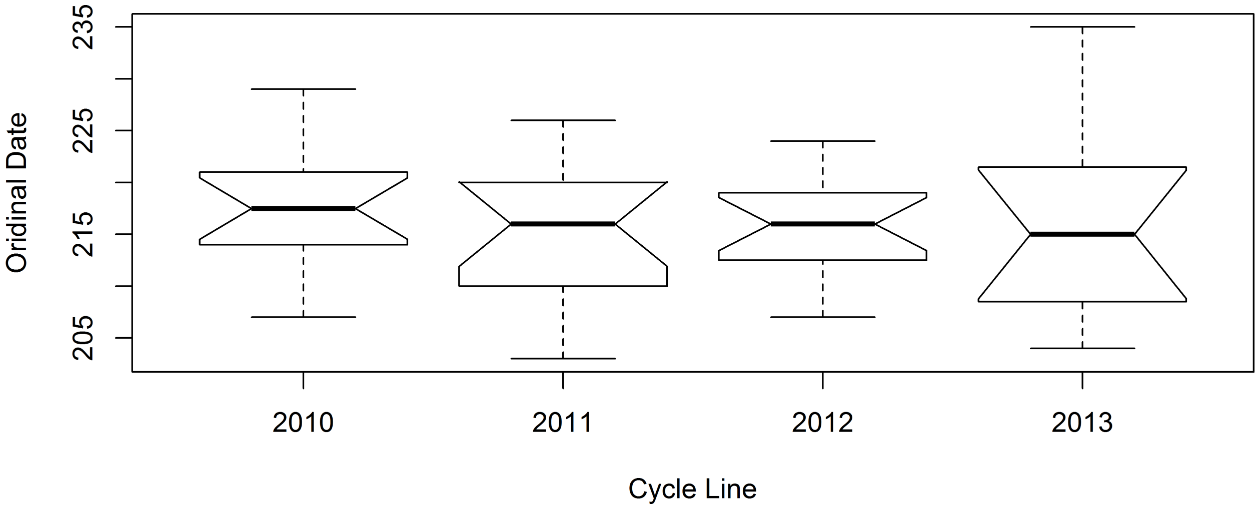


Figure 19. Box and whisker plots of Chilko timing dates by cycle line. A cycle line represents shared intergenerational lineage. For example Chilko sockeye returns in 2014, 2010, 2006, . . . represent a common cycle line. Overlap of box notches suggests there is no cycle specific differences in Chilko return timing.

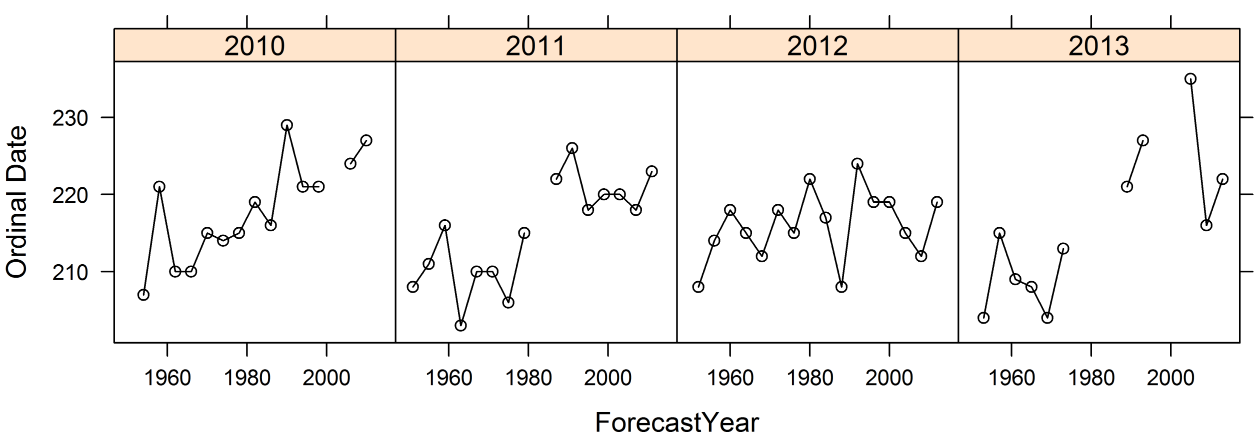


Figure 20. Time series of Chilko median arrival date at Area 20, by cycle line.

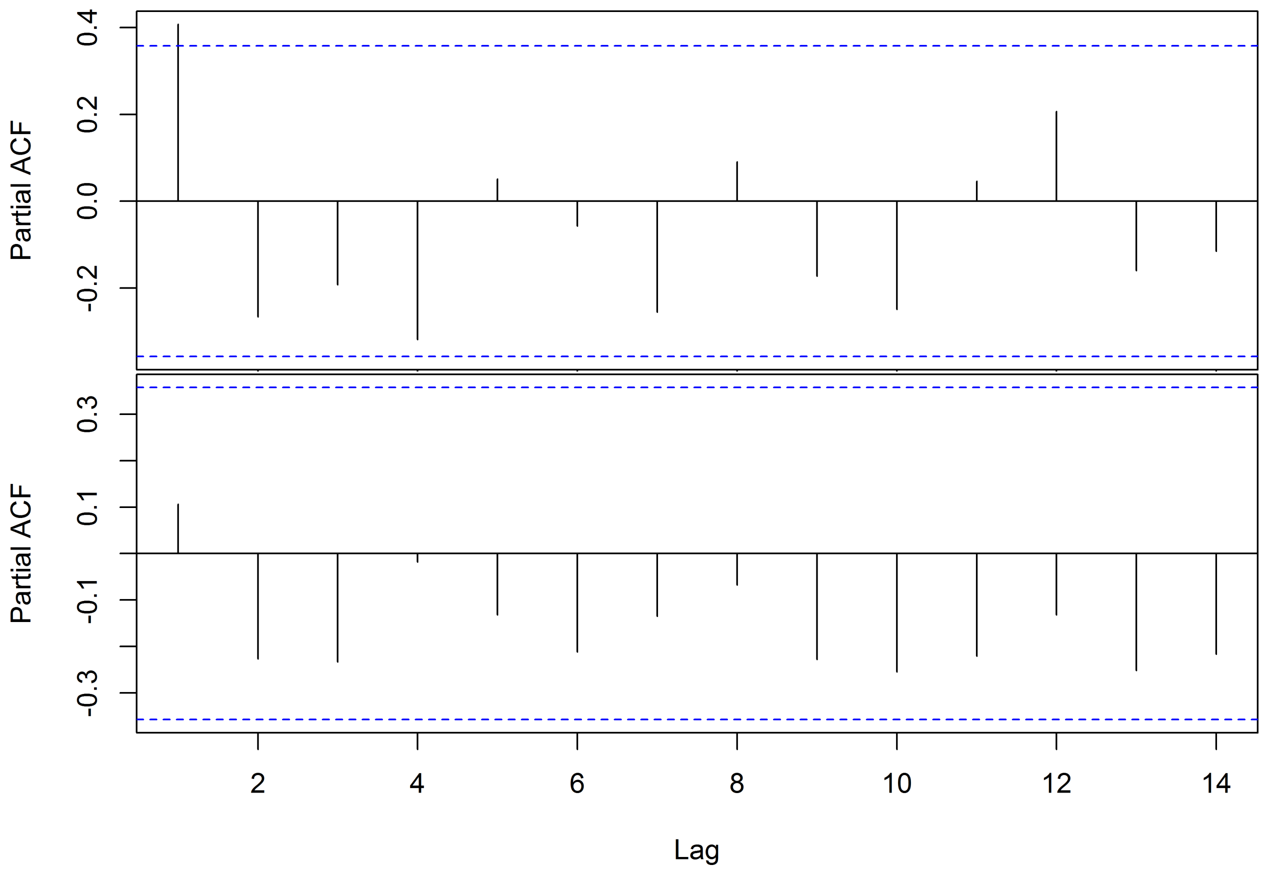


Figure 21. partial autocorrelation function (PACF) of timing for Early Stuart (upper plot) and Chilko (lower plot) sockeye, considering only those years used in the forecasting model fit (1983–2012). The x-axis indicates number of years in the autocorrelation lag. The y-axis value is equivalent to a correlation coefficient such that 0.4 equates to a 40% correlation. The dashed lines represent the critical values under the null hypothesis of white noise ($\pm 1.96/\sqrt{n}$). Values outside these lines are statistically significant. Unlike the autocorrelation function (ACF), a PACF estimates the autocorrelation, within a time series (x), between x_t and x_{t+k} that is not accounted for by lags 1 to $k-1$. Results suggest a statistically significant lag one year autocorrelation for the Early Stuart timing series and no autocorrelation in the Chilko timing series.

values (i.e. 40% $\leq$ ND $\leq$ 60%; see Figure 5 in McKinnell et al. (1999)).

Beginning in 1995, Fraser sockeye total exploitation rates declined significantly (e.g., average marine area exploitation rate 1996–2013 of 23% of the total return, M. Lapointe, 2015, PSC Pers. Comm.). Furthermore, international allocations of the total allowable catch (TAC) to fisheries in United States waters on the southern migration route decreased over time reaching 22.4% of the TAC in 1999 and further declining to the current (2015) 16.5% by 2002. These reductions in overall exploitation rates and TAC shares, coupled with reduced fisheries in marine area waters in Canada, effectively eliminated the capacity to obtain accurate estimates of ND from commercial catch data on each approach route. Consequently, the estimates of ND for this most recent period are heavily dependent on the relative CPUE obtained from test fisheries occurring in Juan de Fuca Strait and Johnstone Strait. While data from test fisheries are available at much finer temporal and spatial scales (effectively small areas and daily) than for commercial fisheries (large areas and often for multiple days), each day's test fishery catch represents only a very small fraction of the total daily abundance. The very small harvest rates associated with test fisheries generate considerable imprecision in the daily abundance estimates obtained from them.

For the period prior to the third week of July each year, ND estimates are obtained from the cumulative CPUE in gillnet test fisheries that occur on each migration route. This method implies that the catchability of each of these test fisheries is the same (Putman et al., 2014*a*). Purse seine test fisheries begin during the third week of July, and CPUE data from these test fisheries is used preferentially to that obtained from gillnet test fisheries when both gear types are operating (usually about two weeks). For purse seines the catchability of test fisheries in Johnstone Strait is assumed to be 2.2 times that in Juan de Fuca Strait based on the migration areas available to sockeye salmon and the size of the nets used in each area (Putman et al., 2014*a*). These assumptions about the relative catchability of test fisheries operating in each area can generate biases in the daily estimates of abundance on each route. However, because the ND estimates are cumulative over the course of the season, errors associated with daily variation in test fishery CPUE, catchability, and the associated daily abundances tend to average out via the Central Limit theorem.

Nonetheless, the overall lack of commercial catch data likely means that the ND estimates in this recent period are likely less precise and less accurate than estimates for the pre-1995 period. Lastly, concerning the described revisions for estimation of the ND rate, while the full time series is used in the descriptive plots below, a shorter time series (1992–2012) was used in the evaluation of models used to predict ND rate.

Exploratory Evaluation: Considering the complete time series (1953–2014) there is a significant trend to greater ND values, but this is not the case for the years 1977-2014, which likely represents substantially different marine conditions (Figure 22). As presented in the timing section, ND rate was tested for cycle-specific differences in median value (Figure 23) and trends (Figure 24), and no statistically significant differences were found. There is no autocorrelation in the ND time series (Figure 25).

3.2 THE INDEPENDENT VARIABLES

Eight distinct types of environmental data are gathered for exploration in this work: El Niño indices, Fraser river discharge, relative sea level, SST, SSS, wind stress, ocean current velocity, and earth magnetic field estimates. The El Niño indices are used in an initial exploration of

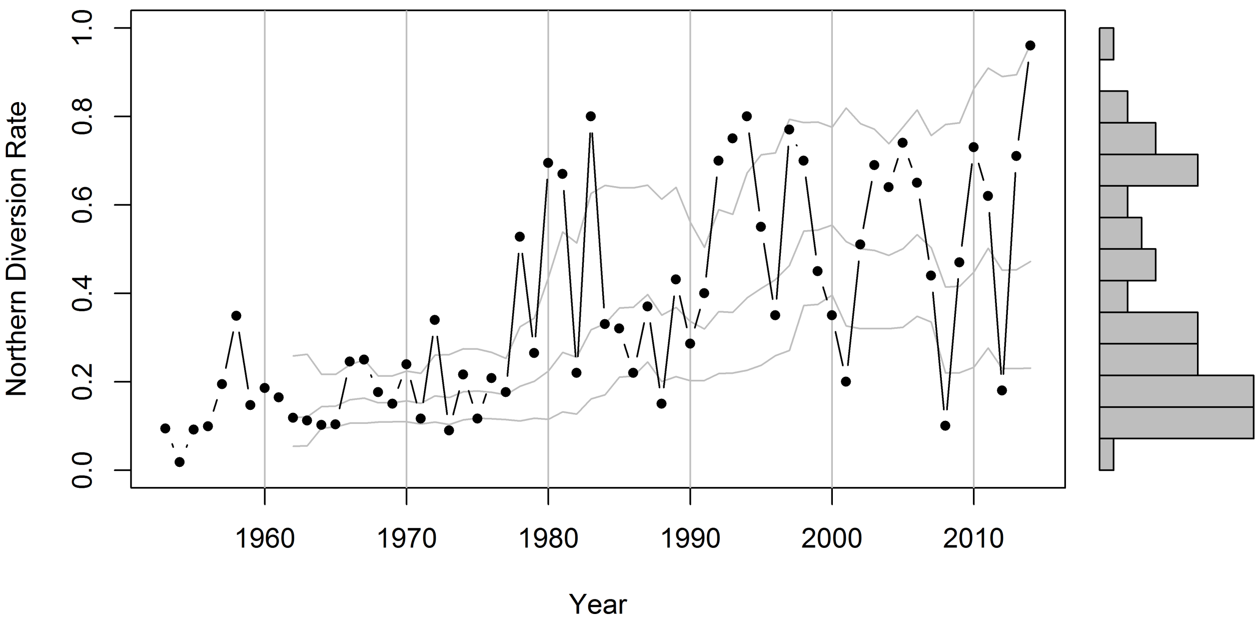


Figure 22. Time series of post-season estimates of the ND rate. The grey lines are the ten year running averages of median and SD, which were calculated in log-space. The histogram is scaled to density (fraction of the total numbers of occurrences).

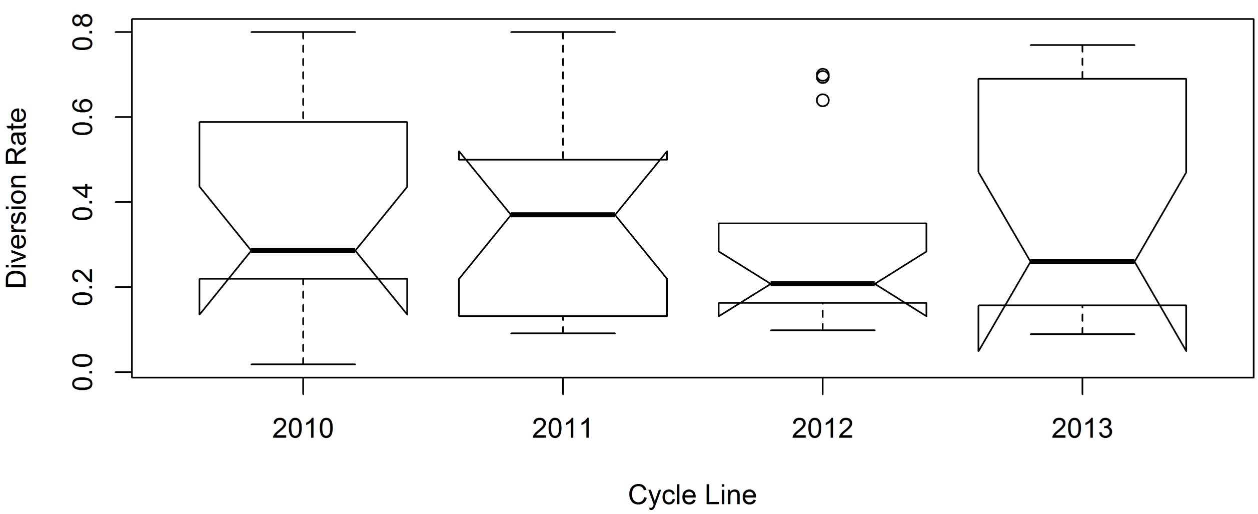


Figure 23. Box and whisker plots of ND rate, by cycle line for 1953–2014. Overlap of box notches suggests there is no cycle specific differences in ND rate.

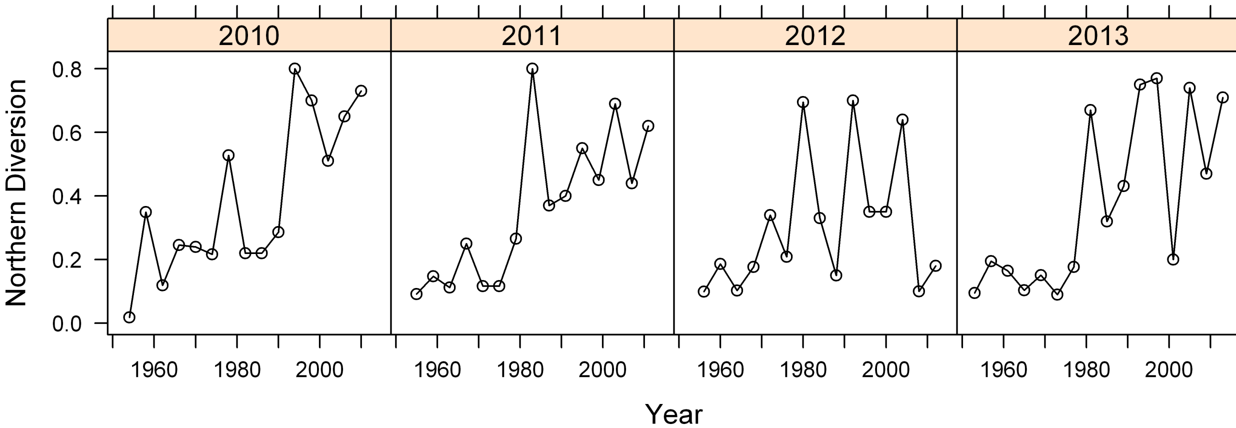


Figure 24. Time series of ND rate by cycle line. Each cycle line appears to be trending to higher ND rates after 1977.

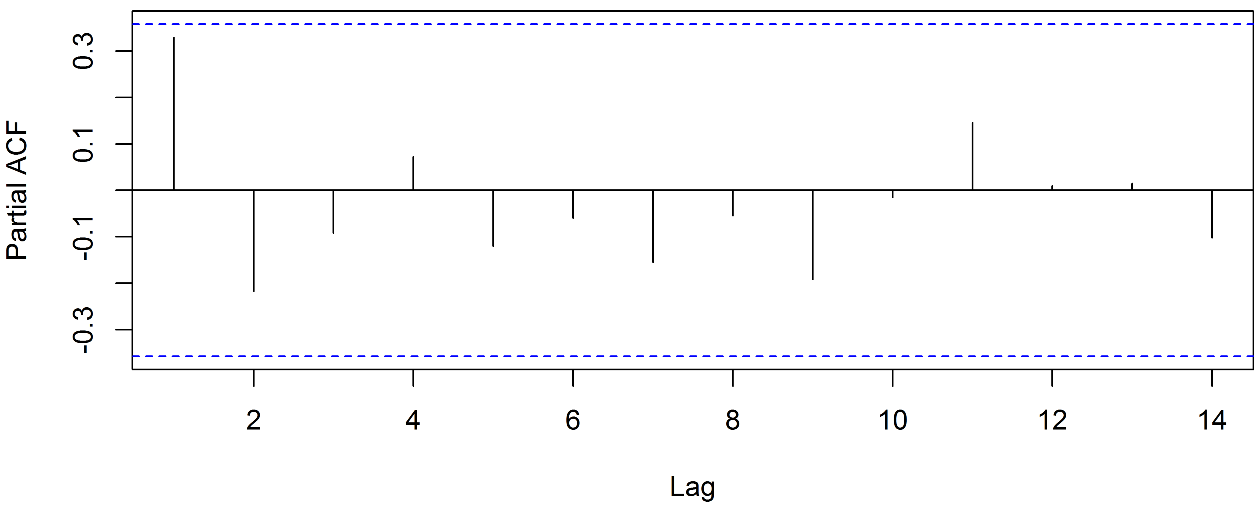


Figure 25. PACF of the ND rate time series for all Fraser sockeye, considering just years used in forecasting model fit (1983–2012). The x-axis indicates number of years in the autocorrelation lag. The y-axis value is equivalent to a correlation coefficient such that 0.4 equates to a 40% correlation. The dashed lines represent the critical values under the null hypothesis of white noise ($\pm 1.96/\sqrt{n}$). Values outside these lines are statistically significant. Unlike the ACF, a PACF estimates the autocorrelation, within a time series (x), between x_t and x_{t+k} that is not accounted for by lags 1 to $k-1$. Results suggest no autocorrelation.

effects on migratory behaviour, but without consideration in any forecasting models. The river discharge and relative sea level series are applied to a re-evaluation of the ND forecast model presented in Wickett (1977). The magnetic field data are used only in ND forecasting models. All other data are considered in the full evaluation of the forecasting models.

3.2.1 El Niño Events

NOAA produces several data series that can each be used as indicators of ENSO events, the three most common are: the Oceanic Niño Index (ONI) (Kousky and Higgins, 2007), which is the three month running-mean anomaly in the Niño region 3.4 SST (Niño3.4), the well known Southern Oscillation Index (SOI) (Penland et al., 2010; Wang et al., 2014), and the Bivariate ENSO Timeseries (BEST) index (Smith and Sardeshmukh, 2000). The BEST index is based on both the ONI and the SOI such that both indices must exceed their 20th percentiles for the BEST value to indicate a La Niña or El Niño event. These requirements make the BEST index a more conservative representation of ENSO events. Figure 26 gives a visual comparison of warm and cold events as defined by BEST, ONI, and the SOI. Within the BEST index, La Niña or El Niño events are calculated by the five month central moving average of its monthly values. The moving average, within any single month, must exceed thresholds of < -1 or > 1, to suggest La Niña or El Niño events for that month. It should be emphasized that these index values are the opposite sign of the SOI (i.e., negative SOI values suggest potential for El Niño conditions). The NOAA operational definition for El Niño and La Niña events is based on just the ONI, which must be greater than +0.5 (Niño) or less than -0.5 (Niña) for at least five consecutive overlapping three month running averages (CPC, 2014).

3.2.2 Fraser River Discharge

Wickett (1977) summed the monthly average Fraser river discharge at Water Survey of Canada (WSC) station 08MF005 (at Hope, British Columbia) for April, May, and June of 1953–1973. The data were downloaded from the Water Survey of Canada. At time of access the data were current up to February 12, 2011. The data are now stored in m^3/s. To confirm there was consistency between values in the present data archive and that were presented in Wickett (1977), the values were converted to ft^3/s. On average the archive values match Wickett's values within ±0.0002 (0.02%).

3.2.3 Sea Level

Wickett (1977) calculated the mean sea level at Tofino, B.C. (Canadian Hydrographic Service (CHS) station 8615) for February-June of 1953–1973. The data were downloaded from the Tides and Water Levels Data Archive managed by the DFO. At time of access the data were current up to June 30, 2013. On average the archive values match Wickett's values within ±0.0009 (0.09%).

3.2.4 Sea Surface Temperature

NOAA Optimum Interpolation Sea Surface Temperature (OI SST) Northeast Pacific data fields: The NOAA OI SST V2 data series, considered one of the most reliable global data sets of SST (Reynolds and Smith, 1994; Reynolds et al., 2002), consists of gridded 1° by 1° data from

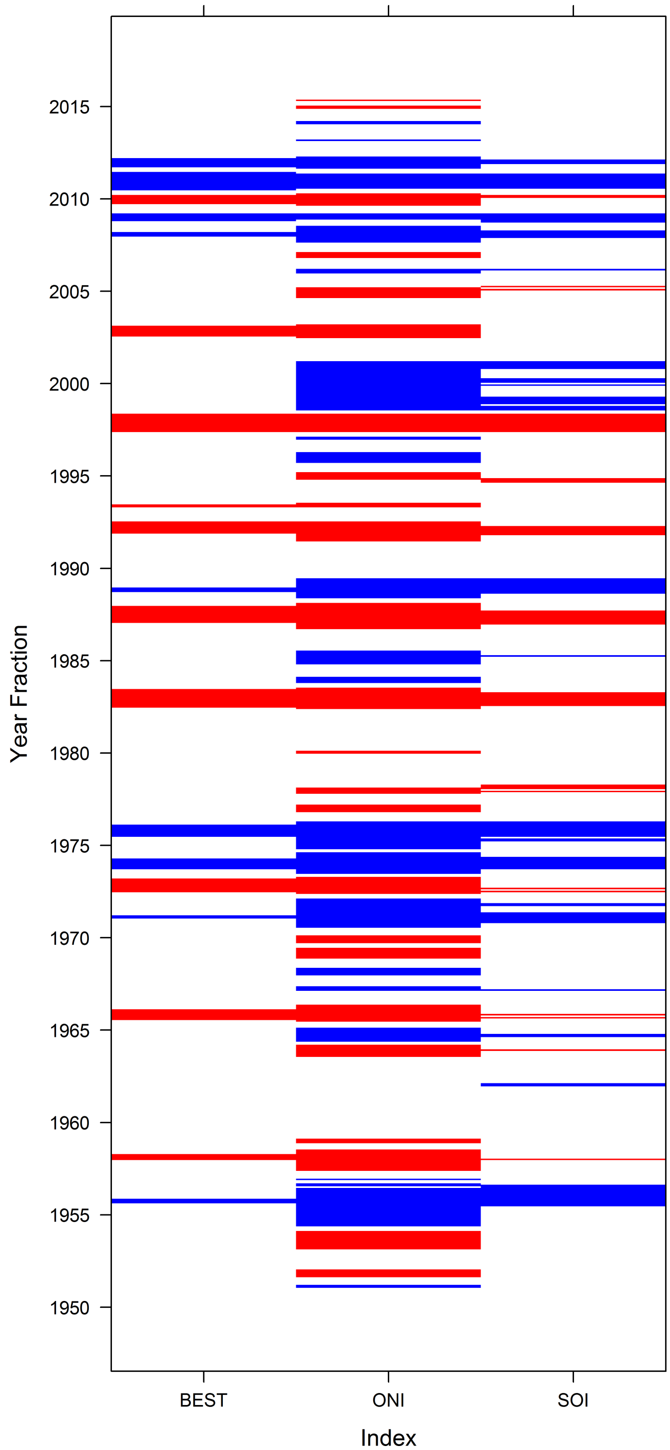


Figure 26. Time series of warm and cold Pacific equatorial events, by month, as defined by three indices of upper ocean conditions: BEST, Niño3.4 (ONI), and SOI. Each thin horizontal line represents the state for a month (blue as cold, red as warm). Not all of these are El Niño/La Niña events, which NOAA defines as requiring five consecutive months with three month running average ONI greater than 0.5 or less than -0.5. Year 1998 is a good example of agreement between indices of an El Niño event. Note that warm water along the west coast during El Niños has cold water in the offshore North Pacific, and vice versa.

in-situ and satellite derived estimates (first available in December 1981). Data are available in weekly and monthly values and provided by the NOAA, Office of Oceanic and Atmospheric Research (OAR), Earth System Research Laboratory (ESRL), Physical Sciences Division (PSD), Boulder, Colorado, USA. Additional information regarding this series is available in the NOAA Optimum Interpolation Sea Surface Temperature Analysis.

The non-NEPSTAR models relied on monthly data. The download of monthly average NOAA OI SST V2 data occurred August 8, 2013[10]. Data used in the non-NEPSTAR models were first spatially averaged using a running mean estimate of 5° latitude by 5° longitude regions. The running mean calculations are described in the following section on Ocean Surface Current Analysis Real-time (OSCAR) sea currents.

For the NEPSTAR-MLR models, weekly OI SST data were interpolated to daily resolution to be consistent with the other daily data sets used in the NEPSTAR-MLR models: shore station SST and SSS, surface wind stress, and current velocity (see below). However these data were not averaged in space and remain at one degree resolution.

Shore station SST data: Formally described as the British Columbia Shore Station Oceanographic Program (BCSOP), this is a multi-decadal series based on once per day samples of SST taken at lighthouses along the B.C. coast. Some of the temperature and salinity records date back to the 1950s. The data series used in this evaluation were derived from shore stations located on the west coasts of Vancouver Island and Haida Gwaii. Five stations were considered, including Langara Island, Kains Island, Nootka, Amphitrite Point, and Race Rocks (Figure 27). For the non-NEPSTAR type analyses, monthly averages were calculated, by station, from each daily series. The data series are described in detail by Freeland (1990); Freeland et al. (1997) and Freeland (2013). The data were downloaded on July 23, 2013.

Sea Surface Temperature Anomalies—The Pacific Decadal Oscillation Index (PDO): The PDO was developed by Mantua et al. (1997) and its potential role influencing migration timing of Alaskan salmon was recently evaluated (Kovach et al., 2015). The data were accessed from the Joint Institute for the Study of Atmosphere and Ocean (JISAO).

3.2.5 Sea Surface Salinity

The time series of daily SSS are also derived from the BCSOP and therefore come from the same locations and times as the daily shore station SST data. Hollister (1953) and Hollister and Sandnes (1972) give descriptions of the sampling process and traits of the salinity data. Because of the simple sampling and measurement procedures (samples are taken at high tide each day by comparatively low resolution instruments), the surface salinity data provide only coarse estimates of local oceanic conditions.

3.2.6 Wind Stress

Surface wind stress is the force exerted by the wind on the ocean surface. It is the downward transfer of momentum from the air to the water which helps drive the surface ocean current. Because it is a more widely available parameter, wind stress is used as a surrogate for the wind-driven surface current and mechanical surface wind mixing. Wind stress data are obtained

[10] The data set is available on a ftp site

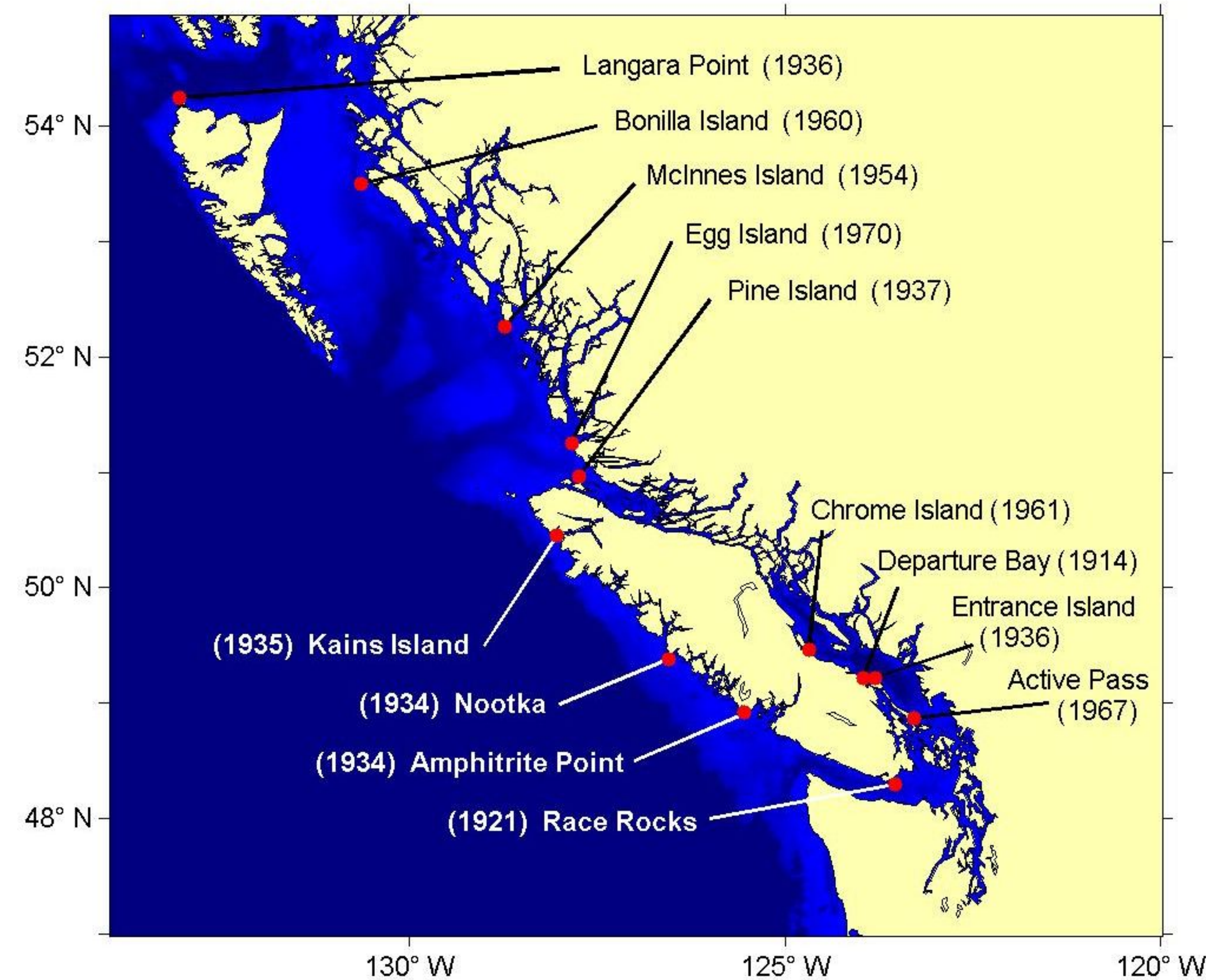


Figure 27. Shore stations with daily time series of SST and SSS. The year beside each name indicates commencement of the time series. Not all time series are continuous.

from the ESRL National Centers for Environmental Prediction (NCEP)/National Center for Atmospheric Research (NCAR) Reanalysis-1 (Kistler et al., 2001). Wind stress is derived from observed winds using the Reanalysis data assimilation model. The original 1.9° by 1.9° 6-hourly northward and eastward velocities were low-pass Kaiser filtered with a 30-hour cut-off and decimated to yield daily values. Wind stress over the northeast Pacific Ocean from grid points between 40–60°N and 180°W to the coast of North America were used.

3.2.7 Modelled Ocean Currents

NEPSTAR: The NEPSTAR *ocean model* is based on the POM (Blumberg and Mellor, 1987), an open-source ocean model developed at Princeton University. It is a finite-difference, prognostic ocean model that can integrate the ocean state forward in time using a time-dependent set of forcing fields, such as winds and atmospheric pressure. The characteristics that make POM a desirable choice for operational modelling are moderate memory and CPU requirements and the relatively simple programming. In addition, the model follows the bottom terrain and therefore increases in vertical resolution as the water depths decrease near the coast and over major submarine features. Adapting the code for specific purposes (e.g. embedded drifter tracking) or to accept diverse forcing data is relatively straightforward. The disadvantages of POM are that there is little choice of advection schemes, mixing parameterization, vertical level scheme (only sigma-coordinates can be used) and other advanced features that some community models employ. However, recent versions of POM have included schemes for wetting/drying cells in intertidal regions, wave-breaking parameterization in surface momentum coupling, an adjoint model for four dimensional variational (4DVAR) data assimilation and code parallelization for running on multiple concurrent CPUs. Here 4D refers to three dimensions in space and one in time. The NEPSTAR model is based on a 29 sigma layer (terrain following) vertical grid with a horizontal resolution of 1/8° by 1/8° (an approximately 12 km grid spacing). The domain is bounded on the south by 40°N and on the west by 180°W (bathymetry and domain shown in Figure 28). The POM does not have a native data assimilation feature, but several contributors within the POM development community have created assimilation schemes of various complexities for ingesting real-time or climatological data. One recently developed method for assimilating temperature and salinity into ocean models, known as “spectral nudging”, is computationally inexpensive and allows temperature and salinity fields to be nudged toward known values without suppressing high frequency variability (e.g. mesoscale eddies), which traditional nudging methods are known to do. A simplified version of the spectral nudging technique has been coded into the NEPSTAR POM and implemented for the initial hindcast model runs.

Modelled current velocity has been hindcast for the period 1980 to 2013 using surface boundary conditions derived from winds provided by the NCEP North American Regional Reanalysis (NARR) at the surface boundary (15-km resolution), and temperature and salinity interpolated from the 1° longitude by 1/3° latitude Global Ocean Data Assimilation System (GODAS) fields (GODAS data provided by the NOAA, OAR, ESRL, PSD, Boulder, Colorado, USA, from the PSD). Velocity fields were archived at a select number of fixed depths (1, 5, 10, 15, 20, 30, 40 and 50 m) at full horizontal model resolution (1/8° latitude and longitude) and a temporal resolution of three hours. Daily mean currents were also archived over the full three-dimensional sigma-coordinate POM grid. It is the daily mean currents at 1° longitude by 1° latitude resolution at 1 m and 30 m depths that were used as independent variables in the NEPSTAR regression analyses.

While these daily mean surface currents are reasonable compared to what is known about the general near-surface circulation in the northeast Pacific (e.g., Thomson (1981)), it was not possible to verify the current velocities in a practical way. This is because comparing them with other modelled currents only reflect differences in modelling systems and model assumptions. It would be preferable to compare the model simulations with measured near-surface currents but these data are rare. Even when current velocity time series exist, they are mostly at subsurface depths over short periods of time. Also, comparing model and observations (which is most possible for coastal areas where current observations are available) would mainly reveal the inability of models to resolve fine-scale temporal and spatial variability, rather than the ability to model larger-scale characteristics.

OSCAR: The OSCAR data series (Bonjean and Lagerloef, 2002) is described as *"near real-time global ocean surface currents derived from satellite altimeter and scatterometer data"*. This data series is distinct from and should not be confused with the previously used OSCURS series (Ingraham and Miyahara, 1988). While the satellite data sources and methods of derivation for OSCAR and OSCURS may have extensive overlap, the degree of similarity between series has not been appraised. The OSCAR series commences 15-October-1992. Both five day mean and monthly mean values are available at a spatial resolution of 1° latitude by 1° longitude, however the series has recently been recalculated to 1/3° latitude by 1/3° longitude and demonstrated to be a substantially superior representation (in accuracy and precision) of local current velocity (Kathleen Dohan, Earth and Space Research Institute, Seattle (ESR) Seattle, Pers. Comm.). Additional information is available at the ESR OSCAR webpage.

The monthly mean sea current vectors, binned 1/3° latitude by 1/3° longitude, are represented as two variables. Current is a vector that can be represented by its magnitude (m/s) and compass direction. Because of the "2π discontinuity" in compass direction (e.g., 0° is identical to 360°), this format is awkward to manage. As a consequence, the standard approach is to store the vector values decomposed into Meridional (northward) current velocity (V current velocity) and Zonal (eastward) current velocity (U current velocity) components. Summing these two components (using trigonometry, not addition) returns the original vector magnitude and direction. Converting (decomposing) all current vectors to their equivalent in northward and eastward values allows for much easier analysis. The geographic range evaluated spans from 40°N–60°N and 120°W–180°W. To allow for a more generalized representation of current velocity by larger geographic areas and to avoid local anomalies, running averages were calculated in 5° latitude by 5° longitude groups. As the data are binned 1/3° latitude by 1/3° longitude, there are 15 by 15 cells (i.e., 225 values) in the 5° latitude by 5° longitude group. The running means are still binned every 1/3° latitude by 1/3° longitude. To reduce calculations and standardize the data to the same level as the OI SST, we only included data centered on 1° by 1° locations. Figure 29 is a diagram representing the estimation of running mean within each grid location. The data were accessed on 7-Aug-2013 from the OSCAR webpage[11].

[11] As each year-long time series for the complete globe is approximately 450 MB in size, we advise use of the GUI from OSCAR, where the user can specify: Data Type= "monthly mean"; Filter type= "unfiltered (1/3 degree)"; Variable type= "U & V mean"; and constrain the geographic coordinates to 40°N–60°N and 120°W–180°W. The compressed data file will be approximately 15 MB in size.

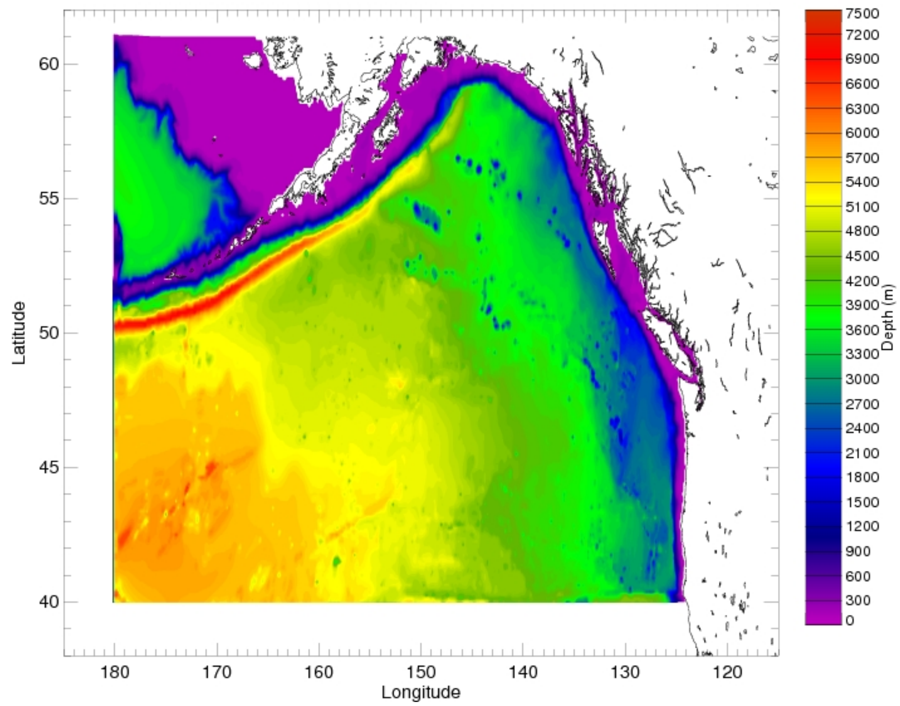


Figure 28. The NEPSTAR POM domain. The POM grid is a regular 1/8° by 1/8° (latitude, longitude) grid (not shown) which overlays this domain.

3.2.8 Magnetics

"Earth's main field" is the term used to describe the dipolelike[12] magnetic field encompassing the planet. The International Geomagnetic Reference Field (IGRF) is a mathematical representation of the earth's magnetic field, and defined in Finlay et al. (2010). Magnetic field values can be estimated from the IGRF model as the magnetic field behaves somewhat predictably, not unlike tidal heights that are also estimated by mathematical models. The field is represented by three components: declination (the angle separating Earth's geographic north pole from its magnetic north pole), inclination (the angle at which field lines intersect the Earth's surface) and intensity (Campbell, 2003), (Figure 30). Field intensity is described in units of nanotesla (nT).

The three field components are calculated by using the [IGRF model version 11 Fortran code]. This routine is now compiled in the R package *oce* (published on CRAN but most current versions should be accessed from [the oce GitHub site]). Further information on the IGRF, including algorithms to estimate magnetic field values, model coefficients, and on-line calculators are available from the [IGRF model webpage]. We then follow the data processing methods of Putman et al. (2013):

> *We determine the values of both magnetic field strength (total field intensity) and inclination angle. . . at the mouth of the Fraser River (49.1°N, 123.25°W), the seaward entry to the Queen Charlotte Strait (51.0°N, 128.0°W), and the seaward entry to the*

[12] *dipolelike* describes the pattern of an electric or magnetic field, created by the arrangement of two charges of opposite sign (an *electric dipole*).

Figure 29. Diagrammatic representation of the running mean estimation of OSCAR current velocity and North Pacific SST. The window size of each running mean is 5° latitude by 5° longitude. The plot represents the geographic extent of data hypothetically available. There is a data point every 1/3° for the OSCAR current velocity data and 1° for the SST data. The mean value in each solid colour cell (red or black) is derived from the cross hatched area of the same colour. The solid grey area represents the resulting geographic region of running mean estimates incorporated in the statistical analysis. Note that this example does not represent the true geographic range of data sampled from the North Pacific series.

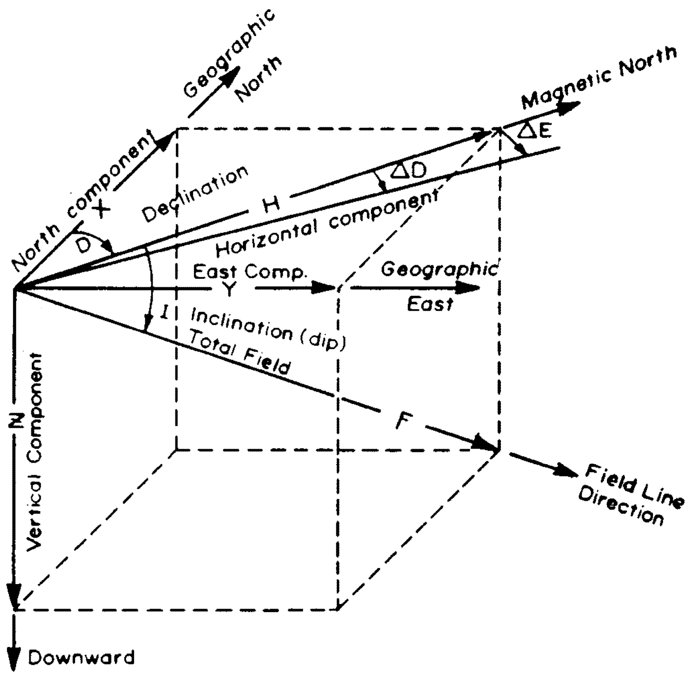


Figure 30. The seven magnetic elements that are used to describe the earth's magnetic field: declination (D), inclination (I), horizontal intensity (H), which is comprised of north (X) and east (Y) intensity), vertical intensity (Z), and total intensity (F). Image copied with permission from Campbell (2003)

> *Strait of Juan de Fuca (48.45°N, 124.6°W)... We calculate the difference in magnetic values between the mouth of the Fraser River and each entryway assuming a 2-year time lag between fish leaving the river as juveniles (April–May) and returning to spawn at maturity (June–August).*

However, unlike Putman et al., we estimate mid-monthly values for April and May, then average those two. We do not limit our evaluation to the difference between values estimated in April–May (smolt year) and June–August (return year). Instead, we calculate geomagnetic values for each month the fish are in the marine area, and subtract those from the April–May (smolt year) value. Thus we are fitting models for each month the fish are assume to be in the marine area. The field value differences were calculated up to June of each return year as estimates based on July–August would not have practical application for pre-season forecasting. The locations where magnetic field data are assessed are defined on the map in Figure 31.

Putman et al. (2014*a*) chose a simpler time period for calculating magnetic differences. In that evaluation the authors subtracted the geomagnetic values estimated on January 1 of the smolt year from the values estimated on January 1 of the return year. That paper was published after our analyses had been completed so we have not considered this variable type in our evaluation.

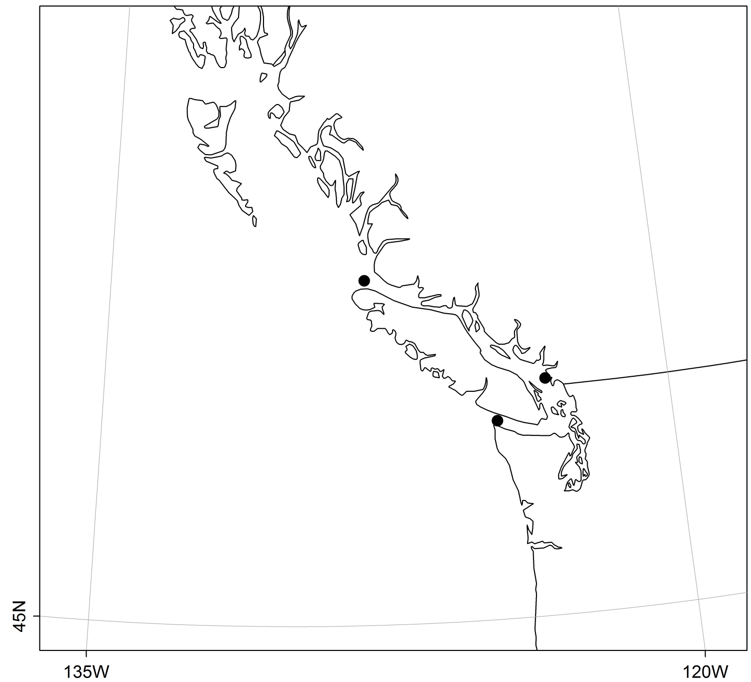


Figure 31. The three locations (defined by solid black symbols) where monthly values of the geomagnetic variables, intensity and inclination, were calculated.

Table 2. Environmental variables used as predictors of Fraser River salmon marine arrival timing and ND rate.

Forecast	Variable	Observed/ Modelled	Description	Temporal Resolution	Grid	Domain	Time Period	URL Footnote
Timing & Diversion	SST	Observed	Shore station	Daily & Monthly	Irregular	Coastal	1987–2013	5
			NOAA OI SST V2[1](interpolated from weekly to daily)	Daily & Monthly	Regular (1° x 1°)	Entire NE Pacific	1982–2013	6
	SSS	Observed	Shore station	Daily & Monthly	Irregular	Coastal	1987–2013	7
	Surface Ocean Currents	Modelled	POM[3] finite difference prognostic model configured with 29 vertical layers and forced by three-hourly oceanic winds and monthly temperature and salinity from the GODAS[4]	Daily	Regular (1/8° x 1/8°)	Entire NE Pacific	1983–2012	8
			OSCAR	Monthly	Regular (1/3° x 1/3°)	Entire NE Pacific	1993–2013	9
	Surface Wind Stress	Modelled	NCEP and NCAR Reanalysis-1[2]	Daily	Regular (1.9° x 1.9°)	Entire NE Pacific	1983–2012	10
	sea surface temperature anomallies (SSTA)	Modelled	Monthly values of the PDO	Monthly	Single estimate	NE Pacific	1951–2013	11
Diversion Only	River discharge	Observed	Sum of the monthly average Fraser river discharge at WSC station 08MF005 (Hope, British Columbia) for April, May, and June.	Monthly	Single Point	Coastal	1953–2013	12
	Sea level	Observed	Mean sea level for February–June at Tofino, B.C. CHS station 8615.	Monthly	Single Point	Coastal	1953–2013	13
	Geomagnetic field intensity	Modelled	Difference between estimate at the Fraser River mouth during April–May of smolt year and the estimates at either Queen Charlotte Strait or Juan de Fuca Strait during June of the return year.	Monthly	Subset of regular grid	Coastal	1952–2013	14
	Geomagnetic field inclination angle	Modelled	As for geomagnetic intensity.	Monthly	Subset of regular grid	Coastal	1952–2013	14

[1] Kistler et al. (2001); Thomson and Hourston (2011)
[2] Reynolds et al. (2002)
[3] Blumberg and Mellor (1987)
[4] Thomson et al. (2013)
[5] Shore station
[6] NOAA OISST
[7] Shore station
[8] not available
[9] OSCAR
[10] NCEP wind stress
[11] PDO
[12] Water Survey Canada
[13] Canadian Hydrographic Service
[14] IGRF

4 METHODS

4.1 NEW MODELS VERSUS PRIOR MODELS

There is inevitably a curiosity regarding the performance of new forecast models compared to that of the prior models. In this evaluation we have not compared new timing forecast models to those falling under the Blackbourn temperature-displacement mechanism. The data sets utilized by the latter cannot be updated as they are not publicly available. Alternatively, comparing models by restricting the time period to that of the data series from the temperature-displacement models would be inappropriate because of limited overlap in forecasting years.

The most recently used ND model has been based on May-June SST at Kains Island and that model was evaluated against new models. Additionally we also evaluated forecasts of ND based on updated data sets for the Wickett Model (see below).

4.2 THE INFLUENCE OF EL NIÑO

The relationship between monthly estimates of El Niño state and stock specific timing or ND is evaluated (in Sections 5.1.1 and 5.2.1) using box and whisker plots (McGill et al., 1978; Benjamini, 1988). Each of the three ENSO series are evaluated separately due to subtle differences in their definition of El Niño conditions. Return timing or ND are related to El Niño events on a monthly basis during the marine period of the Fraser sockeye (predominantly) four year life history (i.e., up to two years prior to adult return). We group the environmental data into two states: El Niño or non-El Niño, where the latter is a combination of La Niña and ENSO-neutral periods. This grouping slightly improves the sample size (in the non-El Niño group), which moderately improves the statistical confidence when differences are noted. However, this data grouping allows us to only test for El Niño effects. Differences in return timing or ND that are related to El Niño events are tested by *anova* (specifically a one-tailed F-test) (Sokal and Rohlf, 1995). Additionally, the statistical differences can be visually discerned in the box and whisker plots. Each box has bevelled edges, *notches*, which show the 95% confidence interval (CI) for each median. When comparing boxes (i.e., timing during El Niño events versus non-El Niño events), if the notches do not overlap there is strong evidence that the medians differ significantly (Krzywinski and Altman, 2014).

Results from this evaluation are discussed in Section 6.1, but no statistical models based on El Niño events are included in the forecasting component of this document.

4.3 STATISTICAL MODEL FITTING

We define a *model* as a statistical fitting between a dependent variable (e.g. timing or ND) and one or more *predictor variables*. As the time series that define a model grow (or are sub-sampled to test model robustness), the model coefficients will change. Strictly speaking, the model changes as data are removed or added thus becoming multiple models of a single group of predictors. Notwithstanding, we wish to consider the *model* in it's simplest definition, a statistical fitting between a dependent variable and one or more *predictor variables*. In the sections that follow, we use statistical models to forecast both return timing and ND rate based on statistical relationships between time series of either timing or ND rate (the dependent data), and environmental/biological (independent) data. Thus, in the search for the best possible forecasting tool we have two components to evaluate: the type of statistical model and the data used in that model. Four different types of statistical models have been considered: naïve, linear regression model (linear model) (single and multiple variable), GAM (Wood, 2006), and SCAM (Chen and Samworth, 2014; Pya and Wood, 2015).

The linear model is the most common statistical fitting method for describing the relationship between correlated data. The linear model is limited by the requirement to know what, if any, transformations of the data structure are required to achieve an approximately linear correlation between variables. In Section 3.6 of their book, Gelman and Hill (2007) outlined a prioritized revision to the requirements in fitting linear models:

1. *Validity . . . the data you are analyzing should map to the research question you are trying to answer. This sounds obvious but is often overlooked or ignored because it can be inconvenient.*
2. *Additivity and linearity. The most important mathematical assumption of the regression model is that its deterministic component is a linear function of the separate predictors.*
3. *Independence of errors. The simple regression model assumes that the errors from the prediction line are independent.*
4. *Equal variance of errors*
5. *Normality of errors*

While Gelman's interpretation of requirements gives the statistics of error a lower priority, he also qualifies their role in forecasting with linear models: *"Normality and equal variance are typically minor concerns, unless you're using the model to make predictions for individual data points."* (Andrew Gelman's Statistical Modeling, Casual Inference, and Social Science).

These aforementioned requirements encourage the exploration of alternative, non-parametric extensions of generalized linear models (GLMs). The GAM (Wood, 2006) and SCAM (Chen and Samworth, 2014; **?**) have no prior assumptions regarding the response between independent and dependent variables. Like GLMs they can support families of error structure beyond just Gaussian (i.e., normal error). The SCAM method is functionally a GAM but with constraints on the curve shape (specifically the slope may not change sign). Prior work (by M.F.) with statistical fitting of the GAM has implied biologically unlikely relationships to the environmental data. Constraining the slope parameter could allow more biologically realistic attributes between cause and effect.

Transformation: With regression models, log-transformation of the dependent data may be required if the residuals of the fit are log-normally distributed. Exploratory examination of the single variable model fit residuals indicates that they are reasonably close to normally distributed and do not require log-transformation. Frequency histograms of the multivariate model residuals are included in the diagnostic plots (results section). These plots confirm that data transformation is not a requirement for the multivariate models.

However, when considering the complete time series of Early Stuart timing, Chilko timing, and ND, they are log-normally distributed. As the naÃŕve time series average (TSA) model relies on the full time series, they were log-transformed prior to application within the TSA model.

Statistical models that are fitted to proportional values (such as ND *rate*) often rely on the *logit* (log-odds) transformation ($log(\frac{p}{1-p})$) for the dependent data, p, which prevents fitting a line to proportions less than zero and greater than one (Sokal and Rohlf, 1995). It has been commonly used in salmon recruitment forecasting models based on marine survival (MS), which frequently averages less than five percent (Holtby et al., 1999). However the logit transformation compels fitting of a logistic curve to the data—meaning we no longer assume a linear response between variables. Diversion models based on non-transformed ND rate show no signs of forecasts outside the 0–1 limits and as such the *logit* transformation was not implemented for these models.

Multicollinearity: All MLR regression independent variables were compared using cross-correlation analysis. Most of the series have low to no correlation ($r < 0.5$), thus data series were not pre-screened from inclusion in the stepwise regression. Correlation coefficients between variables is shown in the diagnostic plots (left panels of Figures 40, 41, 51, 52, 65, 66).

4.4 FORECAST MODEL TYPES

4.4.1 Naïve Models

The naïve models are all founded on the assumption that simple statistics of the historical time series are reasonable indicators of future values. We consider seven models: four year mean (4YrMn), eight year mean (8YrMn), TSA, four year median (4YrMd), eight year median (8YrMd), time series median (TSMd), and like-last-year (LLY). Each approach makes the assumption that no covariates, biological or environmental, can improve forecasting of Fraser sockeye migratory behaviour. The TSA and TSMd models forecast each year considering the average and median, respectively, of all years prior to the forecast year. The TSA is calculated in log-space to account for non-normality of the frequency distributions. The 4YrMd model relies on the median of just the fours years prior to the forecast year, while the 8YrMd relies on the median of the eight years prior to the forecast year. Missing values are tolerated and the statistic will be based on only years available with the time window specified. The LLY model forecasts each year assuming it will be the same value as observed in the prior year.

While a linear regression can be used to test these models, the slope of the line is undefined preventing estimation of both the adjusted R^2 and P-value. As is explained in the section on model qualification (4.5), those two statistics play a role in model selection. We chose not to pre-filter any of the naïve models before they were appraised in the performance analysis (Section 4.7).

4.4.2 Environmental Models

The environmental data evaluation was segregated into two tasks:

1. Fitting of environmental data, considering each of the previously mentioned statistical fitting methods (single variable linear models, GAMs, SCAMs).
2. Stepwise regression to fit, by multivariate linear regression, data from the qualifying single variable models.

Variables analysed in the first step were: shore station SST and SSS, NOAA OI SST, current velocity derived from either OSCAR or the NEPSTAR model, wind stress, PDO, and earth geomagnetic field components (intensity & inclination).

Single variable model selection: The NEPSTAR *regression analysis* relies on just linear regression and follows this protocol, the oceanic environmental variables (shore station SST and SSS, NOAA OI SST, NEPSTAR current velocity, and wind stress) are regressed individually against marine timing or ND to identify which are significantly ($p < 0.05$) correlated with the salmon series, and thus good candidates for inclusion in an MLR model. Correlations are conducted with the environmental variables over a range of time lags (up to three years before river entry), environmental data averaging periods (3 to 91 days), and locations between 40°N and 60°N, while east of 180°W in the case of gridded data. For most variables, there is a band of values in the combination of lag/averaging/location that is significantly correlated with a given salmon time series of timing or ND rate. In all cases, regions of statistical significance appear as bands in lag-averaging-location space. For a variable to be a good candidate and of practical use for forecasting it had to meet the following criteria:

1. The lead time between the variable and timing or ND must be sufficiently long, i.e. ≥ 1 month;
2. The data must be available in near real-time to able to be used for forecasting; and
3. The lead time/location combination must make sense in terms of salmon migration pathways, e.g., locations near the dateline less than a month before river entry are likely not where the fish are at the time and too far away to be of causal influence, but locations near Vancouver Island are far more plausible in terms of direct environment-fish linkages.

The non-NEPSTAR single variable models are based on many of the same data (shore station SST and SSS, NOAA OI SST, OSCAR current velocity, PDO, and earth geomagnetic field components (intensity & inclination)) but with differing time windows. All values are averaged to monthly estimates and Table 2 indicates the geographic grid resolution. The OI SST and OSCAR current velocity are averaged over a larger geographic grid than their equivalents in the NEPSTAR regressions. The averaging process is described in Section 3.2.7. These variables were tested with time lags back to January of the first marine winter (i.e., approximately 19 months prior to river entry). The statistical models we test are linear regression, GAM, and SCAM.

4.4.3 Northern Diversion Based on Wickett Model

The quadratic regression tested by Wickett (1977) and in this review is:

$$ND \sim \text{Normal}(a + b_1\eta + b_2Q + b_3\eta^2 + b_4Q^2 + b_5\eta * Q, \sigma^2),$$

where ND is the ND rate, η is the sea level at Tofino, and Q is Fraser River discharge. The term $\eta * Q$ represents interaction between covariates, not multiplication. Wickett did not remove the trend from either the sea level nor discharge series. We test the fit both using Wickett's methodology (no de-trending), and then with any trend removed.

4.5 MODEL QUALIFICATION

All single variable models were filtered based on three qualifying statistics: the data series must include at least 17 complete data pairs (i.e., combinations of independent and dependent variables) between 1983–2012, $R^2 \geq 0.5$, and the fit must be statistically significant based on the sequential Bonferroni (a.k.a. Holm-Bonferroni) adjustment (Holm, 1979) of the α-value. The minimum sample size of 17 data pairs was derived to suit two aspects of the salmon and environmental time series. The OSCAR series commences in the autumn of 1992 (i.e., the first complete year is 1993) and all model time series end in 2012. Thus, models fit using the OSCAR series can be no longer than 20 years. The Chilko timing data lacks observations for 1997, 2001, and 2002. Removing those years from the OSCAR series reduces it's length to 17 points.

Allowing for a minimum sample size of 17 complete data pairs means we are able to evaluate Chilko timing forecast models based on the OSCAR data.

Akaike information criterion (AIC): When comparing multiple models, the AIC is a moderately common relative measure of model fit. However, (Burnham and Anderson, 2002, section 2.11.1) clarify that *"Information criteria should not be compared across different data sets, because the inference is conditional on the data in hand."* Comparing different statistical models fitted to the same data would allow for AIC comparison, but this opportunity is very rare compared to the more common condition of comparing statistical models based on varied data. As such, the AIC was excluded from the initial step of evaluating single variable models.

4.6 STEPWISE REGRESSION FOR MULTIVARIATE MODELS

The multivariate models based on NEPSTAR-derived current velocity, OI SST, and wind stress are referred to as the NEPSTAR-MLR models. In Section 4.4.2 we refer to the non-NEPSTAR single variable models. Those models are appraised independently of the NEPSTAR-MLR models and once combined into multivariate models are referred to as the non-NEPSTAR-MLR models.

The NEPSTAR-MLR models are constructed as follows, once variables were identified with appropriate lag/averaging/location combinations, they were standardized to z-scores (subtracting the mean and dividing by the standard deviation). This results in model parameters and associated error that can be compared. From these variables several multiple linear regression models were developed using a stepwise approach. In this approach an initial multiple regression model is defined in terms of a subset of candidate variables. The variables included in the initial subset is not particularly important, and can even be no variables or all variables. The method then proceeds as described in the following quote from MATLAB (2007):

1. *Fit the initial model.*
2. *If any variables not in the model have p-values less than an entrance tolerance (that is, if it is unlikely that they would have zero coefficient if added to the model), add the one with the smallest p-value and repeat this step; otherwise, go to step 3.*
3. *If any variables in the model have p-values greater than an exit tolerance (that is, if it is unlikely that the hypothesis of a zero coefficient can be rejected), remove the one with the largest p-value and go to step 2; otherwise, end.*

Depending on the variables included in the initial model and the order in which variables are moved in and out, the stepwise method may build different models from the same set of potential variables. The algorithm terminates when no single step improves the model. There is no guarantee, however, that a different initial model or a different sequence of steps will not lead to a better fit. In this sense, stepwise models are locally optimal, but may not be globally optimal. As a consequence, to find all local optimal models it is necessary to repeat the stepwise approach for:

1. *every possible configuration of initial model in terms of which variables are initially in and out of the model;*
2. *each possible subset of potential variables, and*
3. *each possible order of consideration for each variable in the given subset.*

This thoroughness is practical when the number of potential variables is less than or equal to eight, but takes weeks to run on a standard desktop computer if the number of variables is greater. Here we used all variables that are significantly ($p < 0.05$) correlated individually with salmon timing and meet the first three criteria of good candidate variables above, namely they are at a suitable lead time and location with real-time data to facilitate forecasting. When these selection criteria resulted in more than eight variables, not all possible variable configurations were used to develop NEPSTAR-MLR models due to the excessive computation time required; hence it is unlikely that all possible MLR model configurations were identified.

Stepwise regression is also applied to find the best variable combination in the non-NEPSTAR-MLR models. The iterative approach is similar to that applied for the NEPSTAR-MLR models, but in this case corrected Akaike information criterion (AICc) is used as an index of model "improvement". All data sets considered in construction of the non-NEPSTAR-MLR models were limited to years shared in common. This constraint allows for application of the AICc. Additionally, the non-NEPSTAR-MLR models were limited to three variables.

An advantage of stepwise regression is its ability to consider many variables, however this property may result in the inclusion of "noise" variables (those actually unrelated to the dependent variable) in the model, overestimation of variable coefficients (exaggerating a variable's relative importance), and overestimation of the goodness of fit (Whittingham et al., 2006; Babyak, 2004; Hawkins, 2004; Harrell, 2001; Steyerberg et al., 2001). The latter is due to the fact that there are many more degrees of freedom to help reduce the residual signal variance in the predictor variable screening process than just due to the variables in the final model. These deficiencies can be somewhat compensated for by not relying on a single multivariate model and instead employing results from an ensemble of models. The relative success of these types of models can be determined by various performance measures.

Rule-of-thumb estimates for sample sizes required to avoid over-fitting of statistical models range from 10 data points per predictor (Maindonald and Braun, 2003, section 6.6) and Babyak (2004) to 10–20 points per predictor (when predictors are continuous variables) (Harrell, 2001, section 4.4). There is a substantial range to this suggested value as it is greatly influenced by correlation between predictors and "effect size" of each predictor (Green, 1991).

4.7 PERFORMANCE ANALYSIS AND MODEL SELECTION

A statistical model is used to represent the relationship between a dependent variable and one or more independent variables, and that relationship is defined by the model parameters. This analysis will provide a large number of statistical models, each derived from unique variables across a broad geographic and temporal range. Best candidates can be initially filtered by data availability (minimum sample size) and common measures of fit including statistical significance (p) and coefficient of determination (R^2). However these measures merely tell us how well each model fits the present set of data without indication of how well it may perform as a forecasting tool given new data. As the number of parameters used to fit the model increases toward the total sample size (i.e., the number of data points in the time series), the model fit will improve until it perfectly matches the dependent variables. In this case, there is one covariate to describe each data point and the model has been *over-fitted*. An over-fitted model is not only attempting to describe the relationship between the variables, but also the random error. While it might appear to perfectly describe the relationship of the data, a model fitted to this extent will, almost invariably, poorly predict new values. Additionally, model over-fitting is likely to occur even when the number of covariates is half the data series size. Performance analysis is one means of testing for (and avoiding) models that may be over-fitted to their data. Model validation (Mosteller and Tukey, 1968) was developed to test a model's forecasting ability (or *skill*) against a known data set. Splitting the data into two components, one to fit the statistical model and one to test it, results in a single validation sample. Alternately, splitting the data into multiple samples that can each be tested results in a multiple-validation or cross-validation (CV) estimate. Thus, the derivation of the term known as CV (Arlot and Celisse, 2010).

4.7.1 Validation and Cross Validation

There are numerous approaches to validation and CV and our description is not exhaustive. All methods follow a common theme: Sample some portion of the data to fit a statistical model (these data are known as the training set); and then use the remaining data to test how well the model will predict those known values (the testing or validation set). The holdout method partitions the data series into two components, the training set and the test or holdout set (Arlot and Celisse, 2010). The number of points in these two components isn't necessarily equal and Kohavi (1995) has indicated it is common to apply 2/3 of the data series to the training set and 1/3 to the testing set. Hyndman and Athanasopoulos (2013) suggests the test set is typically 20% of the total sample, but the proportion is dependent on total length of the data series. k-fold cross validation requires randomly partitioning the data set into k samples (folds) of equal size. One of those samples is retained as the testing data while all remaining samples are recombined and used as the training set. The process then iterates through each of the k sampled subsets, which are sequentially considered the testing set while all remaining subsets are recombined. Finally, n-fold CV (n implying number of folds equals data set size), also known as leave-one-out (LOO) (Frank et al., 1965; Mosteller and Tukey, 1968) is a technique similar to jackknifing (Mosteller and Tukey, 1968; Miller, 1974), however there are nuances regarding bias estimation that separate the two methods (Stone, 1974). LOO involves sequentially removing one data point from the original series, fitting the model to all remaining data, testing the fit against the one removed point, then iterating to the next point for removal (while returning the prior testing point back into the data series). This process is repeated until all dependent values in the series have been forecasted. Armstrong (1985) gave his recommendation of validation method based on the quantity of testing (validation) data available (table 3). His qualitative description of data series length (none to large amounts) leaves the user with some understanding of application, given a healthy dose of uncertainty.

Hirsch (1991) warns that use of validation samples cannot check for model bias, which can only be evaluated by application to an independent set of data. The validation sample, by definition, comes from the same data set as the testing sample. Hirsch concisely notes *"a validation sample addresses the role of chance in construction of a model . . . It does nothing to control Type 1 error; it only forces us to be aware that the error exists".* Creation of a validation sample leads to reduced sample size for model fitting. Hirsch notes the frequency of Type 2 errors increases as the sample size for model fitting decreases, and it is a function of both total sample size and the proportion retained for model fitting.

In addition to choosing fold size there is also an option for how to manage the window size of both the training and testing sets. The situation described above is considered *rolling window* such that the training set size (and model fit) never changes when applied to a single testing set (Hyndman and Athanasopoulos, 2013). Alternately, with each iteration, the *expanding window* approach allows for each tested data point to be moved into the training set, which then requires a re-fitting of the model before the next forecast (Rossi and Inoue, 2012; Rossi, 2013). Armstrong (1985) referred to this technique as *successive updating*, while the fisheries literature has used the term *retrospective analysis* (Haeseker et al., 2005; Cass et al., 2006; Haeseker et al., 2008).

The length of the data series incorporated into each statistical model can vary due to two reasons: start time of the series or data gaps within the series. For example, some models are based on 18 years (data points) when updated to 2012. For the retrospective evaluation, this results in 12 training years and six testing years. However there are other models, based on differing data, with series length of 30 years. While the forecast performance of both models is based on the same testing window (2007–2012), the latter model would have a substantially longer training window. This approach also applies to the jackknife analysis, which compares models based on their performance in forecasting years 1996–2012. Thus the jackknife is not strictly applying LOO to every data point, but only to years that all models share in common (1996–2012). The key consistency in this performance analysis is that the testing sets used to compare models are the same within each analysis (i.e., within the separate retrospective and jackknife analyses).

Intuition suggests the length of training window would have some effect on results as a better trained model should give rise to better model forecasts. However, the effect is probably small compared to other sources of uncertainty (Rob J. Hyndman, Monash University, Pers. Comm. April 17, 2014). There is one risk to this approach but only when training sample sizes are substantially different between models. Using different samples sizes to estimate a model may have empirical consequences in the presence of instabilities[13]: the longer the training sample, the better the estimates when there is no instability—and vice versa when there are instabilities (Pesaran and Timmermann (2002) and Barbara Rossi, Universitat Pompeu Fabra, Barcelona Spain, Pers. Comm. June 6, 2014). In this evaluation, training windows range from 12 to 25 data points (retrospective analysis). We assume that time series instability is unlikely to impact comparison between these models due to the small difference in absolute size. The matter is further complicated by the CIs and prediction intervals (PIs) estimated from each model. Due to sample size alone these statistics could vary greatly. However, this will not have relevance during performance analysis, but only when considering uncertainty of individual forecasts from the top performing model(s).

Considering that some of the Chilko timing models are based on 17–18 years of data (ending in 2012), it was necessary to fix the testing window length to no larger than six years. Retrospective analysis of a model based on a 17 year data series, with a six year testing window, results in an initial training window size of 11 years. It was felt that a fit based on 11 points and a testing window based on six points was a reasonable compromise between minimum sample size for the initial statistical fit and maintaining a testing window size large enough to obtain representative performance measure (PM) estimates. Partitioning the series to 11 and six years also comes close to the 2/3:1/3 rule-of-thumb mentioned earlier. At the onset of this evaluation some of the environmental series were updated only to 2012, meaning the models can only predict up to 2012. A six year testing window ending in 2012 must start in 2007.

In the interest of computational efficiency and reduced complexity in results, two methods were utilized to evaluate model performance: The holdout method with expanding window (hereafter referred to as *retrospective* evaluation), and the n-fold CV method a.k.a. LOO (hereafter referred to as *jackknifing*). The flow of each evaluation method is defined in each itemized list:

[13]Model or parameter *instability* is the term used in financial forecasting literature that appears to be synonymous to parameter *non-stationarity*.

Table 3. Methods of model validation, which Armstrong (1985, Exhibit 13-3) referred to as testing concurrent validity. Table copied with permission (J. Scott Armstrong, Wharton School, U. of Pennsylvania, e-mail message to MF, January 7, 2015)

Sample Size	Recommended Procedure	Early Applications
Large	Cross Validation	Minor (1958)
Moderate	Double cross validation	Roach (1971)
Small	N-way cross validation	Wiseman (1972)
None	Random data validation	Montgomery (1975)

Retrospective:

1. Beginning with 2007, sequentially select forecasting year from the range 2007–2012;
2. Fit model with training data (all years prior to forecasting year);
3. Forecast selected year and calculate error from true estimate;
4. Iterate to next forecasting year;
5. Training data set now expanded by one year;
6. Repeat;
7. Once all years are forecasted, calculate PMs for six forecasts.

Jackknifing (LOO):

1. Beginning with 1996, sequentially select forecasting year from the range 1996–2012;
2. Fit model with training data (all years in data set except forecasting year);
3. Forecast selected year and calculate error from true estimate;
4. Iterate to next forecasting year;
5. Repeat.
6. Once all years are forecasted, calculate PMs for 17 forecasts.

4.7.2 Performance Measures

Accuracy measures[14] can be grouped into five categories: scale-dependent[15], percentage errors, relative errors, relative measures, and scaled errors (Hyndman and Koehler, 2006). We define forecast error e_t in year t as the difference between model forecast $\hat{Y}_t$ and the observed value Y_t, ($e_t = \hat{Y}_t - Y_t$).

[14]The term *accuracy* when used in describing performance measures is not synonymous to its use in statistics. (See Hyndman and Koehler, 2006) for details.

[15]We (and Hyndman and Koehler (2006)) use the term *scale* to imply the numerical scale or resolution of the values. This would be more critical if comparing model performance when forecasting two numerically different series e.g., when one averages 10000 while the other averages 1M.

Scale-dependent Measures: Scale-dependent measures include, but are not limited to:

$$\begin{aligned}
\text{mean raw error (MRE)} &= \text{mean}(e)\\
\text{absolute value mean raw error (AMRE)} &= |\text{mean}(e)|\\
\text{mean absolute error (MAE)} &= \text{mean}(|e|)\\
\text{mean square error (MSE)} &= \text{mean}(e^2)\\
\text{root mean squared error (RMSE)} &= \sqrt{\text{mean}(e^2)},
\end{aligned}$$

where e is the time series vector of forecast errors.

The above variables are commonly used in evaluation of forecasting models (Cass et al., 2006; Haeseker et al., 2005, 2008) and are moderately robust measures when comparing models of the same dependent data. MRE is the only measure in this group that can give some indication of model bias, thus a value close to zero is the most desirable result (Haeseker et al., 2005). However, MRE is not necessarily good at representing uncertainty as forecasts that have large, unbiased error will be distributed symmetrically about zero, resulting in MRE values close to zero. Precision is best represented by the latter three measures (MAE, MSE, and RMSE). Additionally, RMSE possesses the useful trait of having the same units as the original data. That said, Armstrong and Fildes (1995) and Armstrong (2001) have demonstrated the sensitivity of squared measures (i.e., RMSE and MSE) to outliers suggesting that MAE may be the best of three options to represent uncertainty. Due to the varying numerical scale of results, scale-dependent measures should not be used when comparing performance of models across multiple sets of dependent data (such as comparing recruitment forecast models across stocks of varying size).

Percentage Errors: Measures based on percentage errors, including the common mean absolute percentage error (MAPE):

$$\text{MAPE} = \text{mean}(|p|), \text{ where } p_t = 100e_t/Y_t, \text{ and } p \text{ is the full time series vector.}$$

are independent of the scale of the data. This trait allows comparison of model performance across varied dependent data sets. The MAPE measure has at least two disadvantages. It has been shown that these measures have extremely skewed distributions when based on observed values that are close to zero (Armstrong, 1985). Additionally, when errors exceed 100% of observation, positive errors are more heavily penalized than negative errors (Goodwin and Lawton, 1999). The MAPE measure has been utilized to compare recruitment forecasting models across stocks, which likely range substantially in values. In this case, standardization to percentage error may be a necessary option. As this analysis is not comparing results of differing forecast data and due to the concerns cited, measures based on percentage errors were not considered.

Relative Errors: Measures based on relative errors are used in the forecasting literature, but possess what Hyndman and Koehler (2006) refers to as a *"serious deficiency"*. The measure is a ratio of two forecast errors, the denominator being error from a benchmark method (e_t^*). The most common benchmark method is a random walk in which the forecast for the current year is equal to last year's observation. When the benchmark error is small, the ratio value can have infinite variance. Adjustments can be made to correct for this trait but it appears this measure offers little new information compared with other measures.

Relative Measures: Relative measures are a progressive step beyond scale-dependent measures. Like the prior approach they are a ratio, but this time a ratio of measures. For example, one can calculate an RMSE based on forecast model one (RMSE$_1$) and another RMSE from model two (RMSE$_2$). The relative measure would be:

$$\text{RelRMSE} = \text{RMSE}_1/\text{RMSE}_2$$

The denominator value is based on model two, and is described as the benchmark method (model). When the benchmark method is a LLY model, the ratio of RMSE measures is Theil's U statistic (U2) (Theil, 1966). Relative measures possess a trait unlike earlier measures, which is ease of interpretation. This statistic indicates the improvement of one model relative to the benchmark model. When RelRMSE< 1 the new model has less error than the benchmark model. This measure can be based on other PMs, such as MRE and MAPE.

Scaled Errors: Scaled errors were proposed by Hyndman and Koehler (2006). The authors indicated some of the limitations possessed by *measures based on relative errors* and *relative measures* and demonstrated the scaled error method avoids all of those concerns. This approach scales each individual forecast error by the benchmark method MAE as follows:

$$q_j = \frac{e_j}{\dfrac{1}{T-1}\displaystyle\sum_{t=2}^{T}|y_t - y_{t-1}|},$$

where e_j is the forecast error in year $j \in 1 \dots T$,
y_t is the observed value in year t,
T is the time series length, such that year $t \in 1 \dots T$.

Here, the denominator is the MAE. Thus, on an individual forecast, a scaled error q_j is less than one if it is superior to the average benchmark method (LLY model). The actual statistic compared, mean absolute scaled error (MASE), is

$$\text{MASE} = \text{mean}(|q_j|)$$

If MASE < 1 the forecast method has, on average, a smaller error than that of the benchmark method. This measure has great utility as it allows for comparison across forecasting data sets that vary in scale. While this trait is not of importance in this review, it's flexibility would become apparent if comparing forecasting models of stock recruitment across stocks that differ by orders of magnitude. This consideration of PM statistics is not exhaustive, but they are the most commonly utilized in the forecasting literature specific to fisheries and, more broadly, to economic and social science forecasting. Gutiérrez-Estrada et al. (2007) present several additional, but uncommon, PMs when evaluating models of Anchovy recruitment forecasting.

4.7.3 On Ranking

Once the selection of PMs are tabulated, we are faced with a challenge of balancing the many varied, often conflicting, results. As mentioned previously, some PMs give indications of bias (MRE) and others precision (RMSE). The relationship (and assumed trade-off) between bias and uncertainty is not absolute, as demonstrated in the PMs values calculated in Cass et al. (2006) (Figure 32). Values are not strictly inversely related, suggesting the assumption of trade-off may not always be correct. Thus each PM should be carefully considered without assuming that it's information content is similar to any other PM . To evaluate the relative success of recruitment forecasting models Cass et al. (2006) ranked all models by PM. The authors then averaged ranks, by model, across PMs to produce an average rank by model. They also chose to exclude MRE from the averaging calculation, and thus from the choice of best model. Unlike the other measures, MRE will range from negative to positive values with zero being optimal. As only the absolute value of this measure can be ranked the authors felt that step would negate the usefulness of MRE compared to MAE. However, not all useful information is lost by transforming MRE to |MRE|. The indication of bias remains in the transformed value, but we are no longer able to discern the direction of bias. We suggest this is sufficiently useful that it should still be included in the ranking process. Other authors have chosen to include MRE in the average rank estimate (Haeseker et al., 2005, 2008; MacDonald and Grant, 2012), but without discussion of the relative benefits. As will become apparent in PM plots, there is a strong correlation between MASE and some other PMs. Including the MASE values in model ranking would give extra weight to the model traits represented by that type of PM. In order to give equal weight to all PMs, MASE was excluded from the calculation of average rank.

The previously mentioned papers all chose to compare PMs by ranking on an ordinal scale. While this approach is commonly used and straight forward for calculation it does unnecessarily remove information from the data that, given another scaling method, could be retained. We rank each PM on an interval scale such that minimum value becomes an arbitrary zero point. Scaling the rank value by the relative distance between values of each PM allows for fractional ranking between zero and the number of models to be compared (equation 1). This is a linear scaling approach such that the rate of change between points is equal to the number of models/unit(PM), and the x-intercept (where rank=0) is the minimum PM value. Converting the data to an interval scale maintains a sensitivity to the relative distance of PM values between models that is lost when ranking on an ordinal scale. It should be noted that ratios of these ranks is not allowed (i.e., we cannot say a model with rank 2.5 is 2.5 times worse than a model with rank 1). But, given three ranks: (0,1,2.5), where rank 0 is the best, it is possible to compare ratios of differences. Thus rank 2.5 is $(2.5-0)/(1-0) = 2.5$ times further from the best than is rank 1.

This approach can result in subtle changes to the overall average of PM ranks. An example is given in Table 4 that compares ranks on an ordinal scale with those on an interval scale. The differences between scaling methods is outlined in Table 5. Like ordinal scale ranking, this method keeps all PMs ranks on the same scale, so that PMs ranks will have equal weight during averaging of PMs ranks by model. But additionally the ranks are scaled to their relative distance. The maintenance of information, while keeping all PMs ranks on the same scale for equal weight when averaging, may more fairly represent the overall average rank of models.

$$\frac{rank}{\mathrm{unit}x} = \frac{N}{\max x - \min x}$$

$$rank(x_i) = \frac{rank}{\mathrm{unit}x} * (x_i - \min x), \tag{1}$$

where x is a vector of values for one PM with length N models and,
where $i \in \{1 \dots N\}$

4.8 OVERALL METHODOLOGY

The process of model evaluation follows these steps:

1. Select predictor variables by location, time (day, week, month), and duration of averaging window.

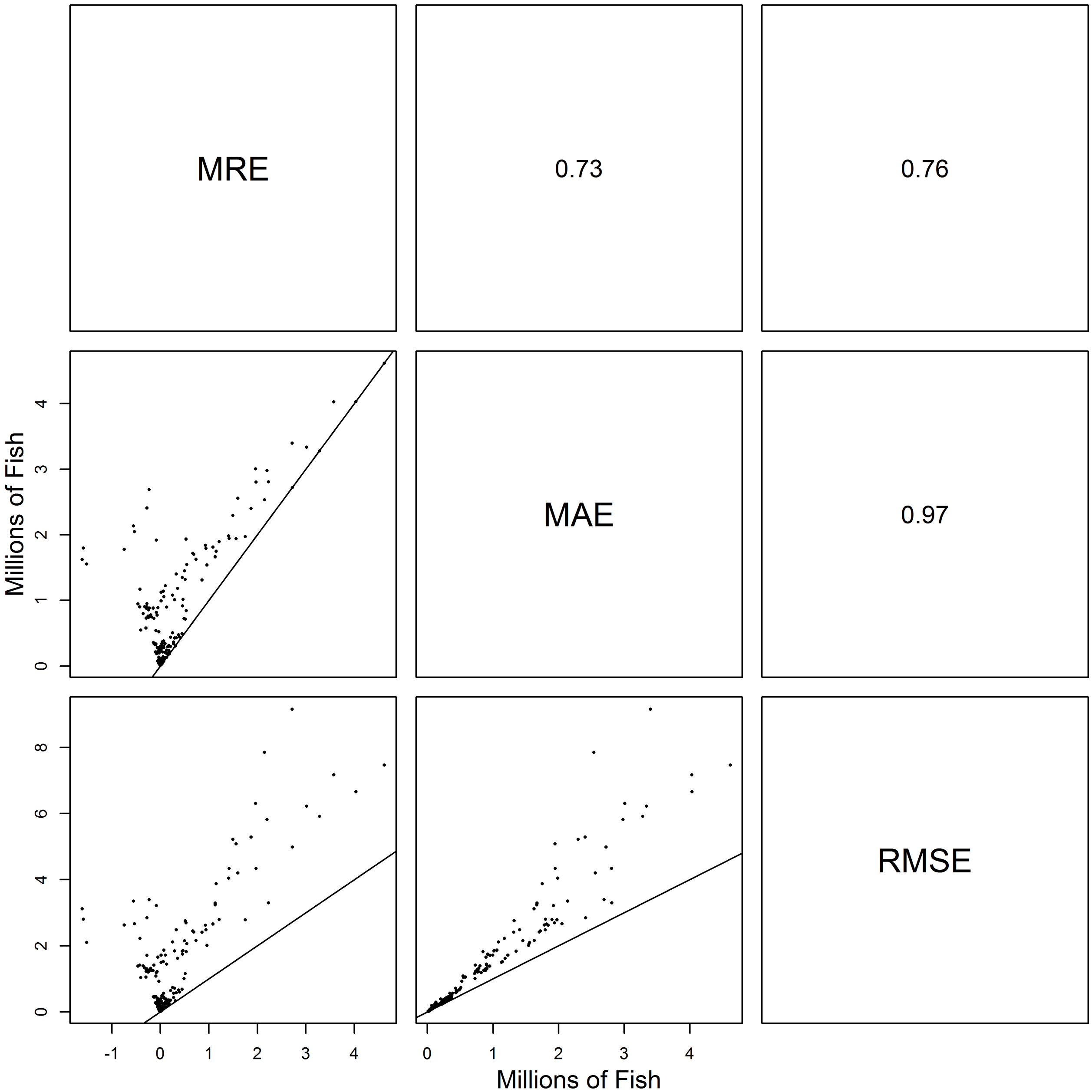


Figure 32. Pairs plot of PMs used to compare approximately 10–17 recruitment forecast models for each of 19 Fraser sockeye stocks. Each point represents the error measure for a type of model of a particular stock. The PMs include: mean raw error (MRE), mean absolute error (MAE), and root mean squared error (RMSE). All three PMs have units in millions of fish. The diagonal line has slope of one and intercept of zero, which indicates the relative sensitivity of each PM to model error. Numbers in the top right panels represent correlation coefficients, R, between PMs. Data taken from Cass et al. (2006).

Table 4. Example of two ranking methods (interval and linear) applied to two hypothetical sets of performance measures from five models, and their affect on average rank.

			Ranking Method				Average of ranks by scaling method	
Model	PM1	PM2	PM1 Ordinal Rank	PM2 Ordinal Rank	PM1 Scaled Linear Rank	PM2 Scaled Linear Rank	Average Ordinal Rank	Average Scaled Linear Rank
1	1.5	1.5	1	1	0.00	0.00	1	0.00
2	2	4.5	2	3	0.45	2.73	2.5	1.59
3	4	4	3	2	2.27	2.27	2.5	2.27
4	6	6	4	4	4.09	4.09	4	4.09
5	7	7	5	5	5.00	5.00	5.00	5.00

Table 5. Ranking based on scaling method and measures of their relative traits.

Measure of rank	Method				
	Ordinal (no scaling)	Interval scale, with line	Interval scaled to min	Interval scaled to max	Interval scaled to mean
Rank value	Ranks are fixed size intervals	Ranks are fractional varying in value.	Ranks are fractional varying in value.	Ranks are fractional varying in value.	Ranks are fractional varying in value.
Rank limits	1 to N	0 to N	1 to $\frac{max(x)}{min(x)}$	$\frac{min(x)}{max(x)}$ to 1	$\frac{min(x)}{mean(x)}$ to $\frac{max(x)}{mean(x)}$
Numerical range	1 to $\gg$ 1	0 to $\gg$ 1	1 to >1	>0 to 1	>0 to >1
Comparing ranks between variables	Rank range same across variables	Rank range same across variables	Rank range can vary greatly across variables.	Rank range always within 0:1	Rank range can vary greatly across variables.
Representation of ranks	Ranks of each variable are less sensitive to relative distance between values	Ratios of ranks represents relative distance from best	Rank represents relative distance from best	Rank represents relative distance from worst	Rank represents relative distance from mean rank
Small range in variables to be ranked	Average ranking unaffected	Average ranking unaffected	Average ranking moderately affected	Average ranking moderately affected	Average ranking moderately affected
Large range in variables to be ranked	Average ranking unaffected	Average ranking unaffected	More weighting on ranks with large value than ranks based on small values. A model with several good ranks and one bad rank will have a poor average rank.	Average ranking moderately affected	Average ranking moderately affected

2. Sequentially fit statistical models (linear model, GAM, SCAM) to predictor variables.
3. Filter for statistically acceptable single variable models ($N \geq 17$ during 1983–2012, $R^2 \geq 0.5$, $p \leq 0.05$ based on sequential Bonferroni adjustment).
4. Apply stepwise regression to construct multivariate linear regression models, considering only variables that qualified in prior step.
5. Filter for statistically acceptable multivariate models ($n \geq 17$ during 1983–2012, $R^2 \geq 0.5$, $p \leq 0.05$ based on sequential Bonferroni adjustment).
6. Test all qualifying models (single and multivariate) with performance analysis via both retrospective and jackknife methods.
7. Within each performance analysis, calculate ranks by PM, then average across the PM ranks by model to obtain model average rank.
8. Compare top ranking models between performance evaluation methods (i.e., retrospective versus jackknife).

Steps 1–4 for the NEPSTAR-based models were undertaken in the Matlab programming environment (MATLAB, 2007), while all non-NEPSTAR regression models were evaluated in the R programming environment (R Core Team, 2013). Steps five forward were evaluated in R.

5 RESULTS

As mentioned in the methods section, the performance analysis is broken into two approaches: retrospective and jackknifing. The results from each of the three analyses (Early Stuart timing, Chilko timing, and Fraser sockeye ND rate) are described in a common format:

1. Summary statistics of models evaluated in the performance analysis.
2. Summary of results by data type.
3. Summary of results by PM.
4. Map of geographic locations for environmental variables.
5. Scatterplot matrices of PMs. This gives indication of correlation between PMs.
6. Diagnostic plots for each statistical model of top ten performing forecast models. Each row of plots represents one model. Within a row, the left column is a matrix that shows the Pearson correlations between all variables. The top row of each matrix presents the correlation between the y-variable and independent variables. The x-axis labels in the correlation matrices correspond to each of the single variable model names that contribute to the multivariate model. The x-axis label/model name is reduced to the initial three characters so that OSCAR becomes “OSC” and OI SST becomes “OIS”. All lower rows of each matrix show correlation between independent variables. This is useful for evaluation of multicollinearity. The second column of panels shows the relationship between residuals and the fitted values (with a lowess fitted line to indicate potential trends). This plot should show any influence of fitted value on residuals (heteroscedasticity and bias, Gelman and Hill (2007); Wood (2006). An important data point to follow is the 2005 residual (an extremely late timing year). Year 2005 is always the highest value on the x-axis (fitted values). If that data point is an outlier it will have a large positive residual value and the point will be associated with the label “05”,

indicating it is an outlier. The third column of panels shows standardized residuals in a quantile-quantile plot, which can reveal potential outliers (Augustin et al., 2012). The right-most (fourth) column of panels shows Cook's distance/leverage plots (Maindonald and Braun, 2003). Dashed contour lines define where Cook's distance is one. Points beyond these lines (going in the direction of larger leverage on the x-axis) could be be outliers that are also influencing the statistical fit. Within the middle two panels, two digit values alongside some data points correspond to years of potential outliers from the model fit.

7. Summary of model ranking.
8. Scatter plots of RMSE versus MRE for all models, with model average rank shown as the data point. This allows us to differentiate locations of top performing models, and consider changes to PMs with declining average rank.
9. Forecast plots showing post season estimate (timing or ND) and forecast by best model of each data type (NEPSTAR-MLR, non-NEPSTAR-MLR, OSCAR, OI SST), and shore station data).
10. Table of statistics for all qualifying models, sorted by average of PM ranks. The average rank of each model was calculated by averaging the ranks of four PMs (MRE, MAE, RMSE, U2).

Each of the measures from the two analyses gives a signal regarding the accuracy and precision of each statistical fit and their accuracy in forecasting. We will demonstrate that these measures can also give conflicting information regarding which model performs best under varying conditions. Model selection, given these results, will be addressed in the Discussion section.

Statistical fitting of GAMs: The fitting of GAMs frequently resulted in biologically unrealistic relationships between independent and dependent variables. The algorithm attempts to separate the series into sections (which are separated by knots), fit a polynomial function to each section, without allowing kinks between sections, and maintaining a reasonable limit to the 'wiggliness' of the fit. The latter component proved to be the hardest to control when evaluating so many series. The procedure was excluded from evaluation. However, the SCAM, which are constrained to not change the sign of their slope, did produce acceptable results. If sample size is reduced ($\lessapprox 20$), and there is not substantial variation in the data, the SCAM frequently simplifies to a linear fit. We see a few examples of this in the results tables where two rows have same data source, month, location, and resulting PMs, while they differ only in model type (linear model and SCAM).

5.1 RETURN TIMING

5.1.1 The Influence of El Niño Events on Timing

While there is considerable variability in marine timing within each type of ENSO period, *anova* confirms that the median date of Early Stuart timing is significantly later in years that the BEST index indicates El Niño conditions during May or June of the return year (Figure 33). There is no significant relationship between Early Stuart timing and El Niño events (defined by the BEST index) two years prior to return (no Figures presented). El Niño events, as defined by either the ONI or SOI, have no significant effect on Early Stuart timing (no Figures presented).

Chilko return timing is significantly later when any month between December (of the year prior to adult return) to May of the return year indicates El Niño conditions as defined by the BEST index (Figure 34). There is no significant relationship between Chilko timing and El Niño events (defined by the BEST index) two years prior to return (no Figures presented). As with the Early Stuart stock, El Niño events, as defined by either the ONI or SOI, have no significant effect on Chilko timing (no Figures presented).

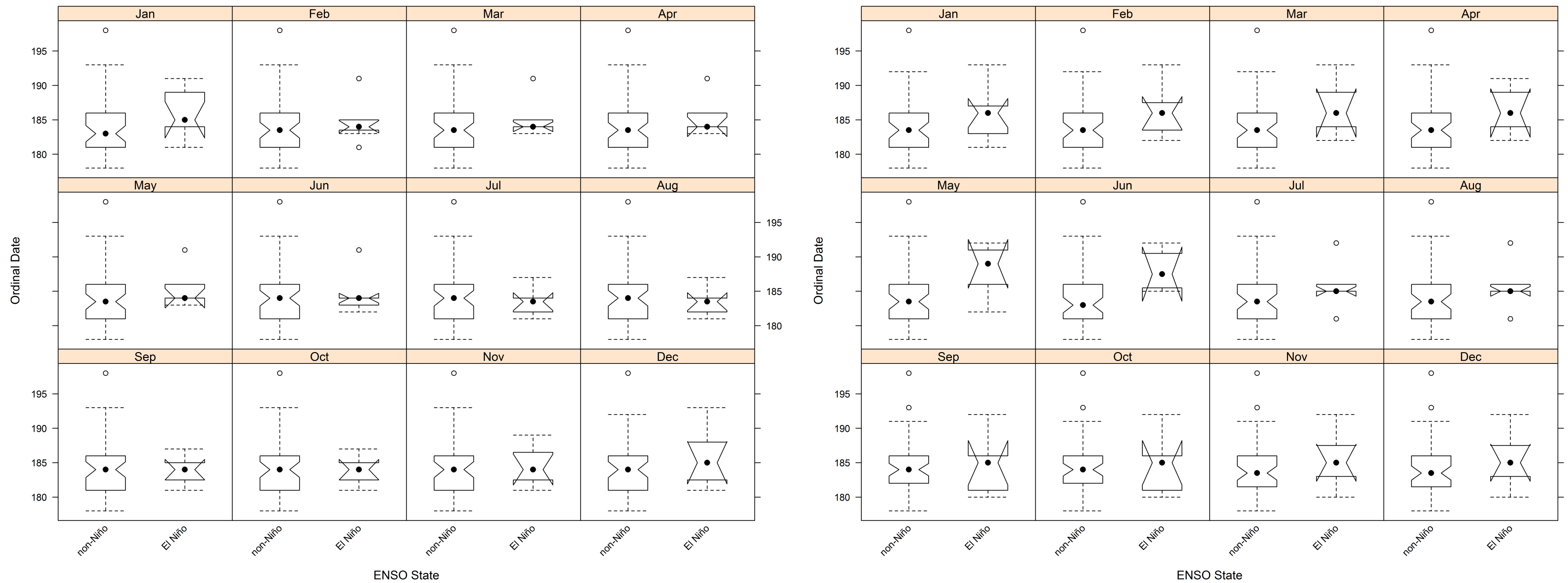


Figure 33. ENSO effects (represented by the BEST index) on Early Stuart timing for years 1952–2013. The plots are in chronological order such that the left panel relates timing to monthly ENSO values of year prior to return and right panel shows ENSO values of return year. Each boxplot show the median (bold black point), interquartile range (IQR) (aka the hinges or limit of the box, representing the middle 50% of the data), the whisker values, and possible outliers (open circle points). While median and hinges have a common definition across virtually all statistical programs, this isn't always the case for the whiskers. These whiskers are Tukey style (Tukey, 1977; Krzywinski and Altman, 2014), and extend to the most extreme data point that is within $1.5 \times$ *IQR of the box edge. Each box has bevelled edges,* notches*, which show the 95% CI for each median. When comparing boxes, if the notches do not overlap this is strong evidence that the medians differ significantly (Krzywinski and Altman, 2014). Except for May of the return year (right panel), all notches in these plots appear to overlap, suggesting timing is not significantly different during El Niño years. See Figure 34 for examples of non-overlapping notches.*

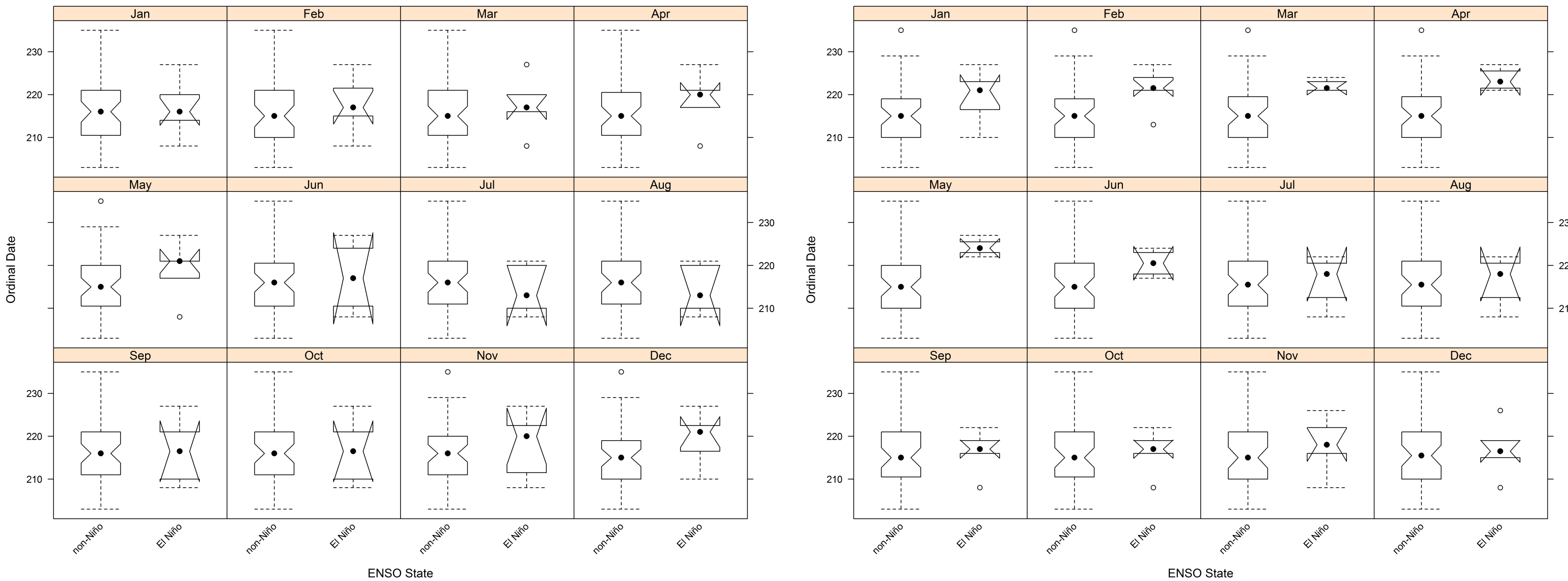


Figure 34. ENSO effects (represented by the BEST index) on Chilko timing, for years 1951–2013. The plots are in chronological order such that the left panel relates timing to monthly ENSO values of year prior to return and right panel shows ENSO values of return year. Each boxplot show the median (bold black point), IQR (aka the hinges or limit of the box, representing the middle 50% of the data), the whisker values, and possible outliers (open circle points). While median and hinges have a common definition across virtually all statistical programs, this isn't always the case for the whiskers. These whiskers are Tukey style (Tukey, 1977; Krzywinski and Altman, 2014), and extend to the most extreme data point that is within $1.5 \times$ *IQR of the box edge. Each box has bevelled edges,* notches, *which show the 95% CI for each median. When comparing boxes, if the notches do not overlap this is strong evidence that the medians differ significantly (Krzywinski and Altman, 2014). From December of the year prior to return (left panel) to May of the return year (right panel) the box notches do not overlap (i.e., they are significantly different).*

5.1.2 Early Stuart

Approximately 160,000 models were evaluated and 381 passed the initial filter (also excluding any GAM fits) for comparison in the performance analysis. The qualifying models[16] consist of: single variable models using shore station SST: 2, OI SST: 33, OSCAR: 84, non-NEPSTAR-MLR: 221, and NEPSTAR-MLR: 41.

Tables 12 and 13 represent the results of performance analysis for Early Stuart timing forecasts. The former table ranks all qualifying models based on retrospective analysis and the latter table based on jackknife sampling. There is one clear, simple conclusion that we can immediately draw: the forecasts produced by the multiple regression models consistently performed better than the single variable models. The median rank (of all qualifying models) from retrospective is 90.1 (maximum: 335) and jackknife is 67.6 (maximum 381). The variables that were utilized in the top 50 performing models are presented in Figure 35. As all the top 50 models are multivariate, many of the same variables are used repeatedly across models, which is why the number of variables presented in each plot is limited.

Naïve Models: Seven naïve models were evaluated: 4YrMn, 8YrMn, TSA, 4YrMd, 8YrMd, TSMd, and LLY. In the retrospective results, all models ranked worse than the median rank (=90), their ranks ranged: 102 (TSMd)–368 (4YrMn). The same held true based on the jackknife results, which had a median model rank: 67.6, while the naïve models ranged: 121 (LLY)–181 (TSMd).

OI SST: Thirty three models met the initial filter requirements. Based on the retrospective ranking, 10 of the top 50 multivariate models include OI SST, while from jackknife 12 models include OI SST. Of the multivariate models that include OI SST, 43 are ranked superior to the median rank. This implies there are cases of the same OI SST variable being re-used in varied combinations with other data types.

Shore station SST: Just two SST single variable models met the initial filter requirement. They are based on May temperature at Kains Island ($R^2 = 0.59$) and Amphitrite Point ($R^2 = 0.52$). Their retrospective-based ranks are ≈ 156, which is substantially worse than the median rank (90.1). They show similarly poor results based on jackknife analysis. However, a multivariate model including the Kains Island data does rank in the top 14 retrospective ranks and top 37 jackknife ranks.

PDO: The strongest statistical fit between Early Stuart timing and PDO was based on the May values of the return year ($R^2 = 0.22$). As none of the models based on PDO had $R^2 > 0.5$, they were not considered in the performance analysis.

Shore station SSS: None of the models based on shore station SSS had $R^2 > 0.5$. Thus, none of these models were considered in the performance analysis.

NEPSTAR variables: All 41 qualifying NEPSTAR-based models are multivariate. From the retrospective results, one of the 41 NEPSTAR-MLR models ranked in the top 50 models, and 24 were superior to median rank. From the jackknife results, ten of the 41 NEPSTAR-MLR models ranked in the top 50 models and all 41 were superior to the median rank.

[16] See Section 4.5 for qualification criteria.

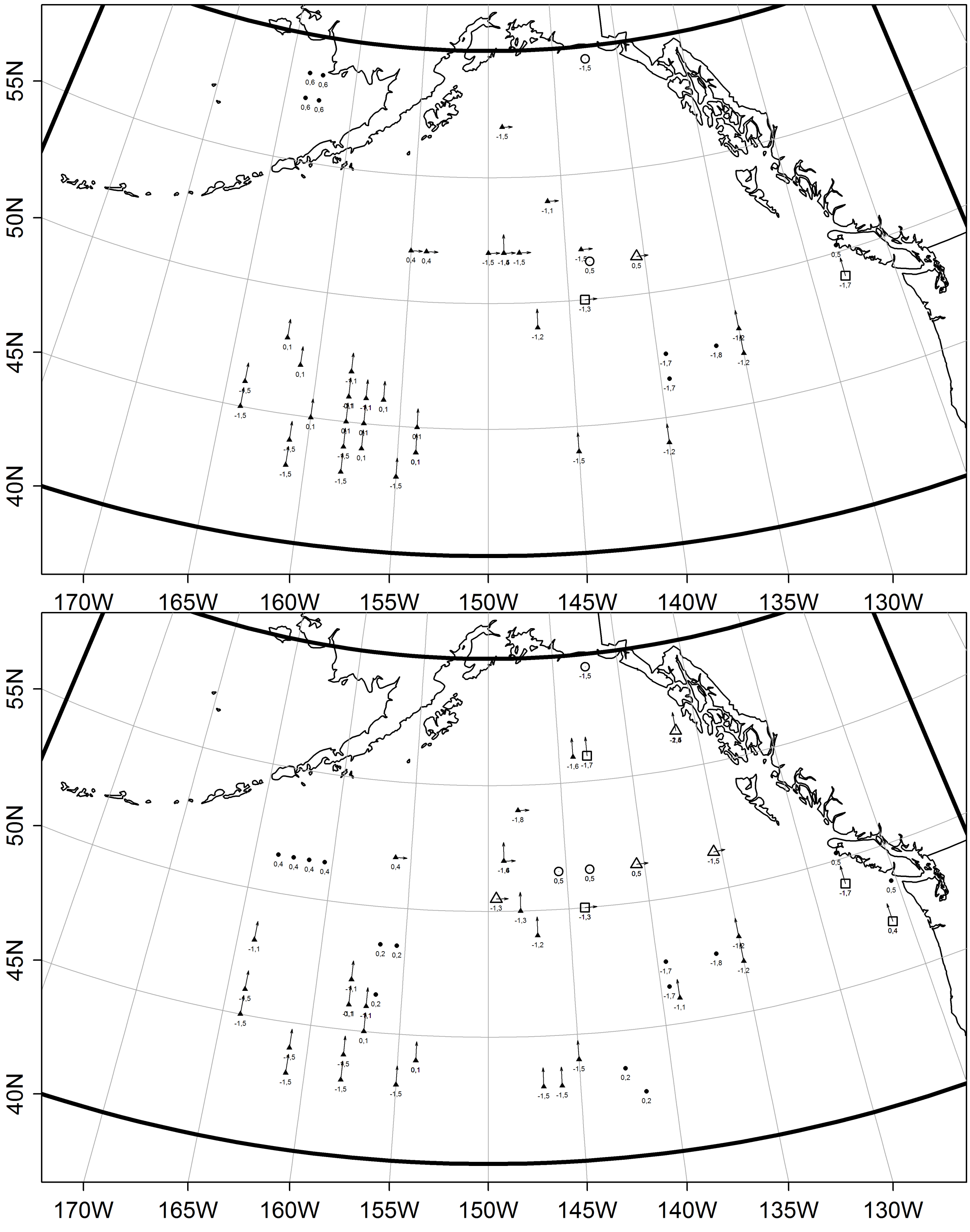


Figure 35. Locations of variables for the top 50 Early Stuart timing forecast models based on retrospective (upper panel) and jackknife analyses (lower panel). Circles represent SST, triangles represent current velocity data, and squares represent wind stress data. Open points are data used in NEPSTAR-MLR models, while smaller, solid points are data used in single variable regressions. Arrows define the direction (but not magnitude) of wind or current velocity variable. The two digits with each point represent the year relative to return year, and month. For example -1,2 indicates data from February of the year prior to return. The area defined by a thick, black line defines the search region—excluding land.

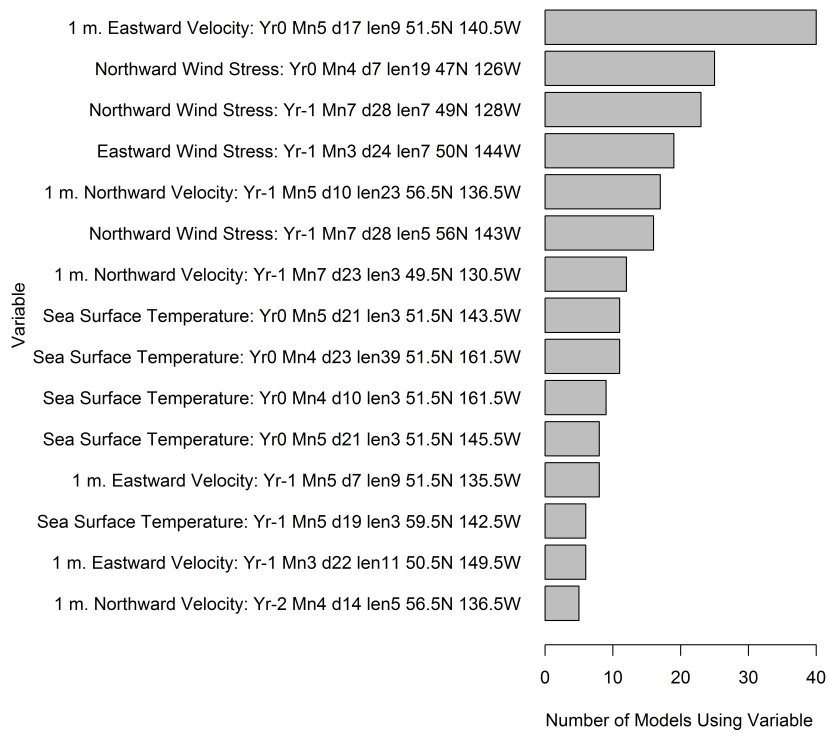


Figure 36. Frequency of use for the 15 variables within each of the 41 NEPSTAR-MLR models of Early Stuart timing. Each variable is uniquely defined by it's data type (current velocity, wind stress, temperature), year, month, start day, averaging window length (in days), latitude, and longitude.

OSCAR: Eighty-four single variable, OSCAR-based fits met the initial filter requirements. Of those 84 models, 59 are based on V current velocity and 25 from U current velocity (Figure 37). The OSCAR data also contributes to the top multivariate models, (49 and 40, respectively, of the top 50 retrospective and jackknife models). Considering the 191 models superior to median ranking, 167 (retrospective) and 142 (jackknife) included OSCAR data. Meridional data are also prominent in the multivariate models. All 221 non-NEPSTAR multivariate models include meridional currents, while just 44 include zonal currents. In contrast, for the NEPSTAR-MLR models, 24 models include meridional currents, and all 41 models include zonal currents.

U2 using TSA benchmark: The U2 PM is an index of model performance relative to that of a pre-defined benchmark model. Generally naïve models (e.g. LLY and TSA) are placed in the benchmark role. Conversely, the statistic is also a simple approach to assess the success of naïve models, relative to other *tested* models. U2 values less than one indicate the *tested* model has superior performance to the naïve model. In this evaluation, we can conclude that all 191 models with rank superior to the median rank (retrospective or jackknife results) performed superior to a TSA model. The minimum U2 value is 0.29 and the maximum within the first 191 models is 0.72. These results were not included in the appendix tables.

U2 based on LLY benchmark model and MASE: Considering the conceptually simplest PMs first, all but two models with rank superior to the median also had U2 and MASE values < 1.0 and most were < 0.7. This means the PMs agree that the majority of models with ranks superior to median rank have, on average, a smaller error than the LLY benchmark model. These PM values are smaller in the jackknife results than in the retrospective results. The MASE and U2 are highly correlated, especially for values less than one (see Figure 38 and 39), so common results would

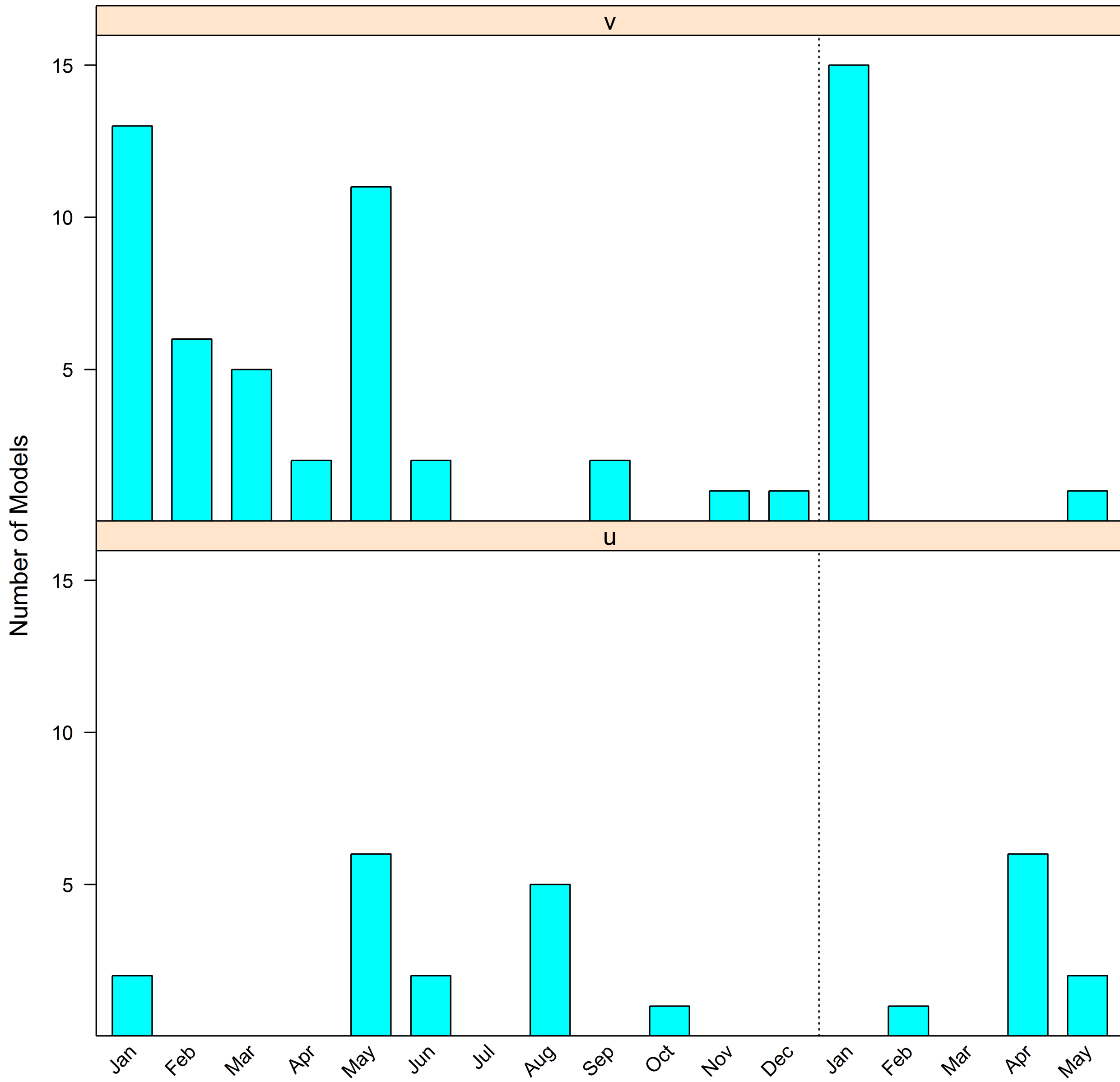


Figure 37. Number of OSCAR data models, by month and current direction, that meet criteria to forecast Early Stuart timing. Currents vectors are: Zonal (eastward) current velocity (U current velocity) and Meridional (northward) current velocity (V current velocity). The month values range from January of year prior to return to May of the return year. The vertical dashed line separates calendar years.

be expected.

MRE: When the average of residuals to a statistical fit does not equal zero, it is indication that the model has a bias. We can evaluate for bias by considering both the diagnostic plots for the top ten models (see Figures 40 and 41) and the MRE column in the results Tables 12 and 13. Six models consistently ranked in the top eight performers in both retrospective and jackknife analyses. Thus, the diagnostics of those models match between the two sets of figures (though their order in the diagnostics won't necessarily match). Additionally, absence of correlation between the residuals and fitted values (second column of plots) confirms that their is minimal information remaining in the residuals (that the covariates could explain). While the MRE column in each of the two results tables is indicative of model bias, the bias estimate is not explicitly derived from the residuals of the fitted model. The MRE is the mean of all the forecast errors with units in days. MRE values for the top 50 models range -0.5–0.8 days and most remain within 0.3 days. The MRE values estimated during jackknife analysis are consistently lower than those from retrospective, the former never exceeding ± 0.3 days. Within the top 50 models there is a reasonable overlap of 19 models common to both retrospective and jackknife. Conversely, 31 models do not match between performance analyses. Two variable models that ranked well in retrospective results have noticeably inferior placing in jackknife results. Virtually all of the two variable models substantially underestimated the anomalously late timing year 2005, which was sufficiently late to be outside the 99.9% probability level of the series. Given the time series of Early Stuart run timing, there is a one in 4231 chance of seeing timing as late as occurred in 2005. The three variable models faired substantially better at forecasting 2005. While the chronic failure of two variable models to accurately forecast 2005 did not substantially influence the MRE it did have a strong impact on both MAE and RMSE. It is those poor results that reduces the overall rank of the two variable models in the jackknife results. While extremely small, the jackknife derived MRE values are predominantly negative. This indicates that, while not statistically significant, the majority of the jackknife top 50 models underestimate timing. The MRE is no larger than -0.29 days (i.e., an *average* underestimation of seven hours). The consistency of this trait across most models would indicate a very minor change to the timing data that the covariates do not capture. The trend, of Early Stuart, to later timing dates was significant until approximately 2007 (see Figure 15), but this pattern has since ceased. The break in trend, immediately before the data period for retrospective sampling, may be why retrospective results do not consistently show negative model bias (i.e., negative MRE).

MAE and RMSE: Within the top 50 models, the smallest MAE values are 0.92d (retrospective) and 1.17d (jackknife), both based on multivariate regression models. The former statistic is from the top performing model, which is based on two variables. As suggested previously, the lack of consistent performance of most two variable models could suggest their exclusion may be appropriate. Considering only models with three or more variables, the same PMs are 0.95d and 1.17d. Note that the latter has not changed as it is based on the best jackknife model, a three variable regression. Seventeen two-variable models ranked in the retrospective top 50, but none ranked in the jackknife top 50.

Diagnostic Plots: The retrospective and jackknife top ten models are all based on multivariate regression (non-NEPSTAR), see Figures 40 and 41. Multicollinearity effects are likely low as most correlation coefficients are well below 0.50, and all are below 0.60 (seen in correlation matrices on each row of plots). Year 2005 had substantially later timing than all years of the series. As mentioned previously, the apparent inadequacy of the single and two variable models may have been influenced by that one point, but this was not thoroughly evaluated. The residual versus fitted value plots suggest the residuals are evenly distributed (homoscedastic), meaning data transformation is not likely necessary.

As seen in the two-variable models, some of the lower ranking (i.e., the 6th–9th) multivariate regression models indicate 2005 to be an outlier from their fits (see the quantile:quantile plots in Figures 40 and 41). Year 2005 is the latest run timing date in the 1951–2013 series, and is outside the 99.9% cumulative probability. The anomalously late Spring Transition in the alongshore wind stress along the west coast (one of the latest on record) delayed upwelling conditions. Everything from plankton to fish and birds along our west coast fared poorly that spring (DFO, 2006). Additionally, there was anomalously low river discharge in the spring and early summer into the Strait of Georgia and Queen Charlotte Sound (Thomson et al., 2012). Year 2005 also had very poor seabird success off Triangle Island associated with very low surface chlorphyll in the spring (Borstad et al., 2011). Finally, there was an El Niño during 2004–05, resulting in relatively warmer coastal waters. There is moderate, but not significant, evidence that Early Stuart timing is influenced by El Niño events (Figure 33). Notwithstanding, 2005 was retained in the series for evaluation in the performance analysis. It is important to note that most of these top ten models share common data, and tend to vary by one variable, so differences between diagnostic plots may be subtle.

Ranks: Retrospective analysis should test the robustness of a forecasting model to changes in the environment (dependants and covariates) that could lead to model failure. Jackknife analysis relies on models fitted to nearly the complete data series, meaning the model performance is tested always with nearly complete knowledge of the system it's meant to represent. One would expect a model that performs well by retrospective analysis to do equally well in jackknife. This assumption is not true for any of the 17 two-variable models, but is apparent for many of the 33 models comprising ≥ 3 variables—19 are common to retrospective and jackknife. The superior performance of models with ≥ 3 variables may be due to the stabilizing effect that a mutli-variable relationship will produce compared to more the sensitive nature of one and two variable regressions.

Figure 42 plots the rank data (MRE, RMSE, and overall average of PM ranks) for the top 50 models based on their ordinal rank, 1–50. The result is similar to a cumulative sum plot, which emphasizes any substantial changes in rank between adjacent models. Additionally, local trade-off between bias and uncertainty become apparent. Retrospective ranks suggest a rapid decline in model performance along the first ten models. All but one of these models are non-NEPSTAR multivariate models. The retrospective rank values are highly varied such that even the top models do not start with averaging ranking less than five. Conversely, for jackknife, the top nine models are all non-NEPSTAR multivariate, and there is a moderate step in rank at the tenth model after which performance declines slowly (Figure 42, right panel). These plots communicate two very different signals. The retrospective plot suggests that model performance declines rapidly during the first ten models, while the jackknife plot suggest there is little difference between the first ten models. These contradicting results are possibly confounded by the presence of many two-variable models in the retrospective plots, which are absent from the jackknife plot. The plots also reveal a reciprocal relationship between bias (MRE) and uncertainty (RMSE) in most models—with retrospective results. However it should be noted that these statistics are calculated from six data points in each model appraisal. The jackknife results suggest similar but less dramatic traits of reciprocity.

Average rank is estimated from four PMs and, on a model-by-model basis, the PMs do not necessarily agree on improving or degrading performance. As negative MRE carries equal weight to positive MRE, models with the same RMSE but opposite MRE (e.g. -0.7d and 0.7d) could be ranked equally. This trait is demonstrated by the line connecting models of declining rank in Figure 43. The line is ratcheting left and right between models of comparable RMSE but opposite signed MRE. A quick evaluation shows there is no significant relationship between bias (represented as |MRE|) and uncertainty (RMSE). However, the data do appear to group into two aggregates, which is most apparent in the jackknife plot. The lower aggregate within each plot comprises the top 5–8 models.

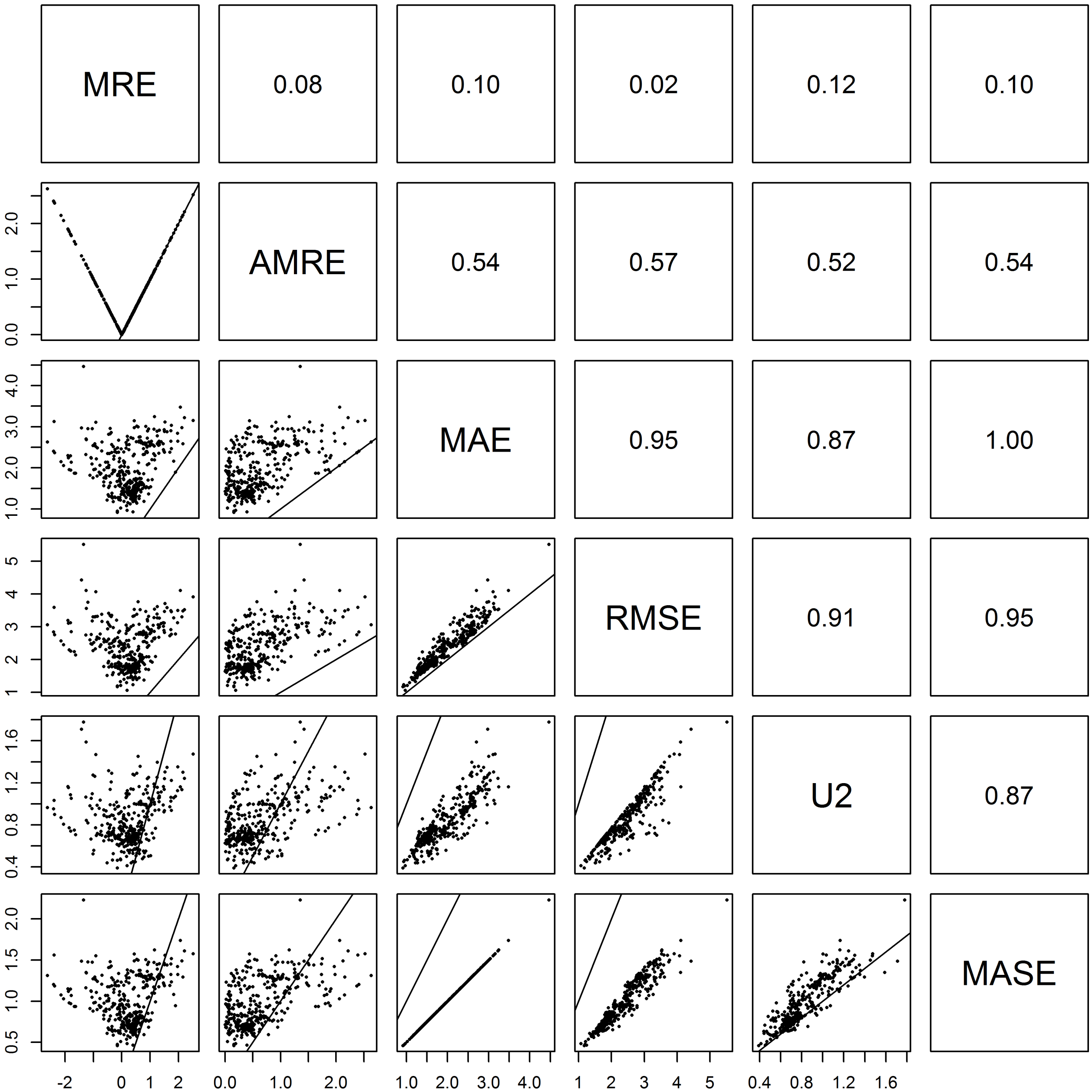


Figure 38. Pairs plot of performance measures based on retrospective testing of 381 models evaluated to forecast Early Stuart timing. The line in each panel represents a slope of 1. Values in the upper right corner represent the correlation coefficient between pairs of PMs. The PMs include: mean raw error (MRE), absolute value mean raw error (AMRE), mean absolute error (MAE), root mean squared error (RMSE), Theil's U statistic (U2), and mean absolute scaled error (MASE). The initial four PMs have units in days. The latter two PMs are unit-less and described in the section 4.7.2.

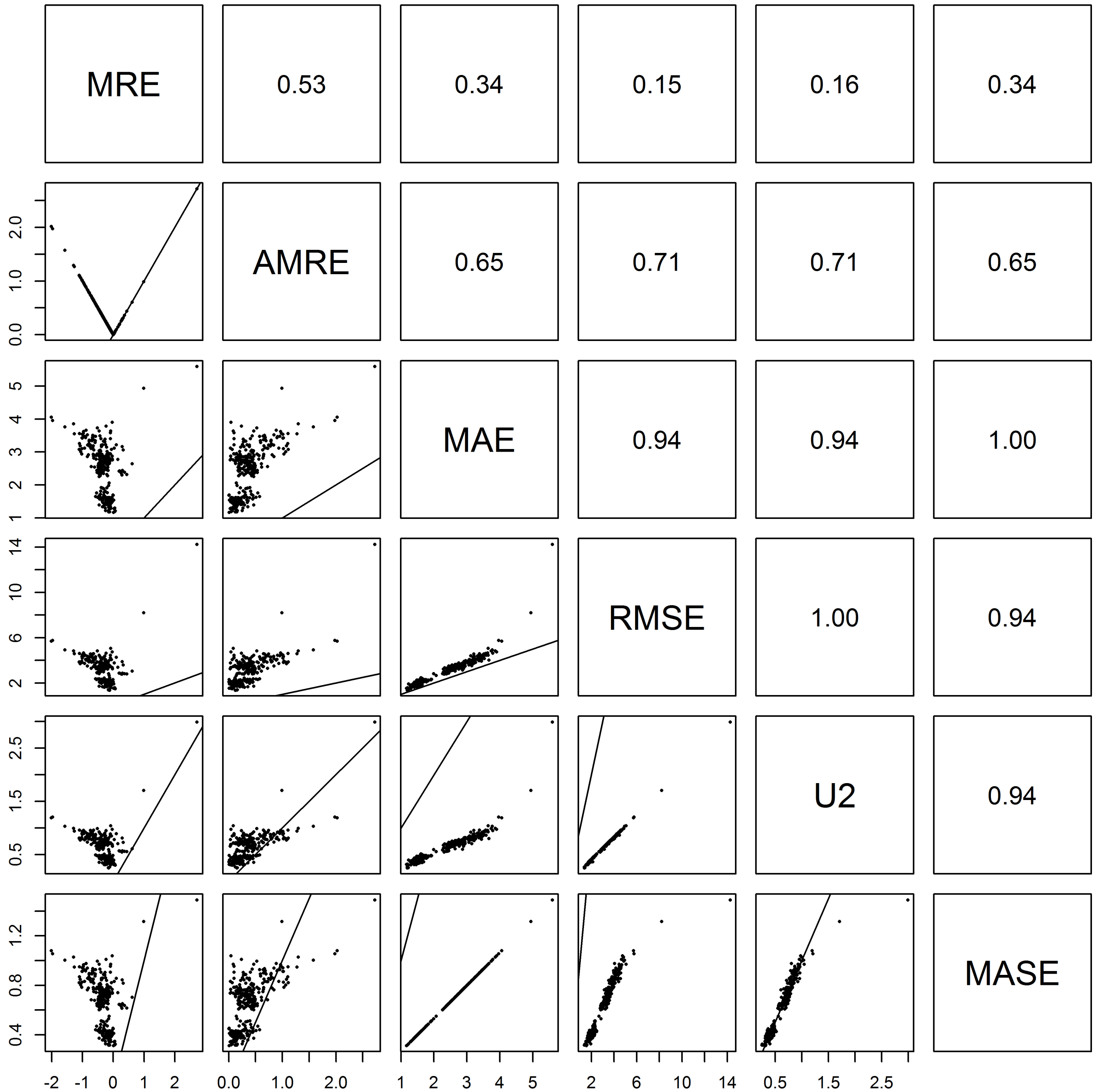
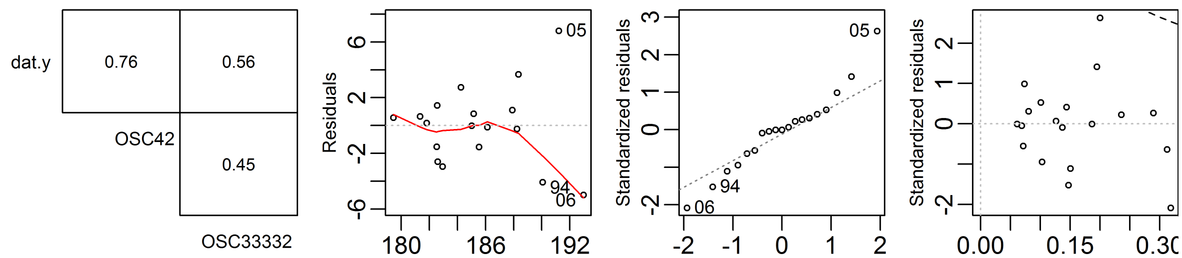
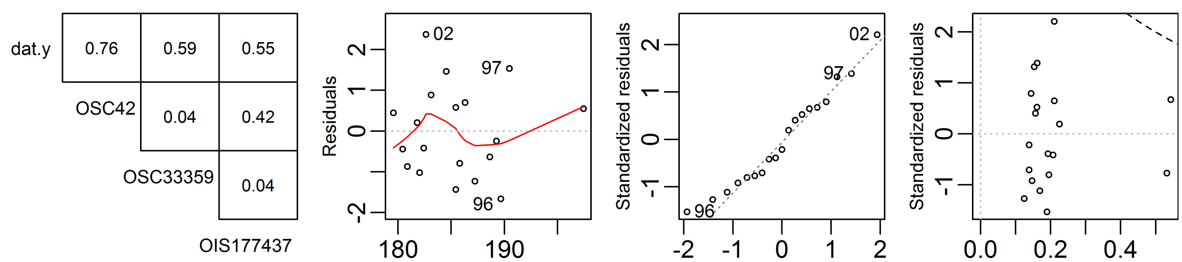


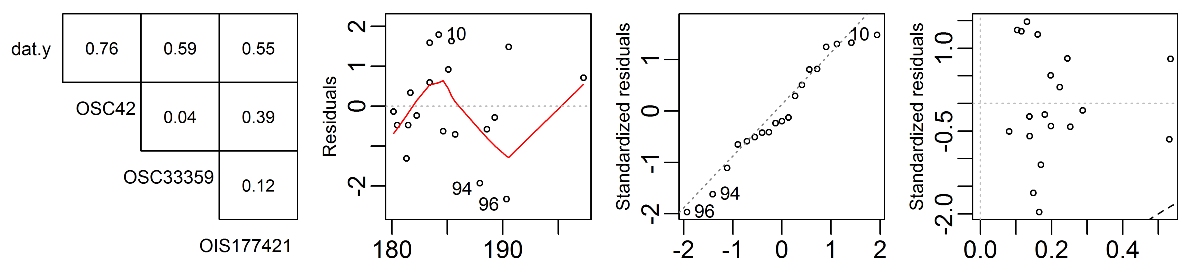
Figure 39. Pairs plot of PMs based on jackknife testing of 381 models evaluated to forecast Early Stuart timing. The line in each panel represents a slope of 1. Values in the upper right corner represent the correlation coefficient between pairs of PMs. The PMs include: mean raw error (MRE), absolute value mean raw error (AMRE), mean absolute error (MAE), root mean squared error (RMSE), Theil's U statistic (U2), and mean absolute scaled error (MASE). The initial four PMs have units in days. The latter two PMs are unit-less and described in the section 4.7.2.



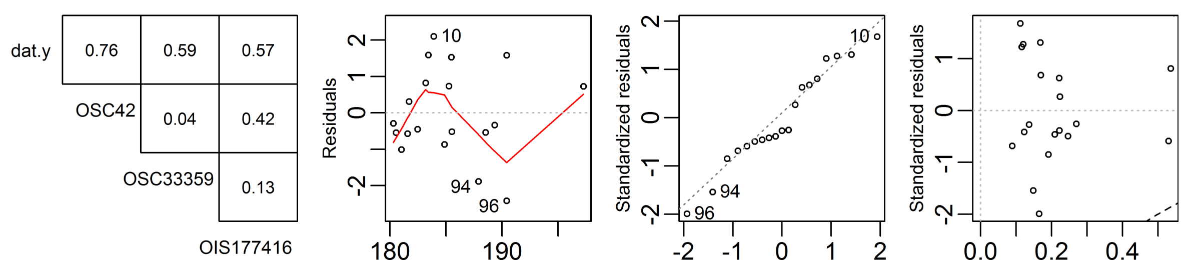
(a) *mlr188*



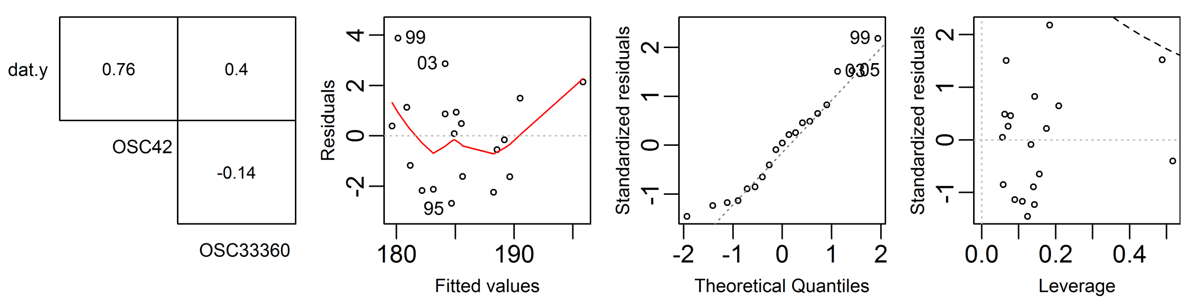
(b) *mlr1*



(c) *mlr2*

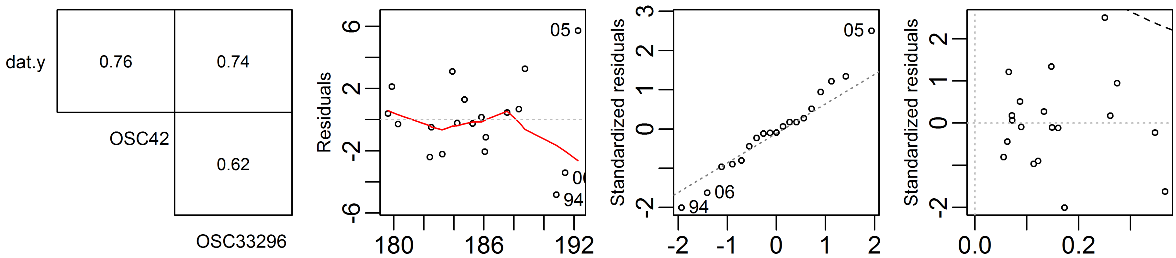


(d) *mlr3*

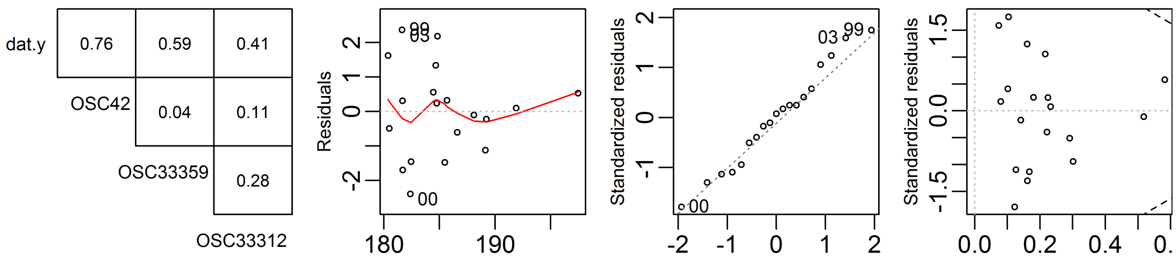


(e) *mlr117*

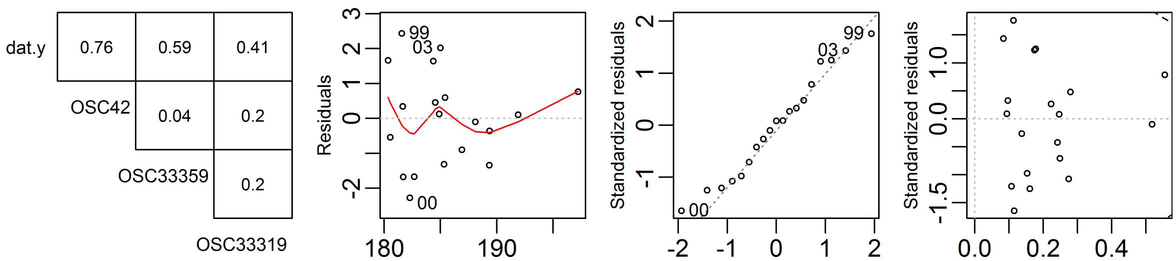
Figure 40. Diagnostic plots for statistical fits to the full data sets of the top ten performing Early Stuart timing models based on retrospective evaluation. Each row of plots represents one model, which is named beneath the row. Plots are described in the beginning of the results section.



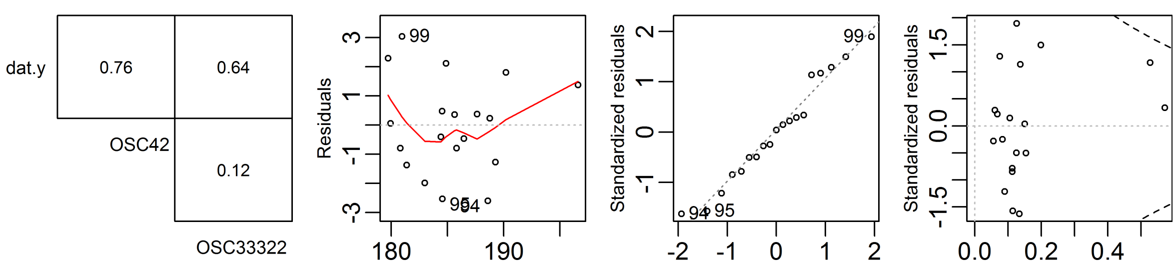
(f) mlr141



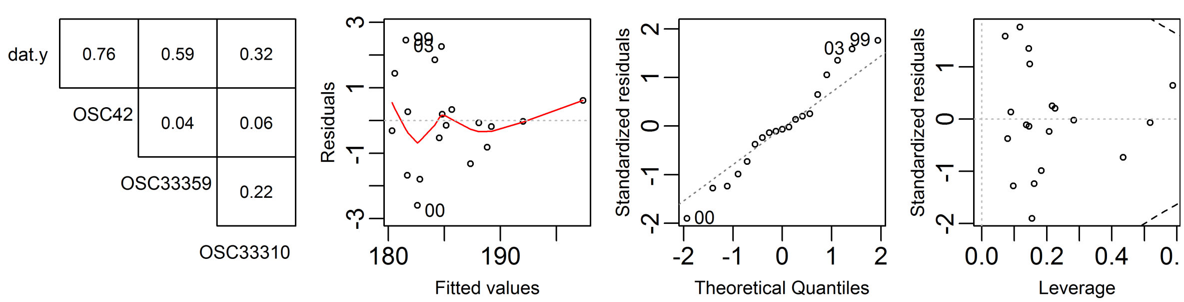
(g) mlr4



(h) mlr6

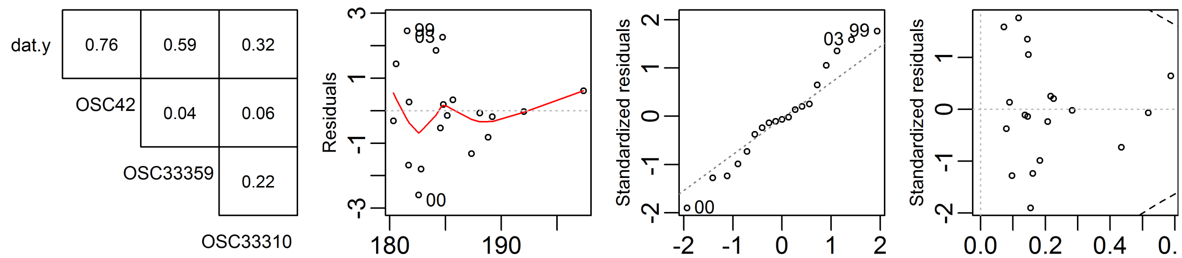


(i) mlr52

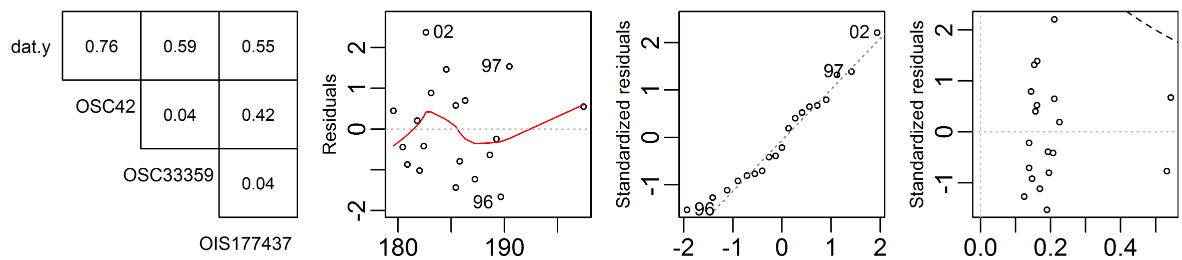


(j) mlr7

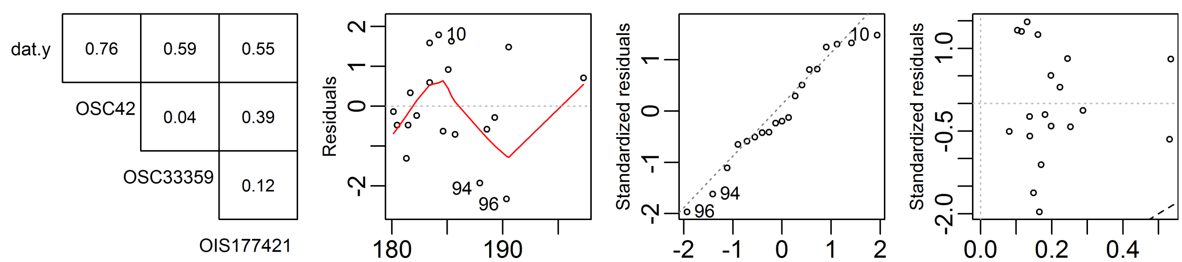
Figure 40. Continued



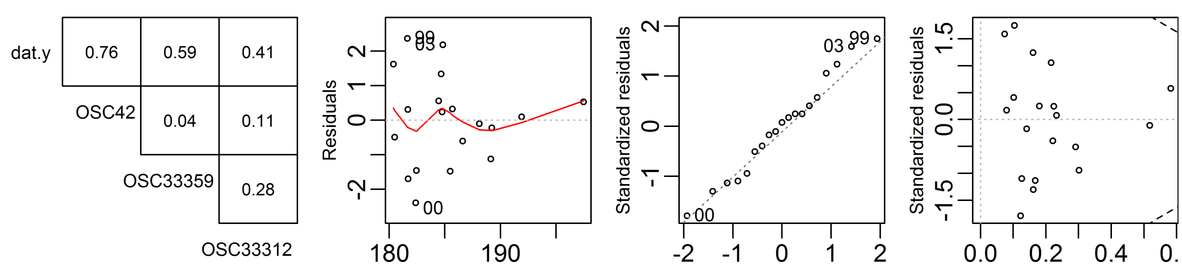
(a) mlr7



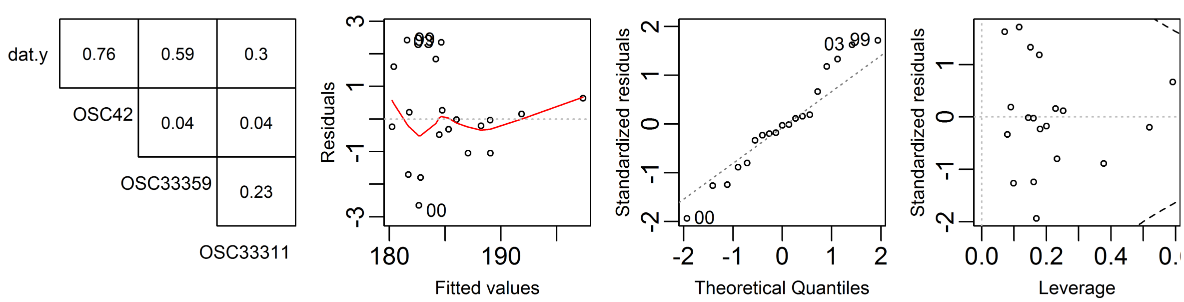
(b) mlr1



(c) mlr2

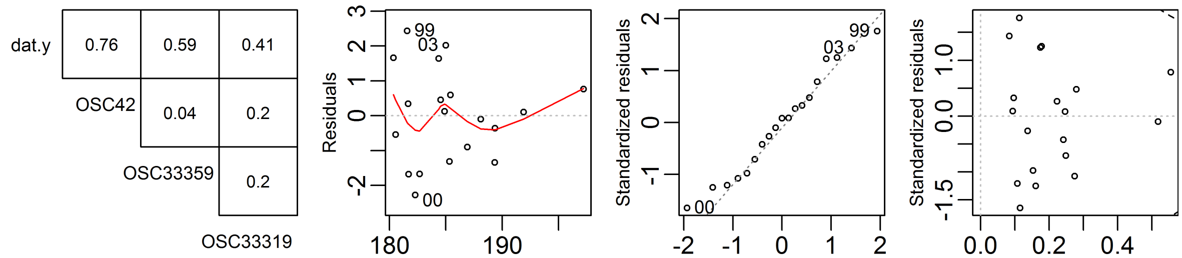


(d) mlr4

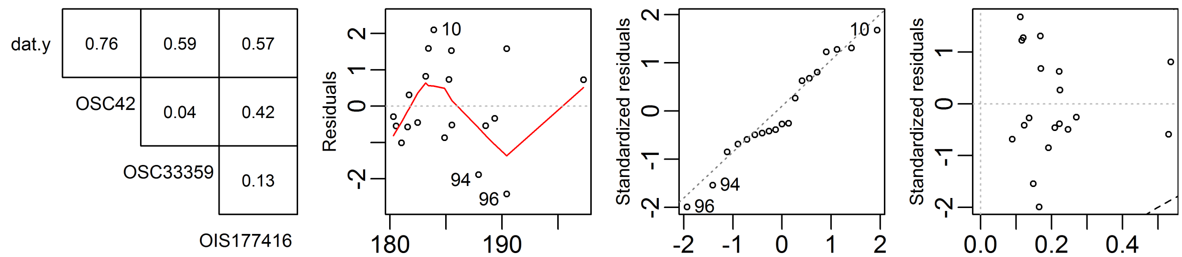


(e) mlr8

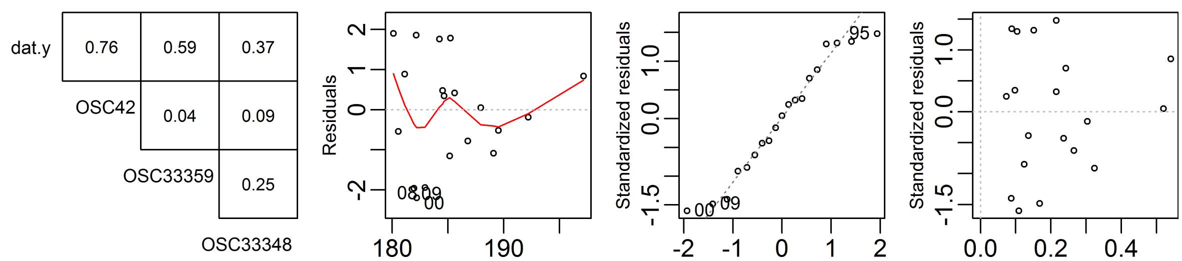
Figure 41. Diagnostic plots for statistical fits to the full data sets of the top ten performing Early Stuart timing models based on jackknife evaluation. Each row of plots represents one model, which is named beneath the row. Plots are described in the beginning of the results section.



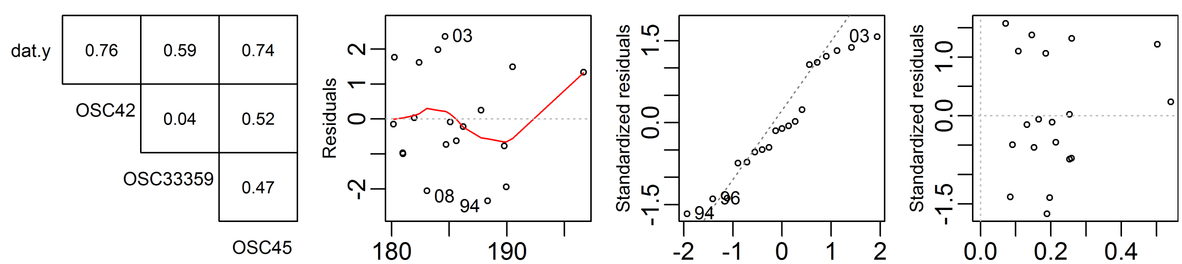
(f) mlr6



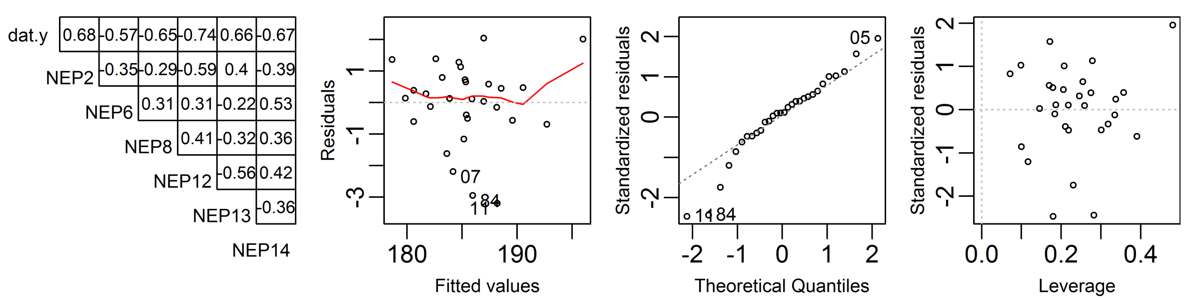
(g) mlr3



(h) mlr5



(i) mlr17



(j) nepstar14

Figure 41. Continued

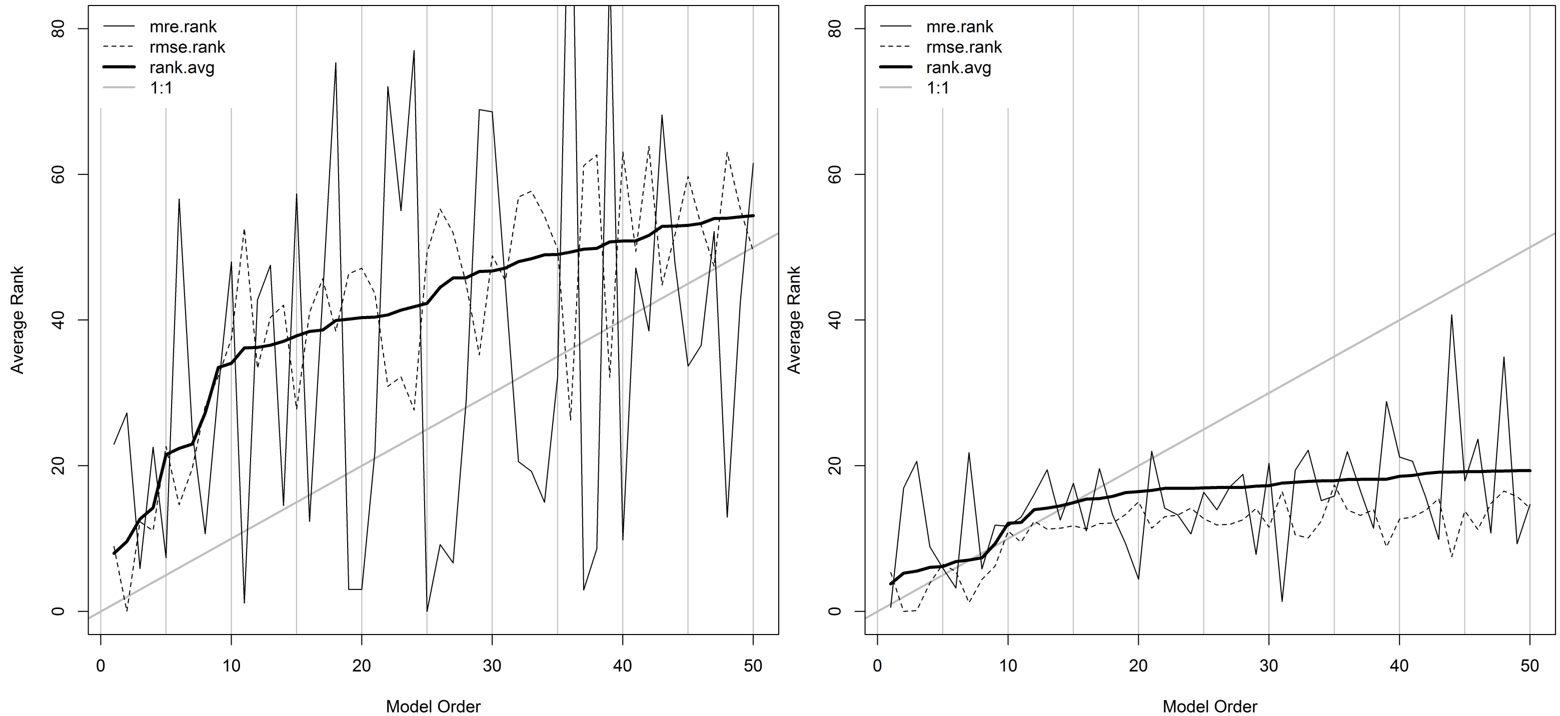


Figure 42. MRE rank, RMSE rank, and average rank for the top 50 Early Stuart timing forecast models. Left panel is results for retrospective analysis, right panel is jackknife. Note that model order does not consistently match between plots, such that the tenth model of the retrospective analysis is not necessarily the same as the tenth model seen in the jackknife results. The diagonal grey line has a slope of one, which allows for comparison to the average rank line.

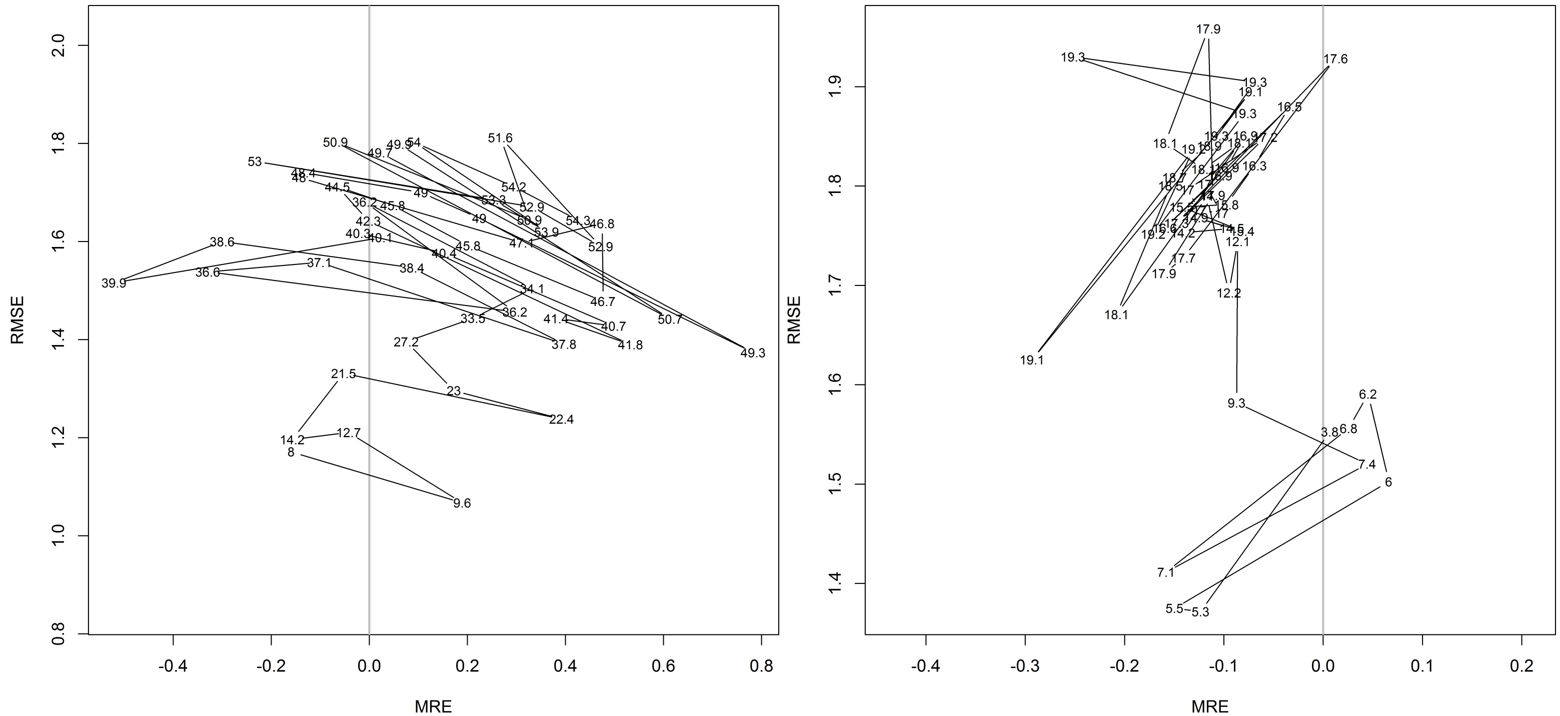


Figure 43. Relationship between PMs: RMSE and MRE for Early Stuart timing forecasts from retrospective (left panel) and jackknife (right panel) analysis. The number of each point corresponds to the average rank of each model. The line joins models from best ranked to worst ranked. The vertical grey line delineates models with a generally positive bias from those with a negative bias. This demonstrates how declining rank is often a process of ratcheting down between positive and negative bias (MRE).

Table 6. Summary statistics of annual forecasts, from the best performing model in each model type, for Early Stuart sockeye timing based on retrospective analysis. All variables except rank have unit days. The variables 'Forecast mean' and 'True mean' are ordinal date. True mean and True SD are the statistics of actual post season estimates, constrained to the same period on which performance analysis was based.

Model (type #)	Rank	All Models Median Rank	Max Positive Error	Max Negative Error	Min Error	Mean Abs Error	Forecast Mean	Forecast SD	True Mean	True SD
mlr188	7.97	90.08	2.13	-1.45	0.02	0.92	183.17	2.79	183.33	2.66
nepstar13	51.63	90.08	2.87	-1.94	0.05	1.52	183.60	3.04	183.33	2.66
OSCAR116447	60.84	90.08	3.27	-2.48	0.33	1.58	183.22	2.10	183.33	2.66
OISST177437	100.37	90.08	2.51	-4.11	0.20	1.92	183.89	1.98	183.33	2.66
shore310799	156.23	90.08	5.07	-2.59	0.66	2.47	184.10	0.68	183.33	2.66

Table 7. Summary statistics of annual forecasts, from the best performing model in each model type, for Early Stuart sockeye timing based on jackknife analysis. All variables except rank have unit days. The variables 'Forecast mean' and 'True mean' are ordinal date. True mean and True SD are the statistics of actual post season estimates, constrained to the same period on which performance analysis was based.

Model (type #)	Rank	All Models Median Rank	Max Positive Error	Max Negative Error	Min Error	Mean Abs Error	Forecast Mean	Forecast SD	True Mean	True SD
mlr7	3.77	67.60	3.06	-2.79	0.03	1.17	185.59	4.25	185.59	4.70
nepstar14	12.10	67.60	3.89	-3.88	0.05	1.29	185.50	4.52	185.59	4.70
OISST177413	54.98	67.60	4.84	-3.81	0.26	2.31	185.87	3.52	185.59	4.70
OSCAR44	64.62	67.60	4.67	-8.43	0.15	2.54	185.41	2.73	185.59	4.70
shore311951	74.20	67.60	5.62	-8.32	0.11	2.75	185.34	3.18	185.59	4.70

Forecast Plots: The forecast plots (figures 44 and 45) are intended to give a realistic view of how the top performing model from each variable type compares in their ability to forecast the observed return timing dates. The time period (x-axis) of each plot equates to the period assessed in either retrospective or jackknife evaluation. The plots include the true timing estimate in each year, forecasts from the middle 95% of all 381 models (to give a sense of the range of forecasts within each year) and, in larger symbols, the forecast from the best performing model of each model type. This format allows us to appraise the absolute difference between models by year. Some useful conclusions can be drawn from this information. However as described previously, results are not necessarily consistent between retrospective and jackknife analysis. Given the retrospective results, the shore station model (based on May SST at Kains Island) has the lowest rank in these plots. The forecasts from this model vary the least (forecast SD is 0.68d), while the best ranked model (*non-NEPSTAR-mlr188*) has a forecast SD of 2.79d, and the SD of the observed timing (2007–2012) is 2.66d (Table 6). The Kains SST series is failing to capture the full range of environmental variation that actually drives Early Stuart timing, and thus forecasts based on this SST also vary by a smaller amount, which is why the forecast SD is the smallest of the four models. All forecasts from model *non-NEPSTAR-mlr188* are within 2.1d of the true value, while each of the subsequent models were sequentially worse (NEPSTAR: 2.9d; OSCAR: 3.3d; OI SST: 4.1d; shore station: 5.3d)—for retrospective. Jackknife analysis shows similar results (maximum annual error *non-NEPSTAR-mlr188*: 3.1d; NEPSTAR-MLR: 3.9d; OI SST: 4.8d; OSCAR: 8.4d; shore station: 8.3d), though OSCAR and OI SST switched position in rank (table 7). There is presumably less value in considering the minimum annual forecast error, which is similar across the top four models types ($< 1/4$d).

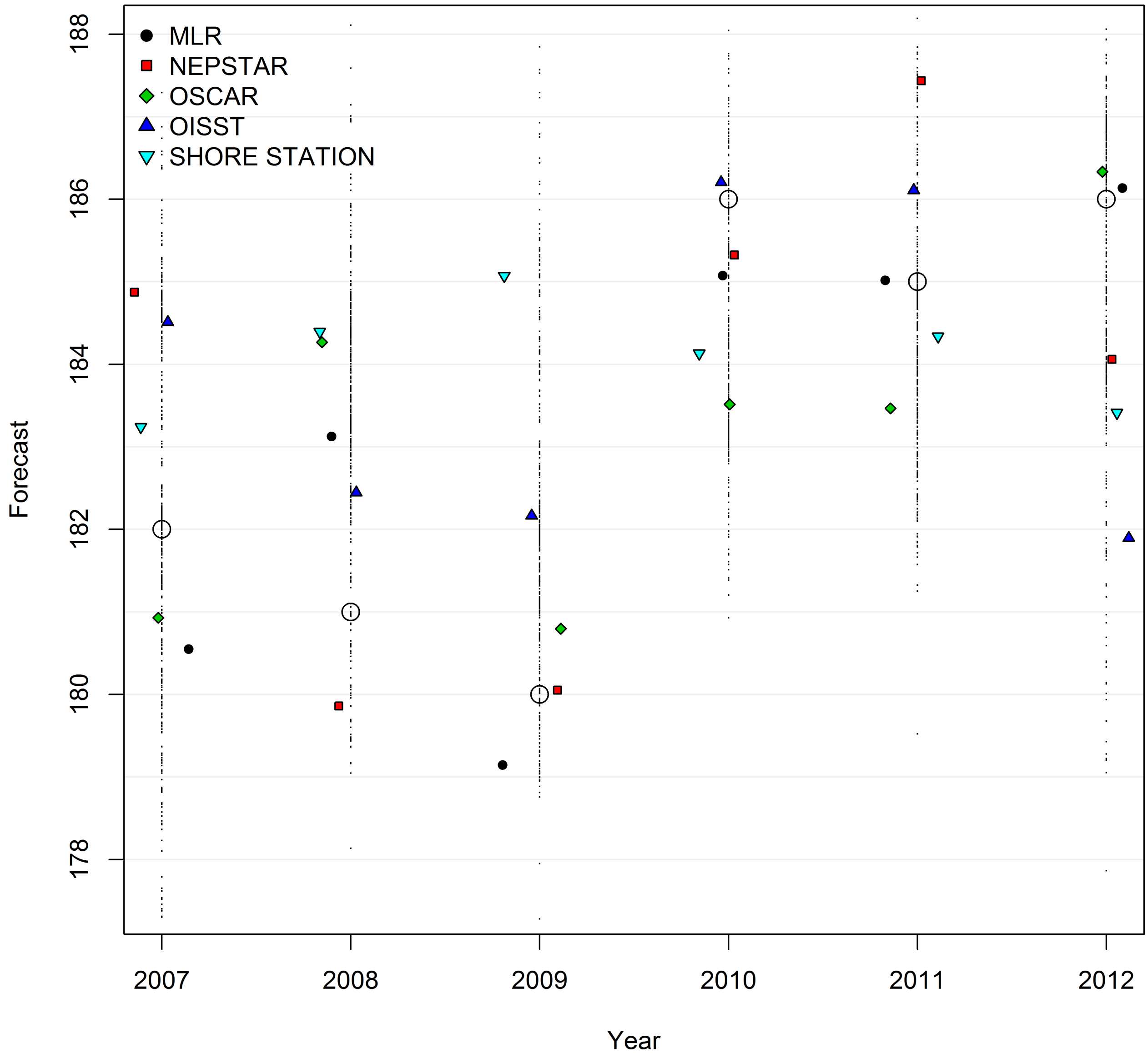


Figure 44. Annual Early Stuart timing forecasts for 2007–2012 from retrospective analysis. Data points for each year comprise approximately the 95% intervals of 381 forecasts. The black, open circle is the post-season observed timing date. The annual forecasts of each best ranked model, by model-type, are given unique symbols. Models are sorted in the legend by rank. The y-axis is ordinal date (days since December 31 of prior year).

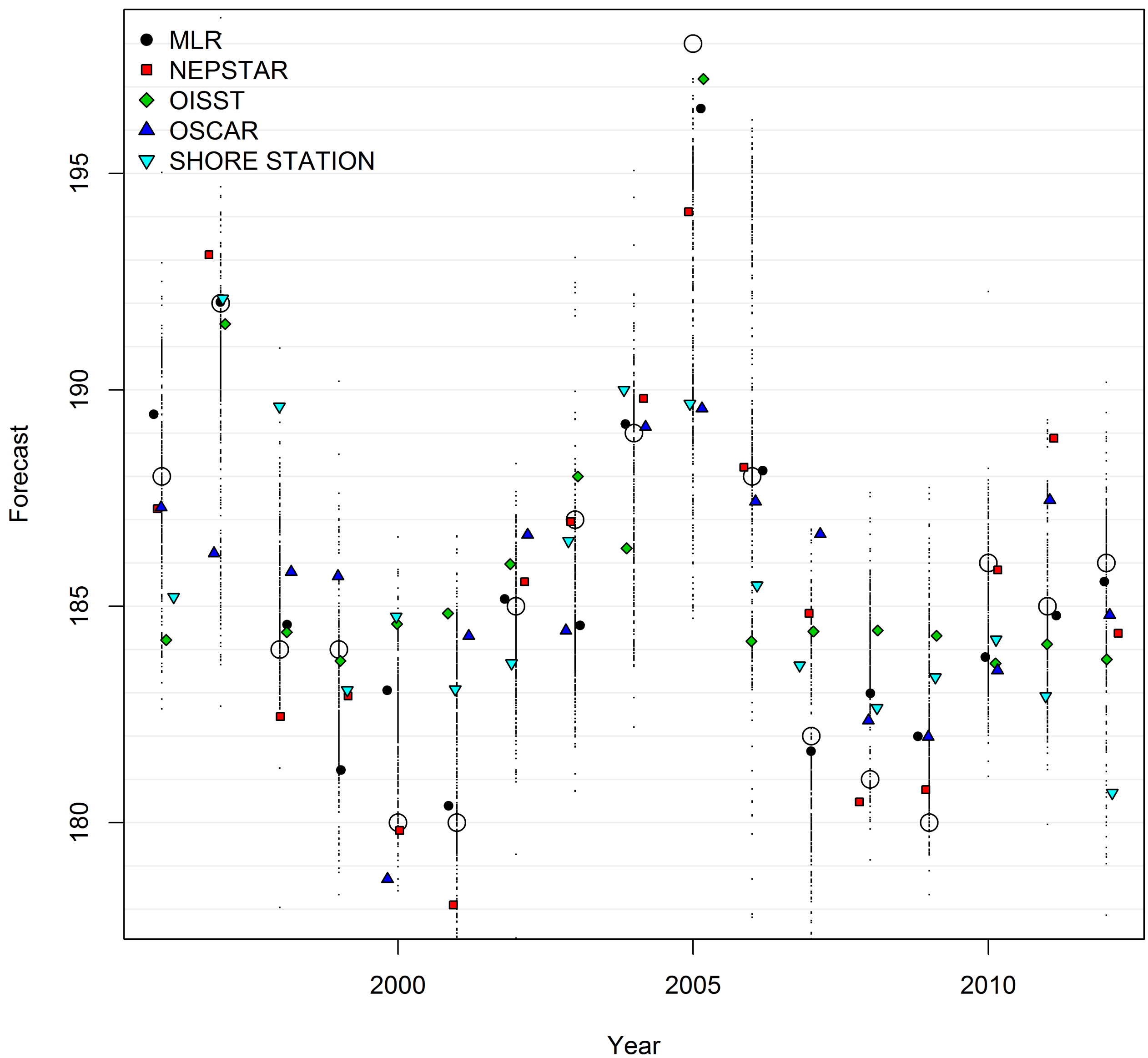


Figure 45. Annual Early Stuart timing forecasts for 1996–2012 from jackknife analysis. Data points for each year comprise approximately the 95% intervals of the 381 forecasts. The black, open circle is the post-season observed timing date. The annual forecasts of each best ranked model, by data-origin, are given unique symbols. Models are sorted in the legend by rank. The y-axis is ordinal date (days since December 31 of prior year).

5.1.3 Chilko

Approximately 251,000 models were evaluated and 249 passed the initial filter for comparison in the performance analysis. The qualifying models are comprised of: single variable (shore station: 1; OSCAR: 81); multivariate: 153; NEPSTAR-MLR: 14. The geographic locations for these variables are plotted in Figure 46.

Tables 15 and 16 represent the results of performance analysis for Chilko timing forecasts. The former table presents all qualifying models based on retrospective analysis and the latter table based on jackknife analysis. Unlike the case for the Early Stuart results, all 14 NEPSTAR-MLR models were top ranked by retrospective performance. From all 249 models, the median of rank from retrospective is 22.0 (maximum: 195.0) and jackknife is 33.2 (maximum: 243.3). The relatively low median rank from both evaluations is due to the final 3–4 models having exceptionally poor PMs. As a result, the initial 245 models have PMs and ranking closer to each other than to those final four models.

Naïve Models: Seven naïve models were evaluated: 4YrMn, 8YrMn, TSA, 4YrMd, 8YrMd, TSMd, and LLY. In the retrospective results, all models ranked worse than the median rank (=22), their ranks ranged: 31 (8YrMd)–54 (TSMd) . The same held true based on the jackknife results, which had a median model rank: 33, while the naïve models ranged: 82 (8YrMd)–193 (TSMd).

OI SST: All of the 353 OI SST models that passed the initial filter requirement were fit by a GAM, which frequently resulted in biologically unrealistic statistical fits, and therefore excluded. Thus none of the 353 models are represented in the previously mentioned 249 qualifying models.

Shore station SST: Just one shore station model met the initial filter requirement. It is a SCAM fit based on SST at Active Pass during April of the year prior to return. In retrospective results this model ranks among the lowest dozen and places well beyond the median jackknife rank. Additionally, while this variable is used in two multivariate models, they do not rank in the top 50. While we could expect a connection between Active Pass April SST, tidal mixing and Fraser River discharge, a link to Chilko timing is tenuous at best. Additionally, it is felt that the time series at this shore station is not representative of the local conditions. We believe any possible link to Chilko timing can be ruled out on physical grounds.

PDO: The strongest statistical fit between Chilko timing and PDO was based on the May values of the return year ($R^2 = 0.23$). As none of the models based on PDO had $R^2 > 0.5$, they were not considered in the performance analysis.

Shore station SSS: None of the models based on shore station SSS met initial filter requirement of $R^2 > 0.50$. Thus none of these models were considered in the performance analysis.

NEPSTAR variables: Fourteen models were evaluated using the NEPSTAR-MLR approach and they were all ranked in the top 14 by retrospective results. Jackknife results placed three of the same models in the top 14 models and 10 in the top fifty models. Each model can comprise data derived from varying months. The latest month of source data for all but one of these models is March of the return year (the remaining model is based on April data for the year of return).

OSCAR: Eighty-one single variable models were OSCAR-based. Twelve single variable models performed superior to the median rank model (retrospective), but just four models performed similarly by jackknife results. This seems to be due to the single variable models' inability to capture the dramatic timing shift experienced in 2005. Forty-four of those models were based on

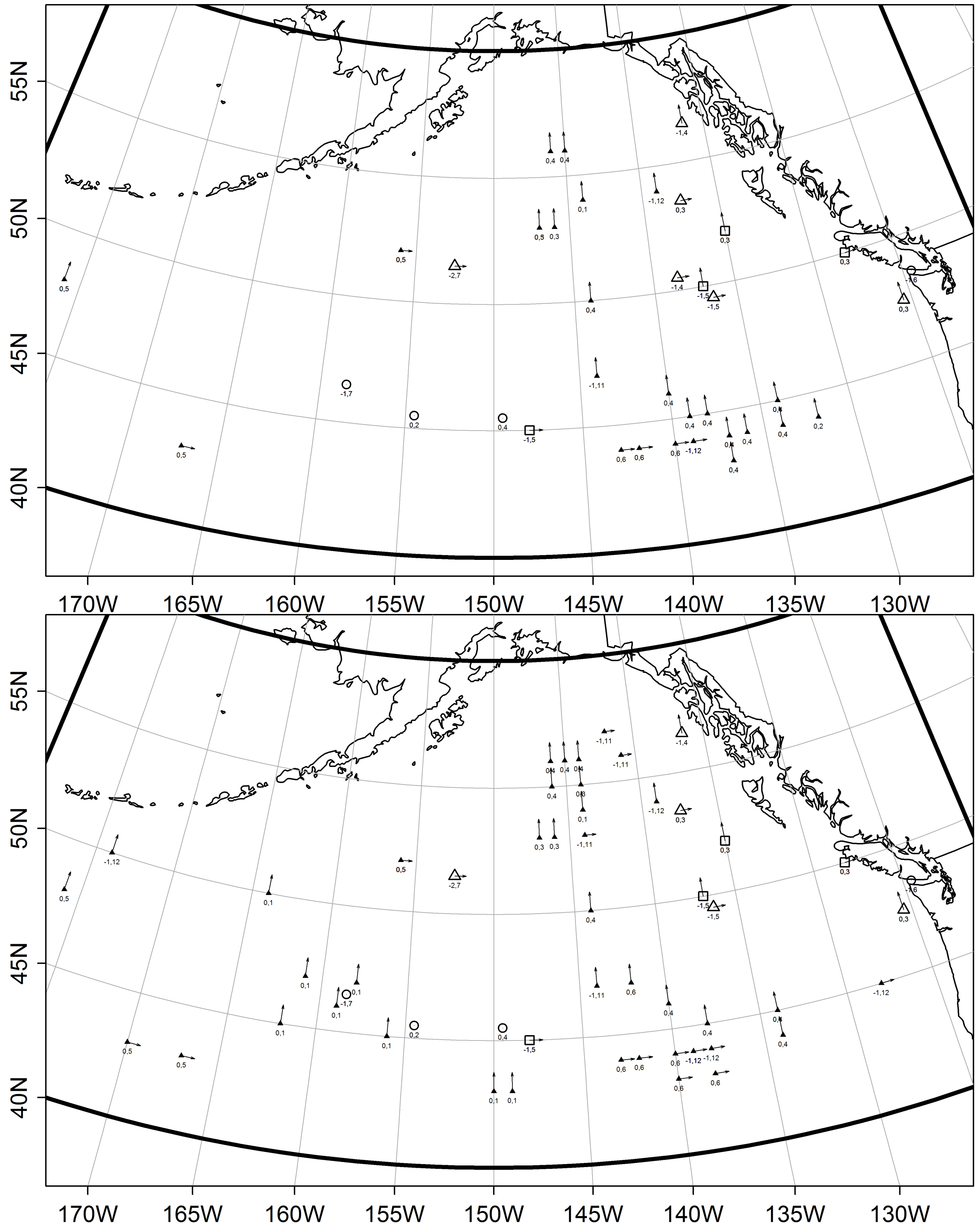


Figure 46. Locations of variables for the top 50 Chilko timing forecast models based on retrospective (upper panel) and jackknife (lower panel) analyses. Circles represent SST, triangles represent current velocity data, and squares represent wind stress data. Open points are data used in NEPSTAR-MLR models, while smaller, solid points are data used in single variable regressions. Arrows define the direction (but not magnitude) of wind or current velocity variable. The two digits with each point represent the year relative to return year, and month. For example -1,2 indicates data from February of the year prior to return. The area defined by a thick, black line defines the search region—excluding land.

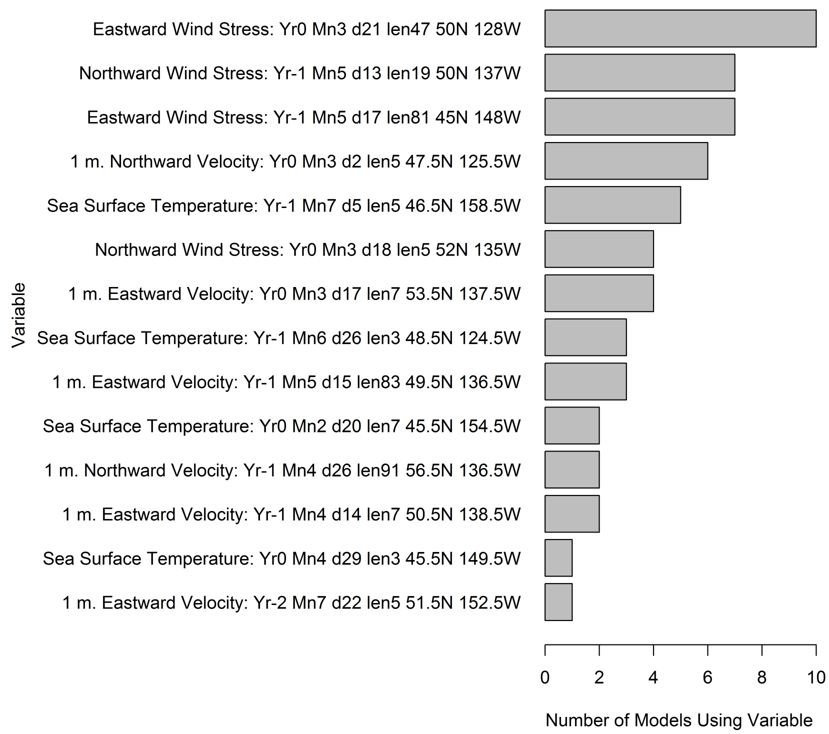


Figure 47. Frequency of incorporation for the 14 variables within each of the 14 NEPSTAR-MLR models of Chilko timing. Each variable is uniquely defined by its data type (velocity/current, wind stress, temperature), year, month, start day, averaging window length (in days), latitude, and longitude.

V current velocity, the remaining 37 were based on the U current velocity components (Figure 48). There is a noticeable difference regarding what months dominate each data series. The northward data are used predominantly from January to April, while the eastward current velocity models rely predominantly on May and June data.

The role of OSCAR-derived current velocity estimates in multivariate models of Chilko timing is substantial. There are 153 multivariate models that include one or more OSCAR variables.

U2 using TSA benchmark: U2 values less than one indicate the *tested* model has superior performance to the naïve model. In this evaluation, we can conclude that all 125 models with rank superior to the median rank (retrospective or jackknife results) performed superior to a TSA model. The minimum U2 value is 0.36 and the maximum within the first 125 models is 0.77. These results were not included in the appendix tables.

U2 and MASE: Considering the conceptually simplest PMs first, 75% of U2 and MASE values were ≤ 0.79 and within the first 50 models, all were ≤ 0.67. This means that the PMs agree that all top 50 models have, on average, a smaller error than the benchmark approach, which was forecasting with a like-last-year model. As mentioned for Early Stuart, the MASE and U2 are highly correlated, especially for values less than one (see Figure 49 and 50), so common results would be expected between these PMs..

MRE: As mentioned previously, the MRE column in Tables 15 and 16 is indicative of model bias, but it is not explicitly derived from statistics of the fitted model. MRE is the mean of all the forecast errors. The range of error for this and the other PMs is greater for Chilko than for Early Stuart. The standard deviation of observed Chilko median timing date is broader than that for

Early Stuart (6.8 and 3.8 days, respectively). This greater range in Chilko timing is likely why there is a broader range in its associated timing model PMs compared to those of Early Stuart. The retrospective estimates of MRE for the top 50 Chilko models spans -1.6 to 1.1 days, while the jackknife derived MRE spans -0.2–0.3 days. This translates to forecast biases that can be as much as 1.6 days for certain models. There is a substantial amount of variation in the MRE values for the top 30 retrospective models and it does not consistently progress from small to large bias with declining rank. This pattern is not apparent in the jackknife results.

Retrospective analysis should test the robustness of a forecasting model to changes in the environment (dependants and covariates) that could to lead to model failure. Jackknife analysis relies on models fitted to nearly complete data series, meaning the model performance is tested always with nearly complete knowledge of the system it's meant to represent. One would expect a model that performs well by retrospective to do equally well in jackknife. This does hold true for several non-NEPSTAR-MLR and NEPSTAR-MLR based models (5 are common to the top 20 models), but not the single variable models (OSCAR, OI SST). The consistent performance of the multivariate models may be due to the stabilizing effect that a mutli-variable relationship will produce compared to the more sensitive nature of single variable regressions (OSCAR, OI SST).

MAE: The smallest MAE values are 1.5d (NEPSTAR-MLR in retrospective) and 1.9d (non-NEPSTAR-MLR in jackknife). The increased error from jackknife would suggest more cases of larger forecast error, potentially based on poor forecasting of 2005. Within the top ten models the MAE quickly increases to values greater than two days. Additionally the values do not plateau at any time, suggesting there is a continuous increase in uncertainty with declining rank.

RMSE: Considering just the top 50 models, the mean standardized root mean squared error (RMSEs) (i.e., the mean of RMSE/MAE) does appear to be sensitive to the number of model variables. Models based on three or four variables produce the lowest RMSEs, while models with fewer (or more) than three to four variables have higher RMSEs. This suggests models based on three or four variables tend to produce the smallest *outliers* relative to their error size.

Diagnostic Plots: The diagnostic plots for the ten best performing models are presented in Figures 51 (retrospective) and 52 (jackknife). As NEPSTAR-MLR models three, two, and nine were in the top ten retrospective and jackknife models, their diagnostics plots are seen in each figure, and will be the same. Multicollinearity effects are likely low as most correlation coefficients are well below 0.50, and all are below 0.79 (seen in correlation matrices on each row of plots). The model residuals are evenly distributed and without trend (second column of plots), suggesting the fitted models should be without bias.

Ranks: Figure 53 presents the ranks of MRE, RMSE, and overall average of PM ranks for the top performing 50 models based on the order of their placing (1–50). As previously mentioned, the result is similar to a cumulative sum plot, which emphasizes any substantial changes in rank between each model. Additionally, local trade-off between bias and uncertainty become apparent. Consistent with Early Stuart results, the retrospective and jackknife ranks tend to fluctuate wildly. In both evaluations the model ranks decline rapidly over the first 19 (retrospective) and 10 (jackknife) models. Within the retrospective results the NEPSTAR-MLR models comprise the first 14 ranks. Following those models, all but one are non-NEPSTAR-MLR models based on OSCAR data. Similar to the retrospective results, the model ranking based on jackknifing declines consistently through the initial ten models and then model ranking slows such that models 11–30 have comparable ranking (and possibly similar performance).

Within the first 50 models there are 24 that are common to both retrospective and jackknife. As was noted in the Early Stuart results, most of the two variable models (15 of 16) that ranked in this range within retrospective failed to maintain that rank when evaluated via jackknife. This may be a case similar to what was described for the two variable Early Stuart models that were unable to capture the dramatic timing shift in 2005. A 2005 forecast is not assessed in retrospective evaluation, but it is in jackknife so we would expect to see model differences in the jackknife evaluation. Similarly, there were three single variable models in the retrospective top 50 that were not ranked comparably in the jackknife results. Models comprised of three and more variables showed much greater consistency between evaluation methods.

As was described in the paragraph on Early Stuart ranks, comparably ranked models with similar RMSE can vary substantially in their MRE values due to sign changes of MRE (see Figure 43). Also similar to the Early Stuart ranking, the top 6–7 Chilko models perform noticeably better than most others within each plot, i.e., there is a noticeable decrease in the slope of the rank average curve after models 6–7.

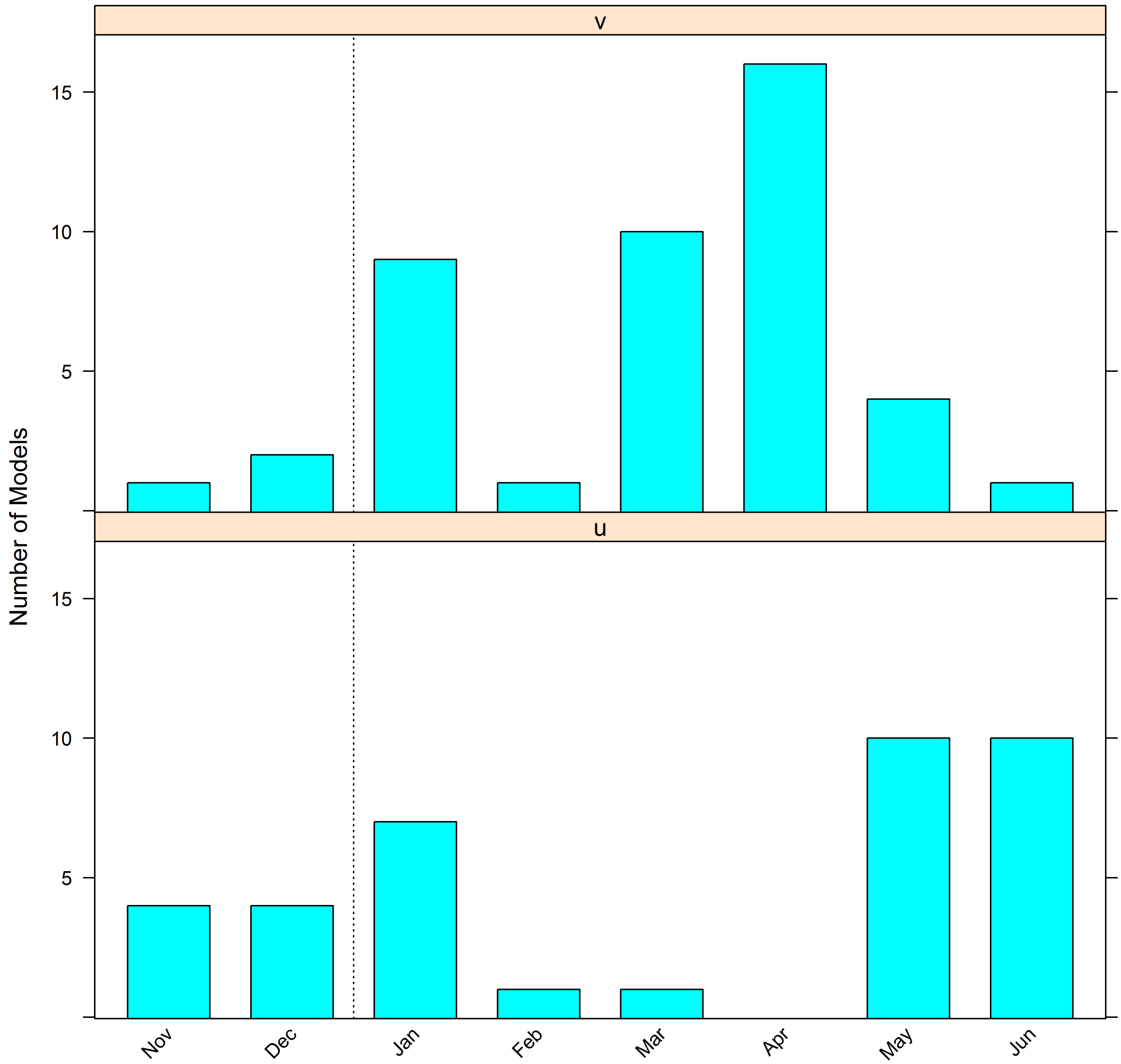


Figure 48. Number of OSCAR data models, by month and current velocity direction, that meet criteria to forecast Chilko timing. Currents vectors are: Zonal (eastward) current velocity (U current velocity) and Meridional (northward) current velocity (V current velocity). The month values range from November of year prior to return to June of the return year. The vertical dashed line separates calendar years.

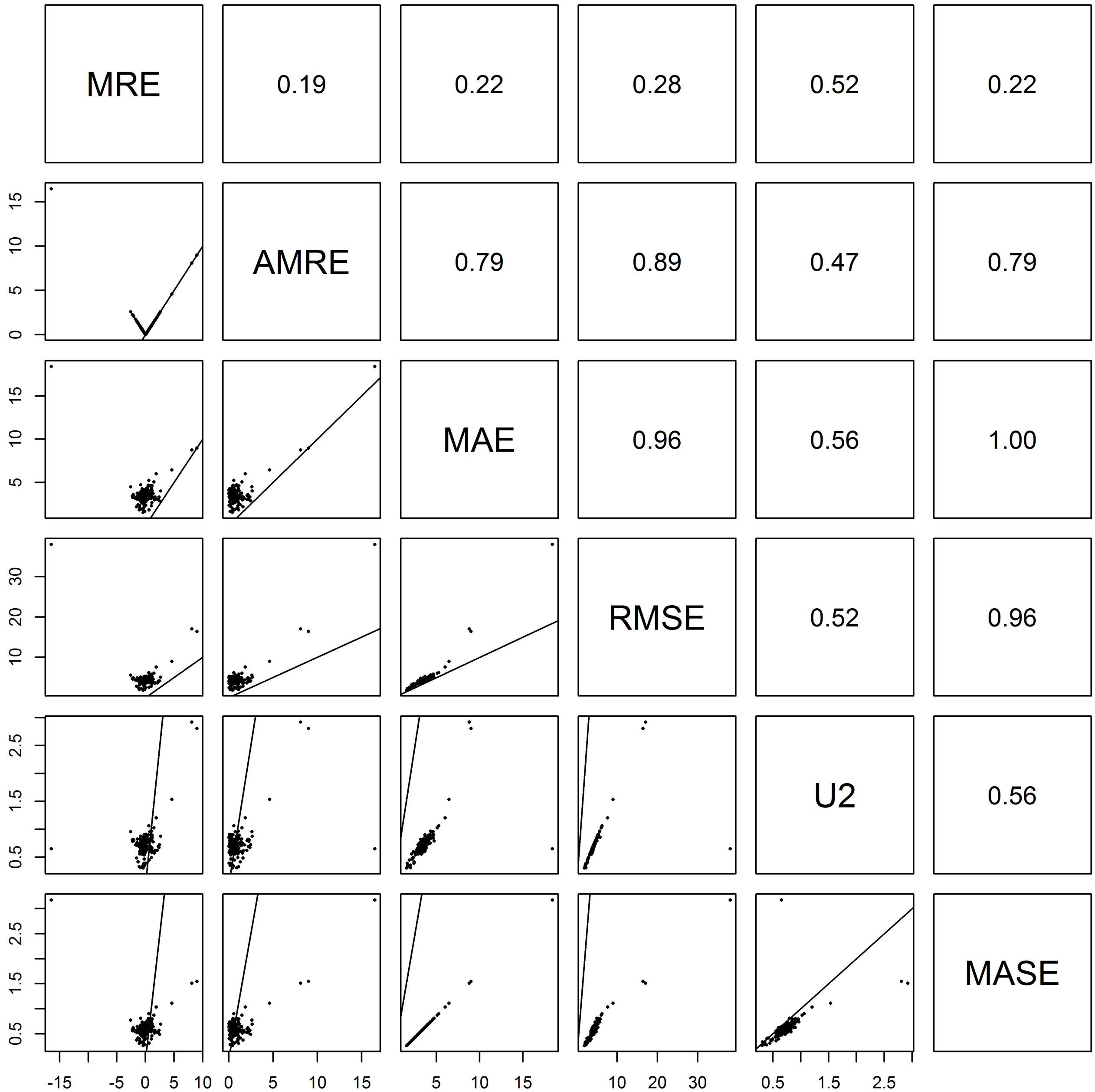


Figure 49. Pairs plot of PMs based on retrospective testing of 249 models evaluated to forecast Chilko timing. The line in each panel represents a slope of 1. Values in the upper right corner represent the correlation coefficient between pairs of PMs. The PMs include: mean raw error (MRE), absolute value mean raw error (AMRE), mean absolute error (MAE), root mean squared error (RMSE), Theil's U statistic (U2), and mean absolute scaled error (MASE). The initial four PMs have units in days. The latter two PMs are unit-less and described in the section 4.7.2.

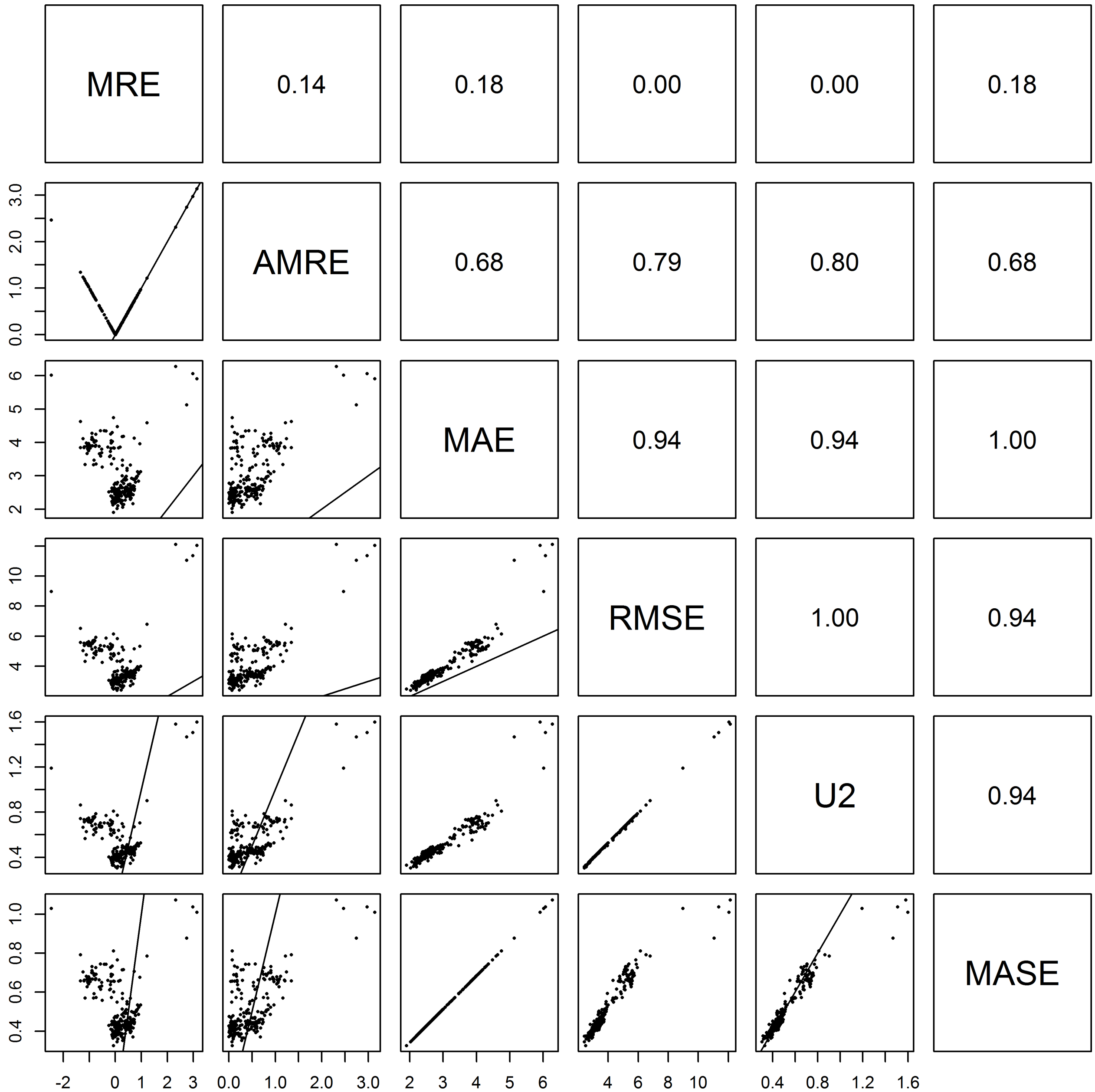
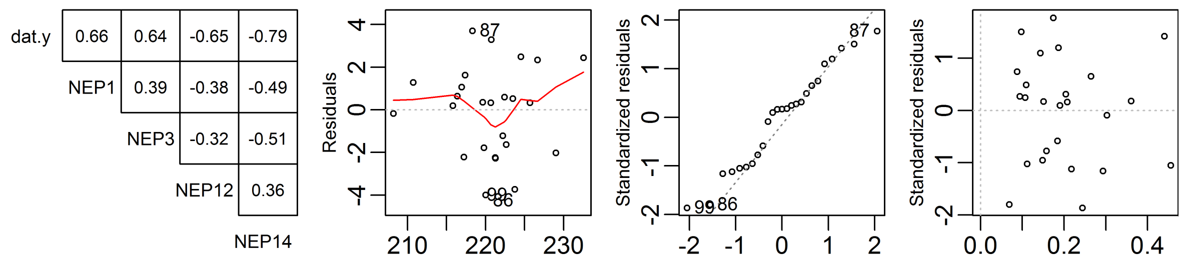
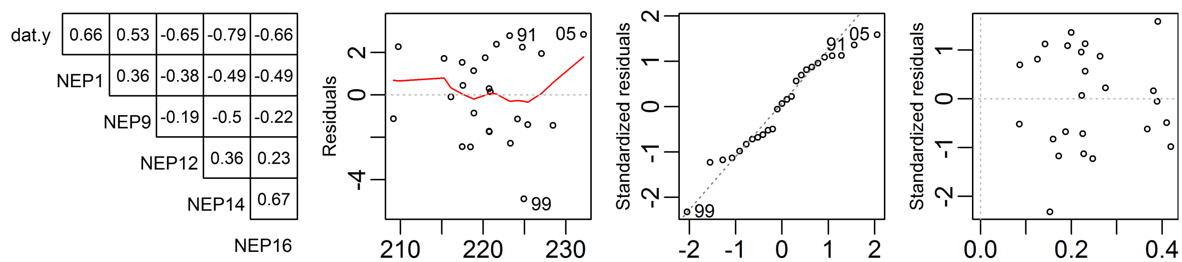


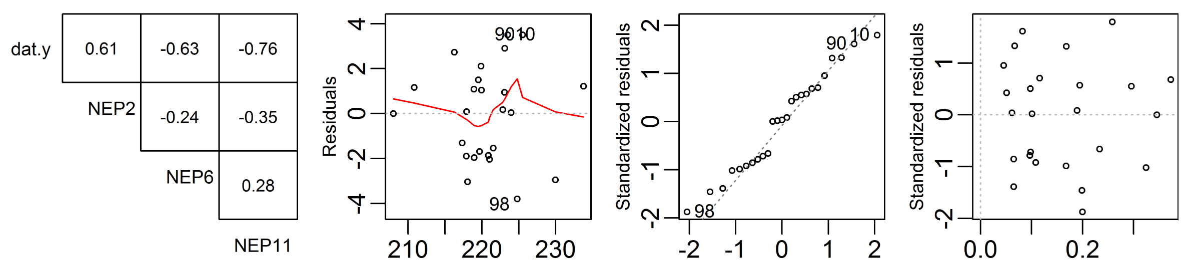
Figure 50. Pairs plot of PMs based on jackknife testing of 249 models evaluated to forecast Chilko timing. The line in each panel represents a slope of 1. Values in the upper right corner represent the correlation coefficient between pairs of PMs. The PMs include: mean raw error (MRE), absolute value mean raw error (AMRE), mean absolute error (MAE), root mean squared error (RMSE), Theil's U statistic (U2), and mean absolute scaled error (MASE). The initial four PMs have units in days. The latter two PMs are unit-less and described in the section 4.7.2.



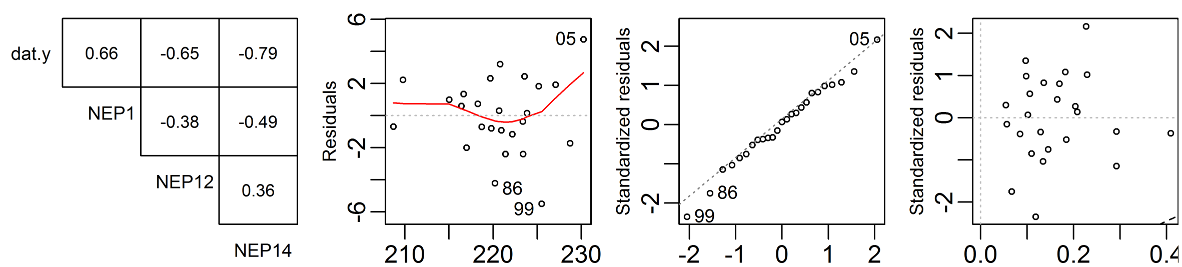
(a) nepstar3



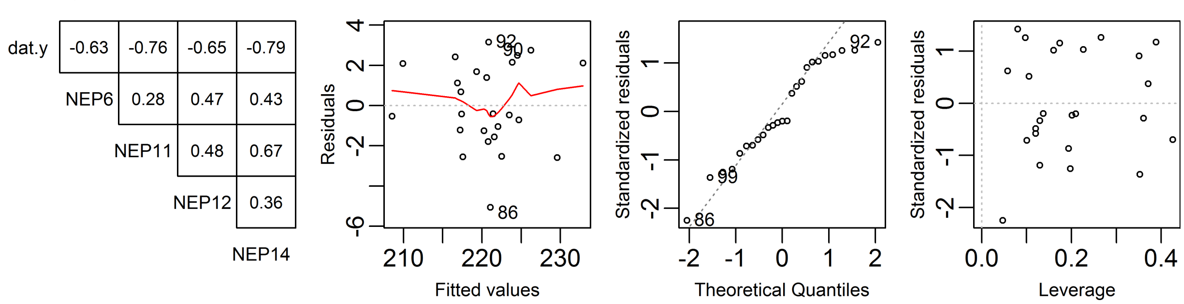
(b) nepstar14



(c) nepstar2



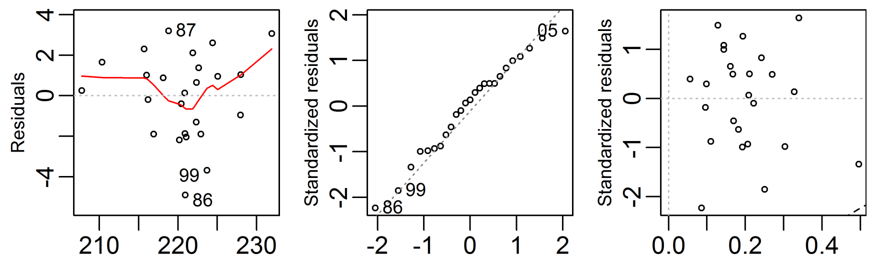
(d) nepstar1



(e) nepstar9

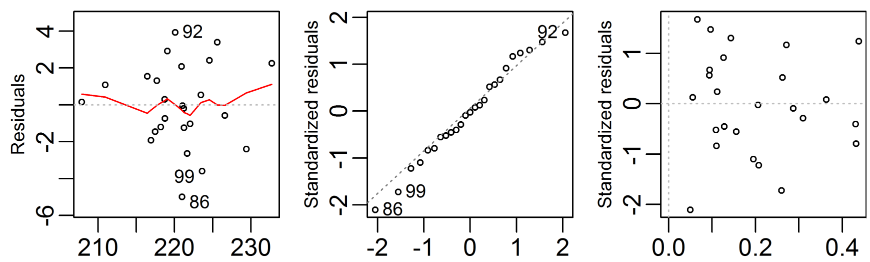
Figure 51. Diagnostic plots for statistical fits to the full data sets of the top ten performing Chilko timing models based on retrospective evaluation. Each row of plots represents one model, which is named beneath the row. Plots are described in the beginning of the results section.

dat.y	0.66	0.63	-0.65	-0.79
	NEP1	0.32	-0.38	-0.49
		NEP4	-0.24	-0.59
			NEP12	0.36
				NEP14



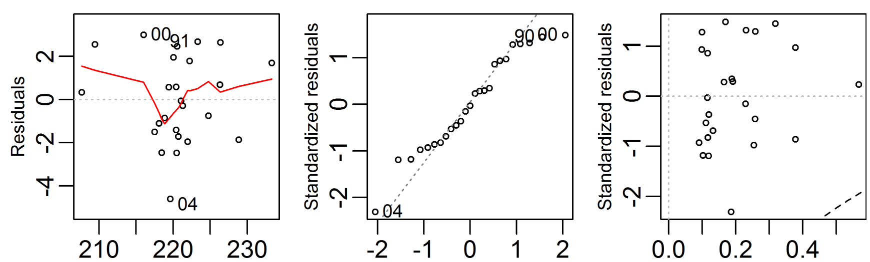
(f) nepstar4

dat.y	0.64	-0.76	-0.65	-0.79
	NEP3	-0.49	-0.32	-0.51
		NEP11	0.48	0.67
			NEP12	0.36
				NEP14



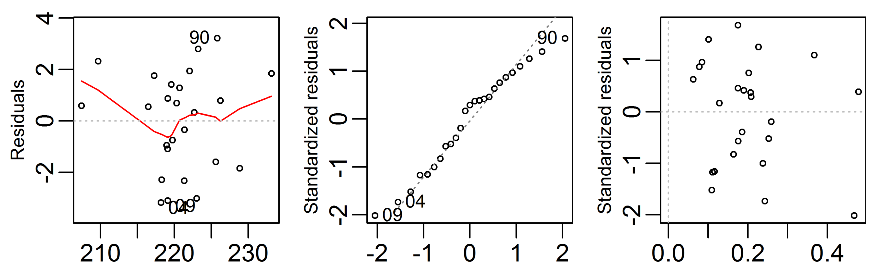
(g) nepstar11

dat.y	-0.49	-0.76	-0.65	-0.66
	NEP7	0.52	0.25	0.09
		NEP11	0.48	0.33
			NEP12	0.23
				NEP16



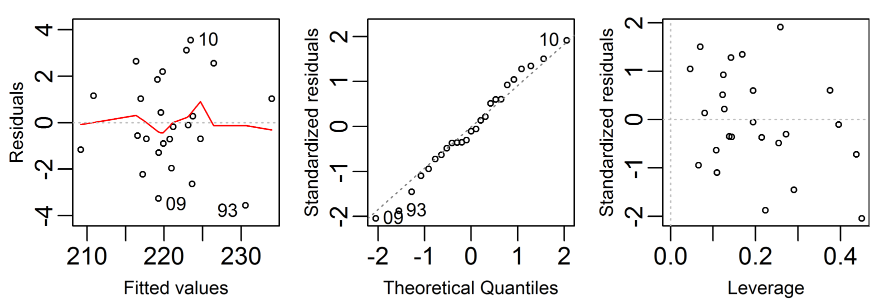
(h) nepstar5

dat.y	0.53	-0.76	-0.65	-0.66
	NEP9	-0.44	-0.19	-0.22
		NEP11	0.48	0.33
			NEP12	0.23
				NEP16



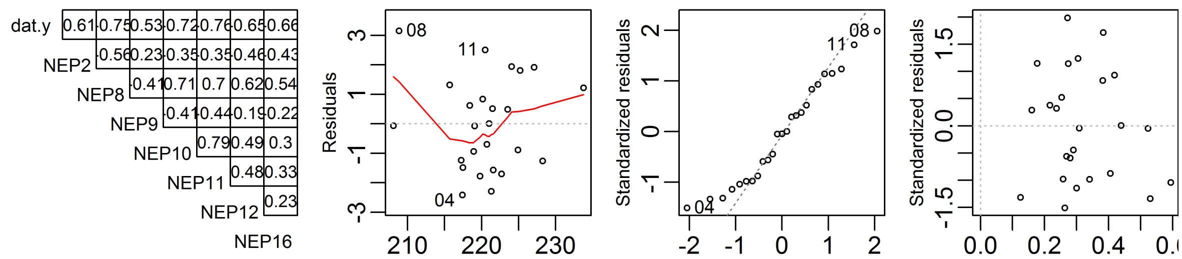
(i) nepstar6

dat.y	0.61	-0.63	0.53	-0.76
	NEP2	-0.24	0.23	-0.35
		NEP6	-0.24	0.28
			NEP9	-0.44
				NEP11

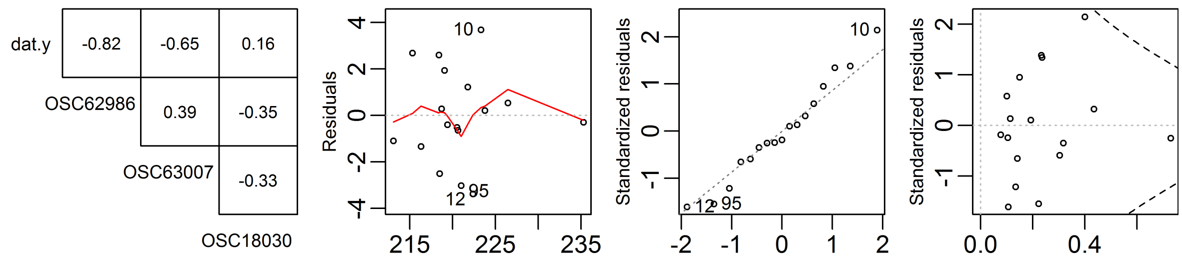


(j) nepstar7

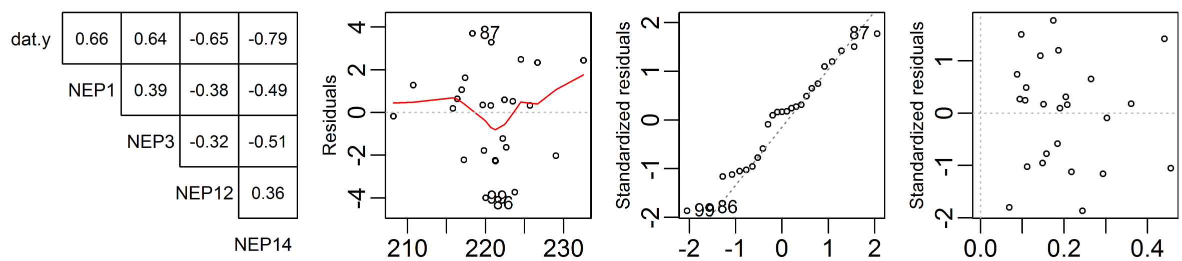
Figure 51. Continued



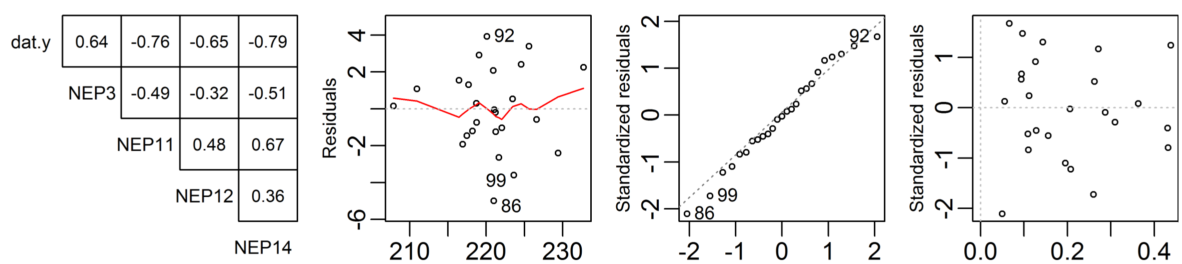
(a) nepstar13



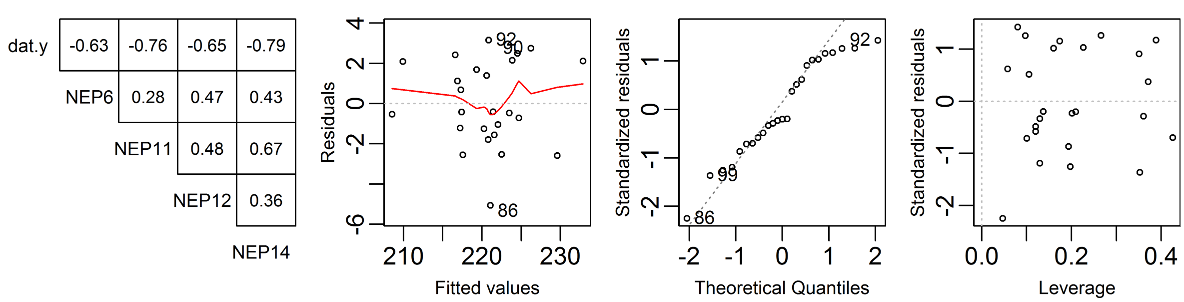
(b) mlr8



(c) nepstar3

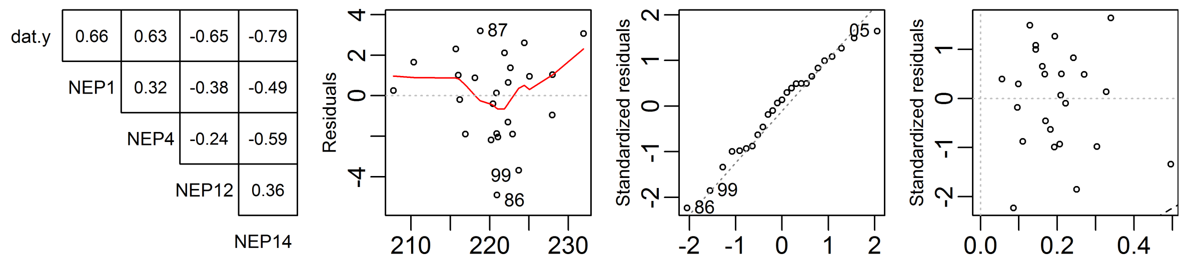


(d) nepstar11

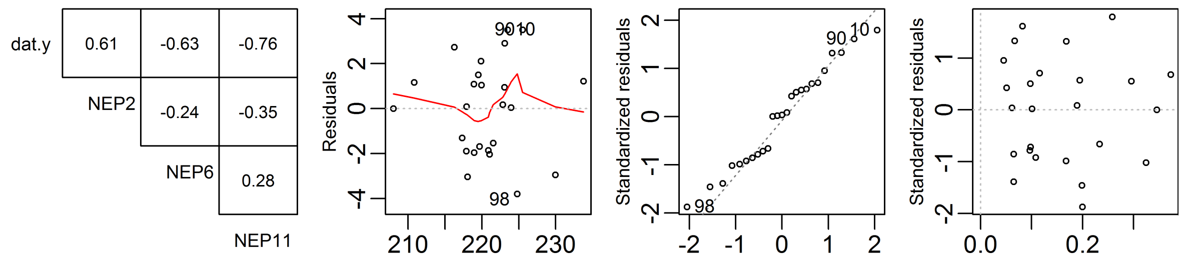


(e) nepstar9

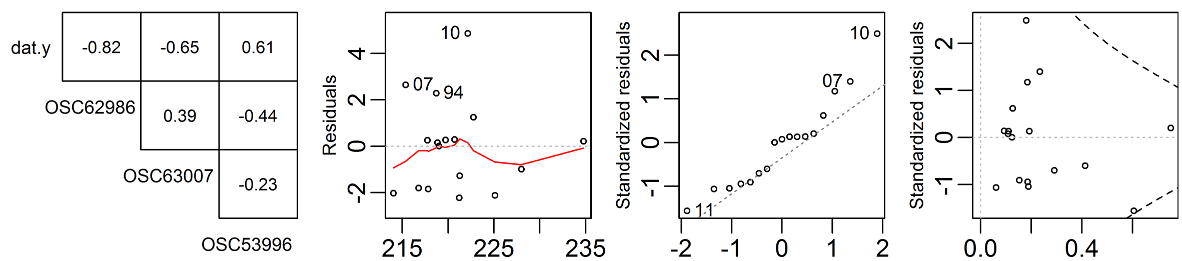
Figure 52. Diagnostic plots for statistical fits to the full data sets of the top ten performing Chilko timing models based on jackknife evaluation. Each row of plots represents one model, which is named beneath the row. Plots are described in the beginning of the results section.



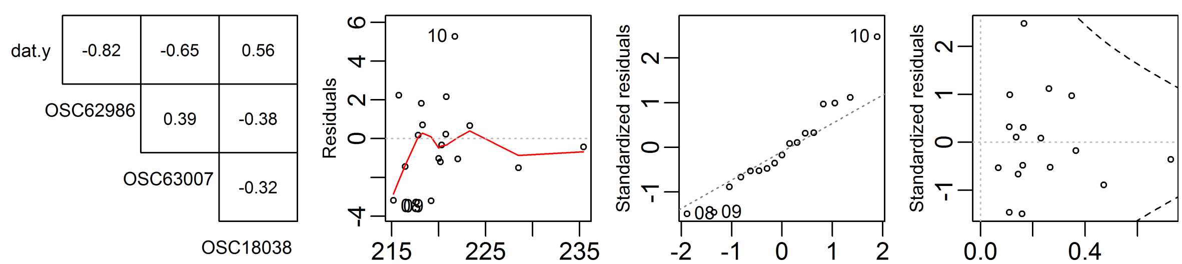
(f) nepstar4



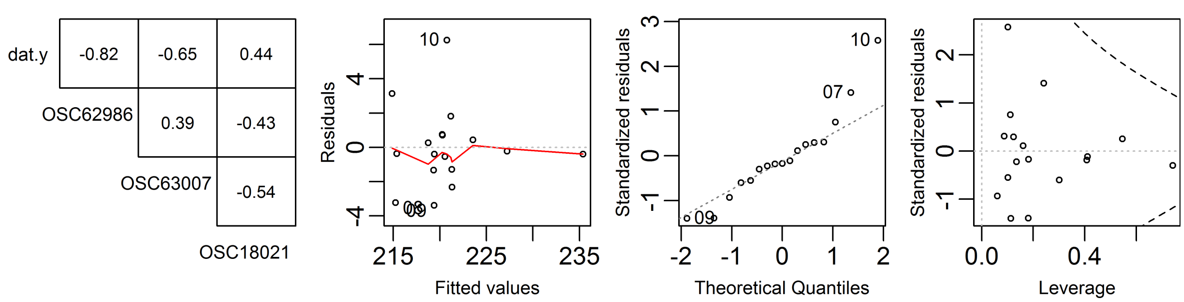
(g) nepstar2



(h) mlr4



(i) mlr17



(j) mlr84

Figure 52. Continued

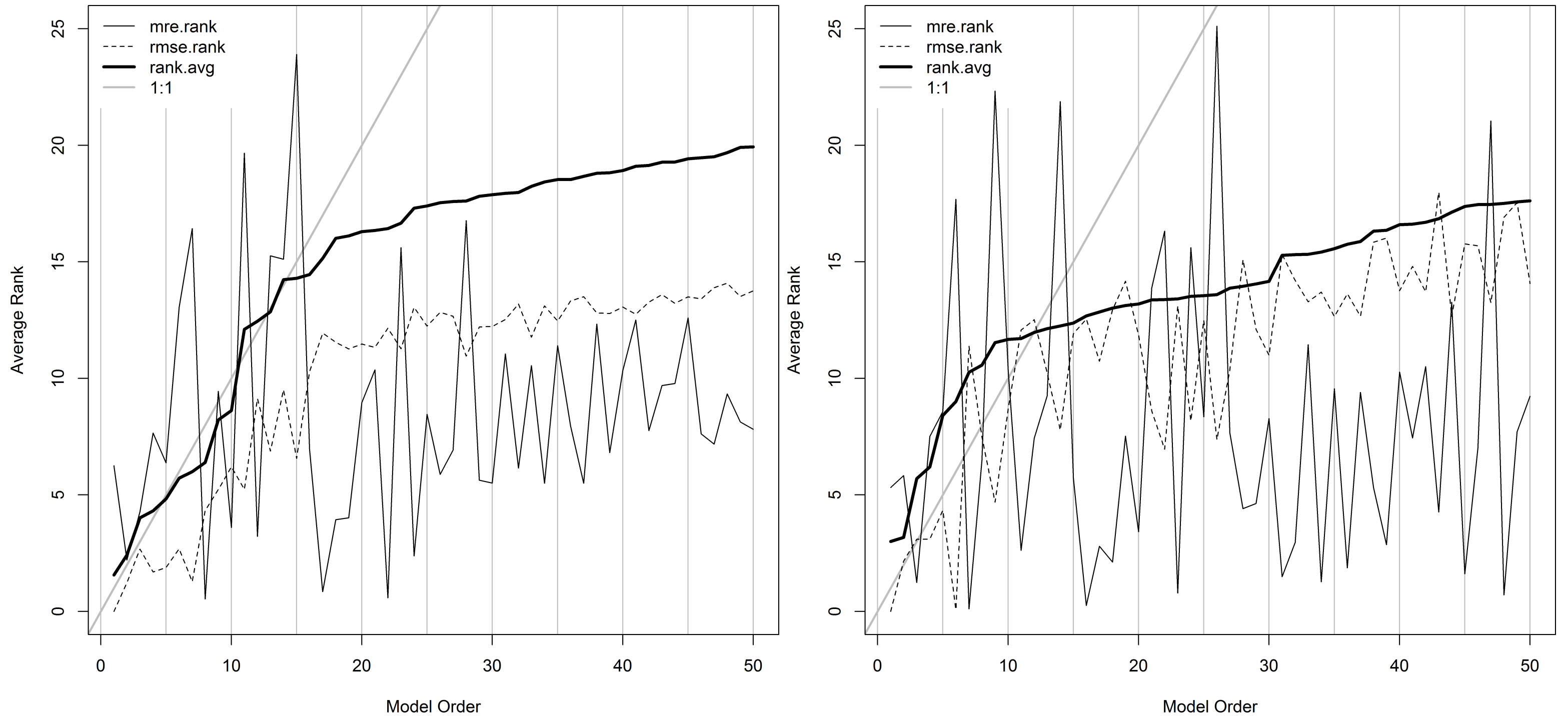


Figure 53. MRE rank, RMSE rank, and average rank for the top 50 Chilko timing forecast models. Left panel is results for retrospective analysis, right panel is jackknife. The x-axis orders the models, by equal distance, based on their ordinal rank: 1–50. The y-axis shows the rank on an interval scale. Note that model order does not consistently match between plots, such that the tenth model of the retrospective analysis is not necessarily the same as the tenth model seen in the jackknife results. Ranks of MAE and U2 were excluded to prevent crowding. The diagonal grey line has a slope of one, which allows for comparison to the average rank line.

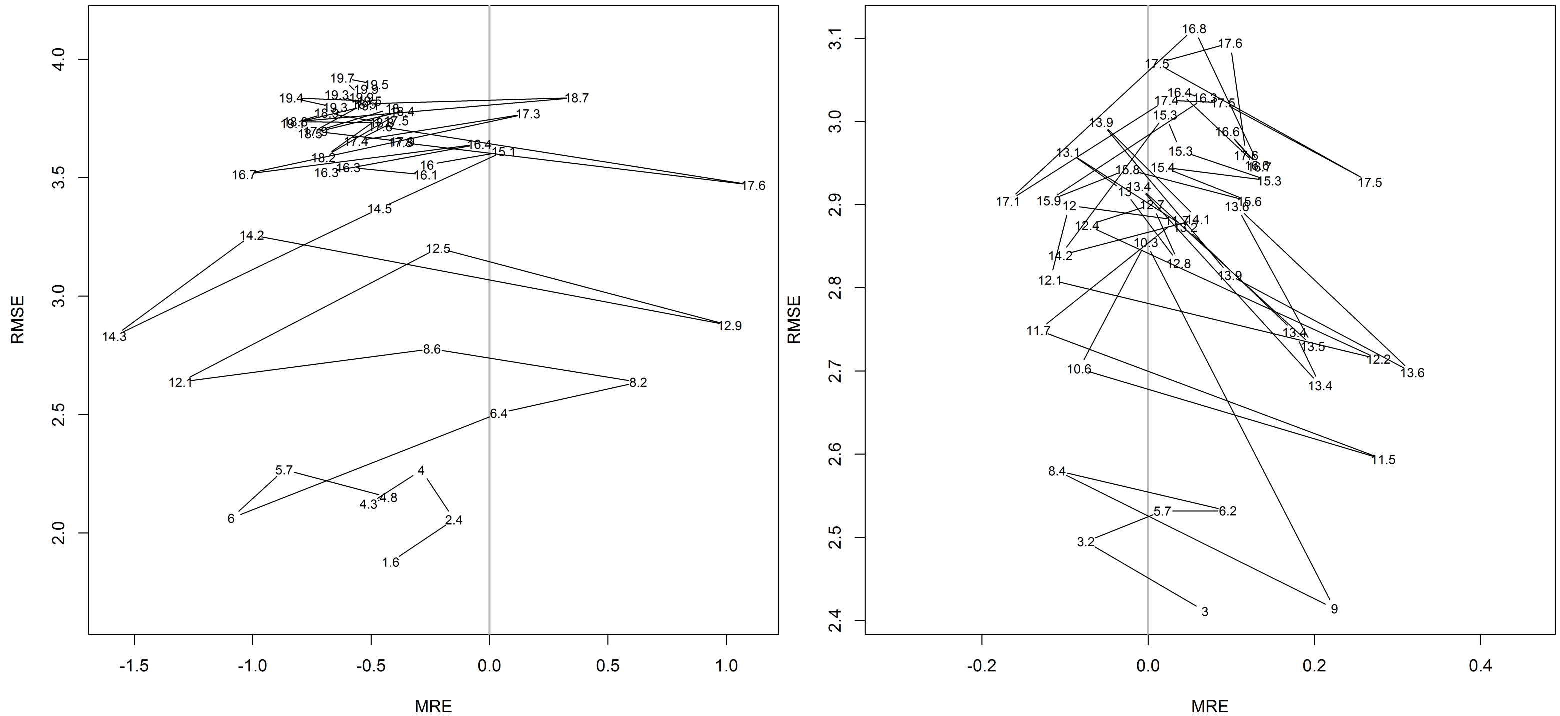


Figure 54. Relationship between PMs: RMSE and MRE for Chilko timing forecasts from retrospective (left panel) and jackknife (right panel) analysis. The number of each point corresponds to the average rank of each model. The line joins models from best ranked to worst ranked. The vertical grey line delineates models with a generally positive bias from those with a negative bias. This demonstrates how declining rank is often a process of ratcheting down between positive and negative bias (MRE).

Forecast Plots: The forecast plots are Figures 55 and 56. No model based on OI SST qualified, thus that data type is excluded from this plot. The summary statistics of data included in these plots are found in Tables 8 and 9. Results are similar to those for the Early Stuart timing models. The SD of post-season, estimated timing is 5.3d and 5.6d (based on time series subsampled for retrospective and jackknife, Tables 8 and 9). As forecast SD from the shore station model (SST at Active Pass in April of year prior to return) is quite narrow (3.03d and 3.22d, Tables 8 and 9), it appears that model is not representing all environmental uncertainty, and consequently not the true timing variability. Relating Active Pass SST to pre-season return timing is unrealistic. Within the retrospective results the greatest annual, model specific error we see is 3.2d (NEPSTAR), -7.2d (MLR), 6.2d (OSCAR), and -9.3d (shore station). Again, consistent with Early Stuart models, the minimum annual error remains small for all models (< 1d). The jackknife results have maximum errors of -4.3d (NEPSTAR), -6.1d (non-NEPSTAR-MLR), -9.8d (OSCAR), and 9.0d (shore station), see Table 9. Results from each of these evaluation methods does emphasize the greater difference between best performers by model type, but fails to represent the particularly close forecasts of the top dozen models (not presented).

Table 8. Summary statistics of annual forecasts, from the best performing model in each model type, for Chilko sockeye timing based on retrospective analysis. All variables except rank have unit days. The variables 'Forecast mean' and 'True mean' are ordinal date. True mean and True SD are the statistics of actual post season estimates, constrained to the same period on which performance analysis was based.

Model (type #)	Rank	All Models Median Rank	Max Positive Error	Max Negative Error	Min Error	Mean Abs Error	Forecast Mean	Forecast SD	True Mean	True SD
nepstar3	1.56	22.00	3.16	-2.63	0.19	1.53	218.75	5.23	219.17	5.27
mlr25	14.23	22.00	2.88	-7.22	0.01	2.10	218.16	2.29	219.17	5.27
OSCAR18038	15.15	22.00	6.19	-5.86	0.98	2.79	219.23	3.34	219.17	5.27
shore72126	35.52	22.00	7.56	-9.28	0.33	4.62	220.31	3.03	219.17	5.27

Table 9. Summary statistics of annual forecasts, from the best performing model in each model type, for Chilko sockeye timing based on jackknife analysis. All variables except rank have unit days. The variables 'Forecast mean' and 'True mean' are ordinal date. True mean and True SD are the statistics of actual post season estimates, constrained to the same period on which performance analysis was based.

Model (type #)	Rank	All Models Median Rank	Max Positive Error	Max Negative Error	Min Error	Mean Abs Error	Forecast Mean	Forecast SD	True Mean	True SD
nepstar13	3.00	33.17	3.27	-4.33	0.01	2.02	220.64	5.42	220.57	5.60
mlr8	3.18	33.17	3.78	-6.14	0.26	1.90	220.38	5.19	220.57	5.60
OSCAR35999	28.73	33.17	3.94	-9.81	0.01	2.74	220.53	4.26	220.57	5.60
shore72126	45.21	33.17	7.95	-8.97	0.10	3.21	220.63	3.22	220.57	5.60

5.2 NORTHERN DIVERSION RATE

5.2.1 The Influence of El Niño Events on ND

When any month between September (of the year prior to adult return) to May of the return year indicates El Niño conditions according to the BEST index, we see significantly higher ND rate than if those months do not indicate El Niño conditions (Figure 57). There is no significant relationship between ND rate and El Niño events (defined by the BEST index) from two years prior to return (no Figures presented). El Niño events, as defined by either the ONI or SOI, have no significant effect on ND rate (no Figures presented).

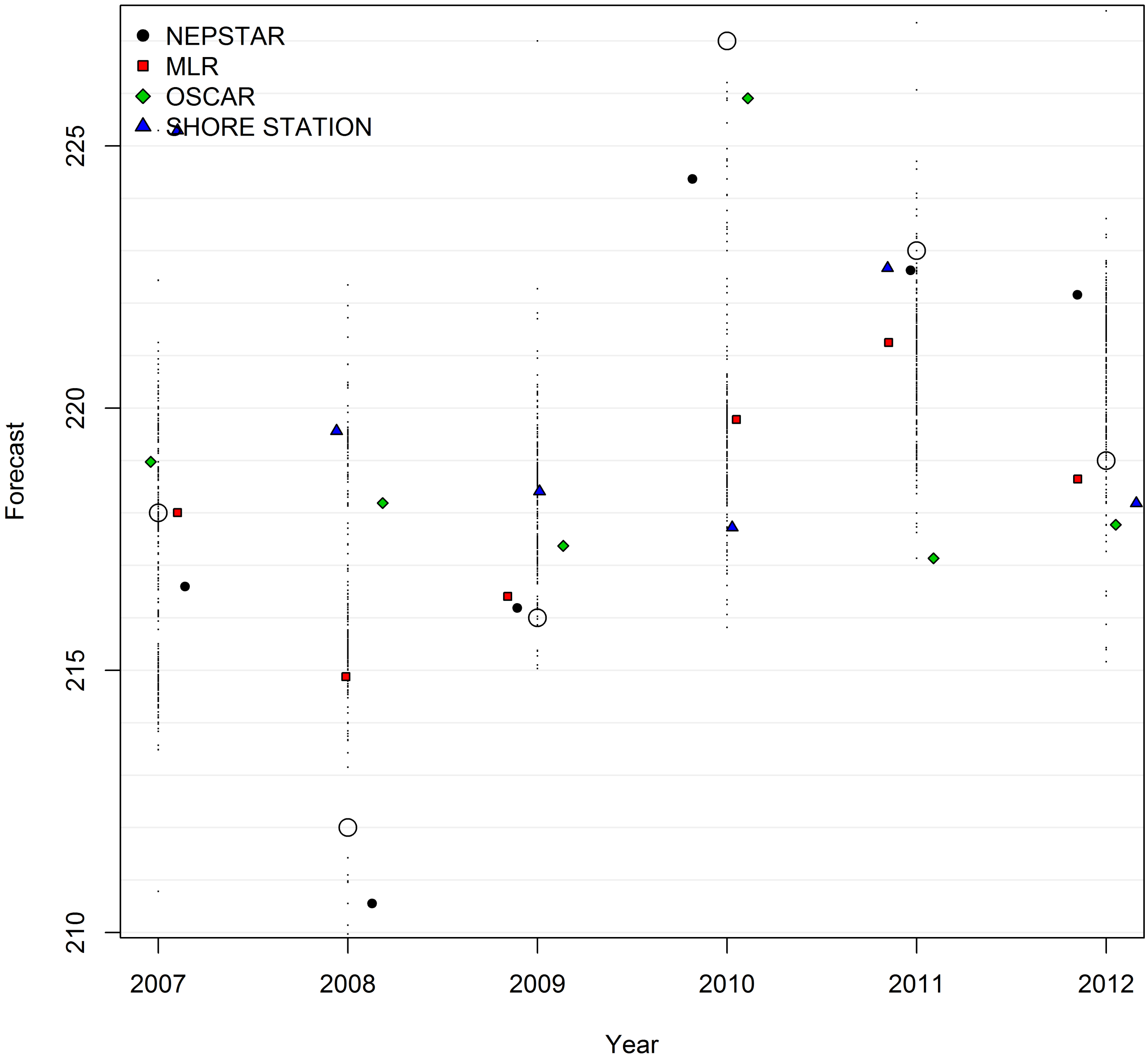


Figure 55. Annual Chilko forecasts for 2007–2012 from retrospective analysis. Data points for each year comprise approximately the 95% intervals of 1596 forecasts. The black, open circle is the post-season estimate. The annual forecasts of each best ranked model, by data-origin, are given unique symbols. Models are sorted in the legend by rank. The y-axis is ordinal date (days since December 31 of prior year).

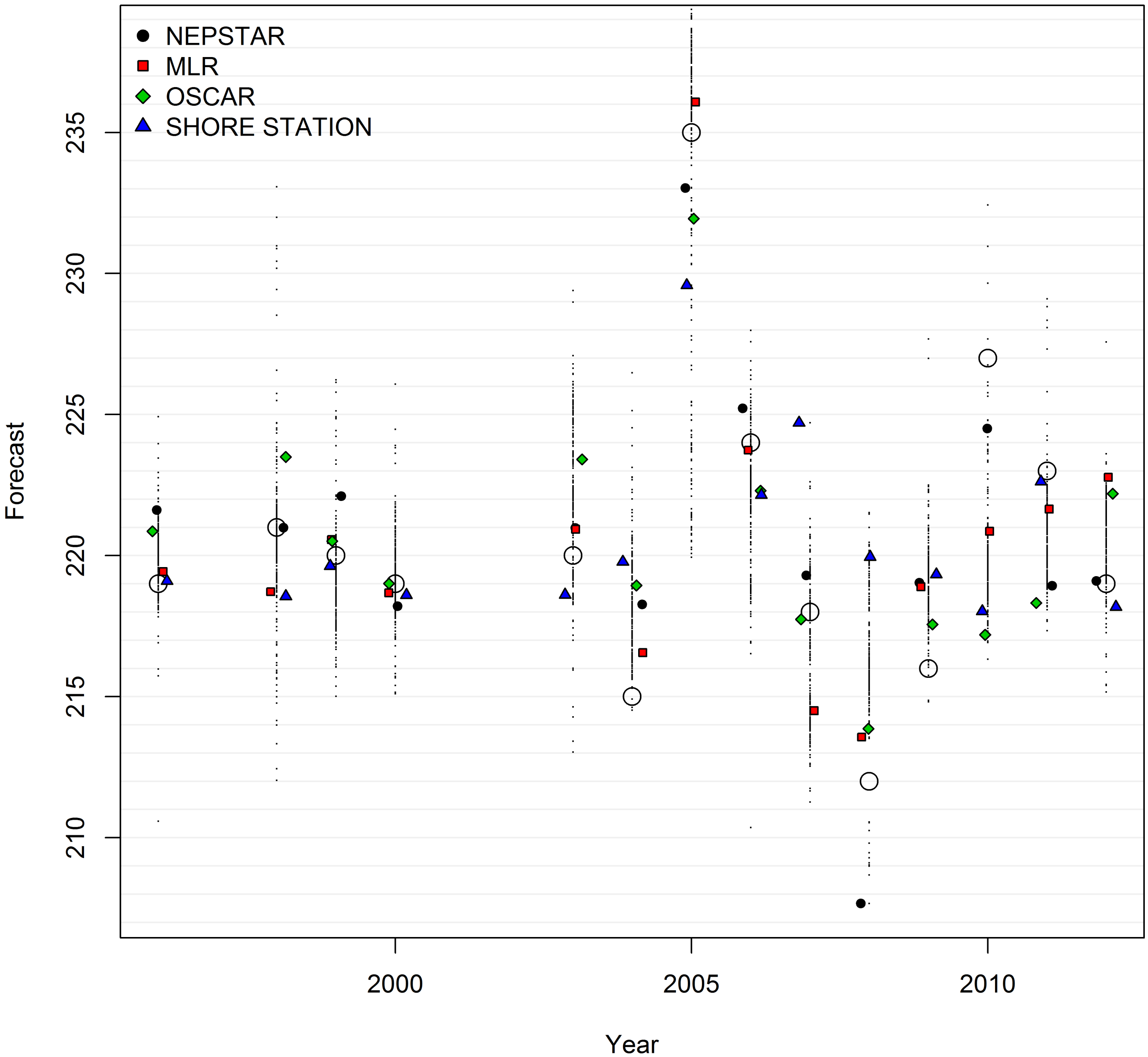


Figure 56. Annual Chilko forecasts for 1996–2012 from jackknife analysis. Data points for each year comprise approximately the 95% intervals of 1596 forecasts. The black, open circle is the post-season estimate. The annual forecasts of each best ranked model, by data-origin, are given unique symbols. Models are sorted in the legend by rank. The y-axis is ordinal date (days since December 31 of prior year).

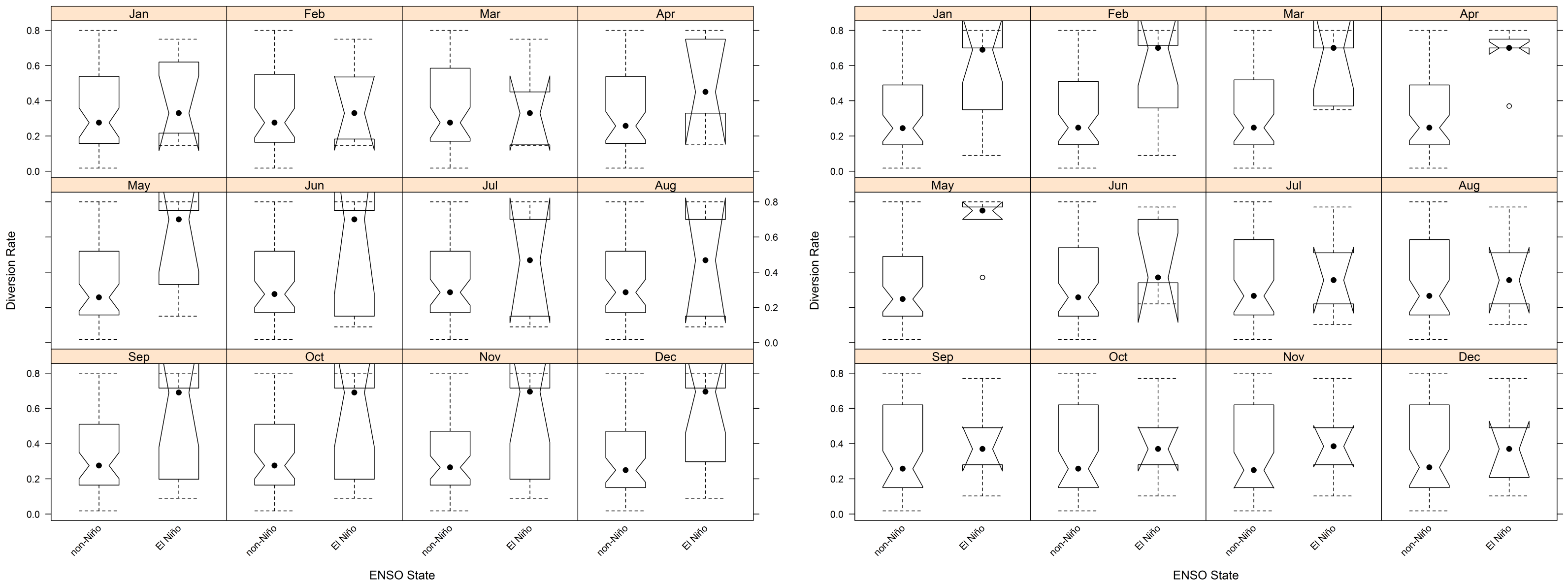


Figure 57. ENSO effects on ND rate for years 1953–2013. The plots are in chronological order such that the left panel relates ND rate to monthly BEST values of year prior to return and right panel shows the relationship to BEST values of the return year. Each boxplot shows the median (bold black point) , IQR (aka the hinges or limit of the box, representing the middle 50% of the data), the whisker values, and possible outliers (open circle points). While median and hinges have a common definition across virtually all statistical programs, this isn't always the case for the whiskers. These whiskers are Tukey style (Tukey, 1977; Krzywinski and Altman, 2014), and extend to the most extreme data point that is within $1.5 \times$ *IQR of the box edge. Each box has bevelled edges,* notches, *which show the 95% CI for each median. When comparing boxes, if the notches do not overlap this is strong evidence that the medians differ significantly (Krzywinski and Altman, 2014).*

5.2.2 Fraser discharge and Sea level

A reanalysis of the regression fit for these data series (1953–2011), without removing any trend, suggests the relation is no longer statistically significant ($P > 0.05$ and adjusted $R^2 = 0.10$). While removing any sign of a trend from the independent variables did reduce the P-value to a significant level ($P = 0.017$), the adjusted R^2 improved just slightly to 0.15. The lack of correlation between the (non-adjusted) variables is apparent in the pairs plot (Figure 58).

5.2.3 New Models

Approximately 290,000 models were evaluated and 177 passed the initial filter for comparison in the performance analysis. The qualifying models are comprised of: single variable (OI SST: 54; OSCAR: 1); multivariate: 107; NEPSTAR-MLR: 15. The geographic locations for these variables are plotted in Figure 59.

Tables 18 and 19 represent the results of performance analysis for ND forecast models based on retrospective and jackknife analyses respectively. In both retrospective and jackknife results 14 of the 15 NEPSTAR-MLR models were the top performing models. NEPSTAR-MLR models that included wind stress did not pass the initial filter, thus all these models are based on combinations of NEPSTAR current velocity and OI SST. Within the top 50 models, the remaining 35 non-NEPSTAR models comprise two and three variable regressions, and just one single variable (OSCAR) regression model. The median of rank from the retrospective analysis is 95.3 (maximum: 174.8) and the jackknife analysis is 128.4 (maximum: 166.0).

Naïve Models: Seven naïve models were evaluated: 4YrMn, 8YrMn, TSA, 4YrMd, 8YrMd, TSMd, and LLY. In the retrospective results, all models ranked worse than the median rank (=95), their ranks ranged: 111 (TSMd)–170 (4YrMd). Only the jackknife results indicated five models performing superior to the median rank (128). These include: 8YrMn (rank 77), LLY (rank 89), 4YrMn (rank 95), 8YrMn (rank 97), 4YrMd (rank 102). However, this moderate improvement does not suggest any merit for further consideration.

Geomagnetics: Consistent with the results given by Putman et al. (2013), there is a superior statistical fit between ND rate and the difference in magnetic intensity between Fraser River (emigration summer) and the return summer at Juan de Fuca Strait than the fit between ND rate and the Fraser-Queen Charlotte Strait intensity difference. Additionally we were able to corroborate Putman's conclusion that magnetic intensity is a superior predictor than is magnetic inclination. Correlation coefficients for our analysis are within 1–2% of their results (ND rate data sets slightly differed as their analysis did not utilize the updated values). Correlations remained below 66%, meaning all R^2 values are below 0.44 (though many fits were statistically significant). The statistical models based on geomagnetic data did not meet the initial criteria of $R^2 \geq 0.5$, and were not appraised in the performance analysis.

OI SST: In contrast to the timing forecast models, the OI SST data have a strong influence in the ND forecast models. Of the 177 models evaluated, 174 included OI SST data. For the non-NEPSTAR-MLR models, the OI SST data locations range between the latitude of Juan de Fuca Strait and Moresby Island, no more than 425km from the coast, and are all during May and June of the return year. The NEPSTAR-MLR models rely on two SST variables located much further offshore (approximately 150°W), and are estimated from June to July of the year prior to return.

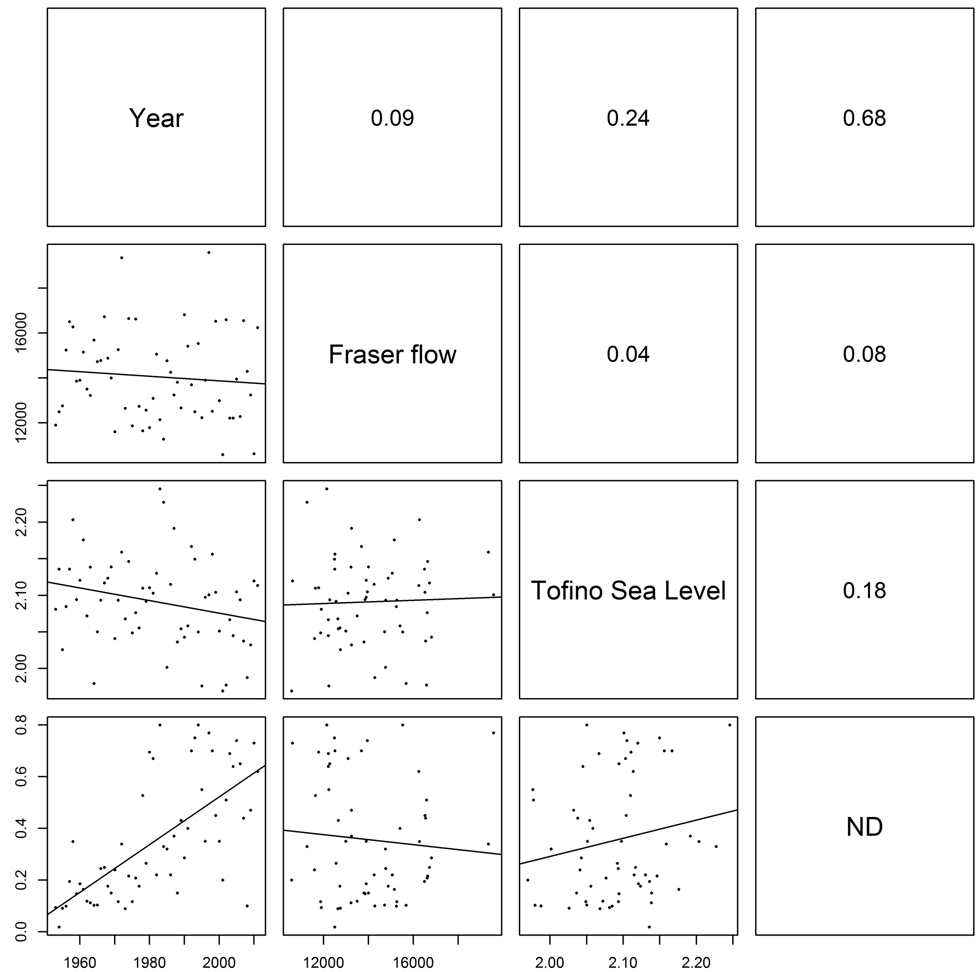


Figure 58. Pairs plot of environmental variables that Wickett (1977) found to have a significant role in the multivariate linear relationship to ND rate. ND is northern diversion rate. The line in each panel shows the linear fit of each variable pair. Variables are described in the data section.

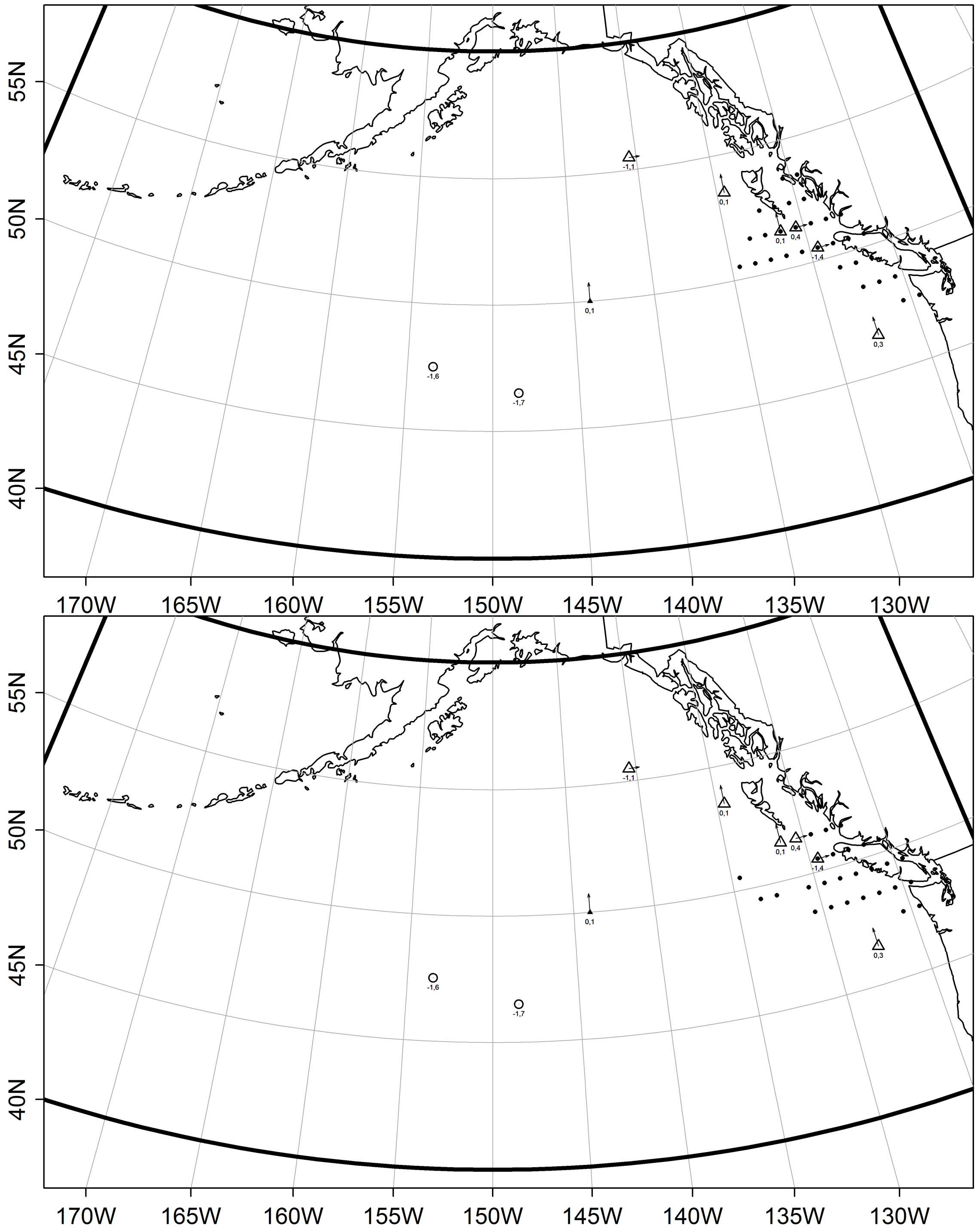


Figure 59. Locations of variables for the top 50 ranked ND forecast models based on retrospective (upper panel) and jackknife (lower panel) analyses. Circles represent SST, and triangles represent current velocity data. Open points are data used in NEPSTAR-MLR models, while smaller, solid points are data used in single variable regressions. Arrows define the direction (but not magnitude) of wind or current velocity variable. The two digits with each point represent the year relative to return year, and month. For example -1,2 indicates data from February of the year prior to return. The coastal SST (small, solid circles) are all based on May and June of return year (months not plotted). The eight NEPSTAR-MLR variables are uniquely combined to make 15 models. Some of the coastal SST points represent data from multiple months, which is why there are less than 54 points. The area defined by a thick, black line defines the search region—excluding land.

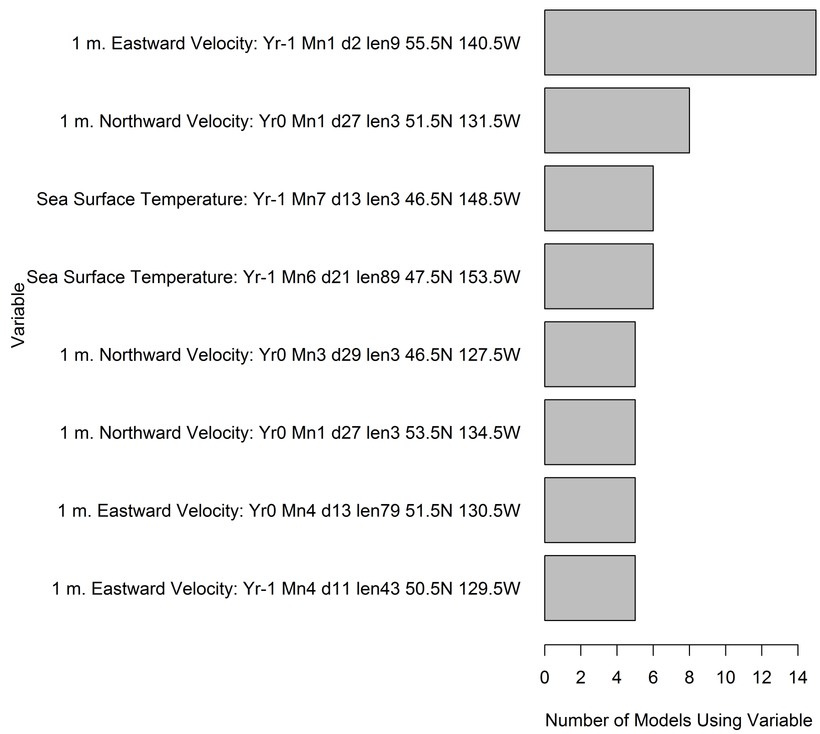


Figure 60. Frequency of use for the eight variables within each of the 15 NEPSTAR-MLR models of Fraser ND rate. Each variable is uniquely defined by it's data type (velocity/current, wind stress, temperature), year, month, start day, averaging window length, latitude, and longitude.

Shore station SST: The ND forecast model used during the last thirty years is based on Kains Island May-June SST. The current statistical fit, based on just June data, had good statistical significance ($P = 8.8 \times 10^{-7}$) but failed to meet the initial filter as its R^2 was 0.49. Of all the shore station data considered, this series had the best R^2 and p value. Thus no models based on shore station SST were evaluated in the performance analysis.

PDO: The strongest statistical fit between ND rate and PDO was based on the May values of the return year ($R^2 = 0.38$). As none of the models based on PDO had $R^2 > 0.5$, they were not considered in the performance analysis.

Shore station SSS: Salinity based models never had R^2 values above 0.25. Thus no results from shore station data will be presented.

NEPSTAR variables: Fifteen NEPSTAR-MLR models were evaluated and 14 were ranked in the top 15 in both evaluation methods — though not the same 14 models in each case. The models are comprised of 15 unique combinations of eight variables. The current velocity variables dominate the contribution to the NEPSTAR-MLRs. One variable in particular, eastward current velocity during January of the year prior to return, was the dominant contributor to 14 of the 15 models (Figure 60).

OSCAR: Just one OSCAR based model passed the initial filter. The model is based on meridional current velocity in January of the return year. In both performance analyses it ranked in the top 50 models, both well above the median ranks. The geographic location of the data is plotted on the variables maps (Figure 59). The effect of using a running average on a variable can be seen in Figure 61. The question becomes: "why, despite the likely similarity of neighbouring data cells due to data averaging, just this 1° latitude by 1° longitude cell would produce an acceptable statistical fit?” Figure 62 is a map showing the adjusted R squared values for all single variable linear model fits (to OSCAR v) using the same time period (January of return year). This confirms that while just one model passed the initial filter, it’s not likely a spurious correlation as five of the eight neighbouring cells have R^2 values that range between 0.45–0.48, i.e. just below the minimum requirement. Thus there is a similar statistical correlation in neighbouring current velocity cells, but they’re just below the established threshold. This variable plays an important role in the three variable models, which consistently rank higher than two variable models.

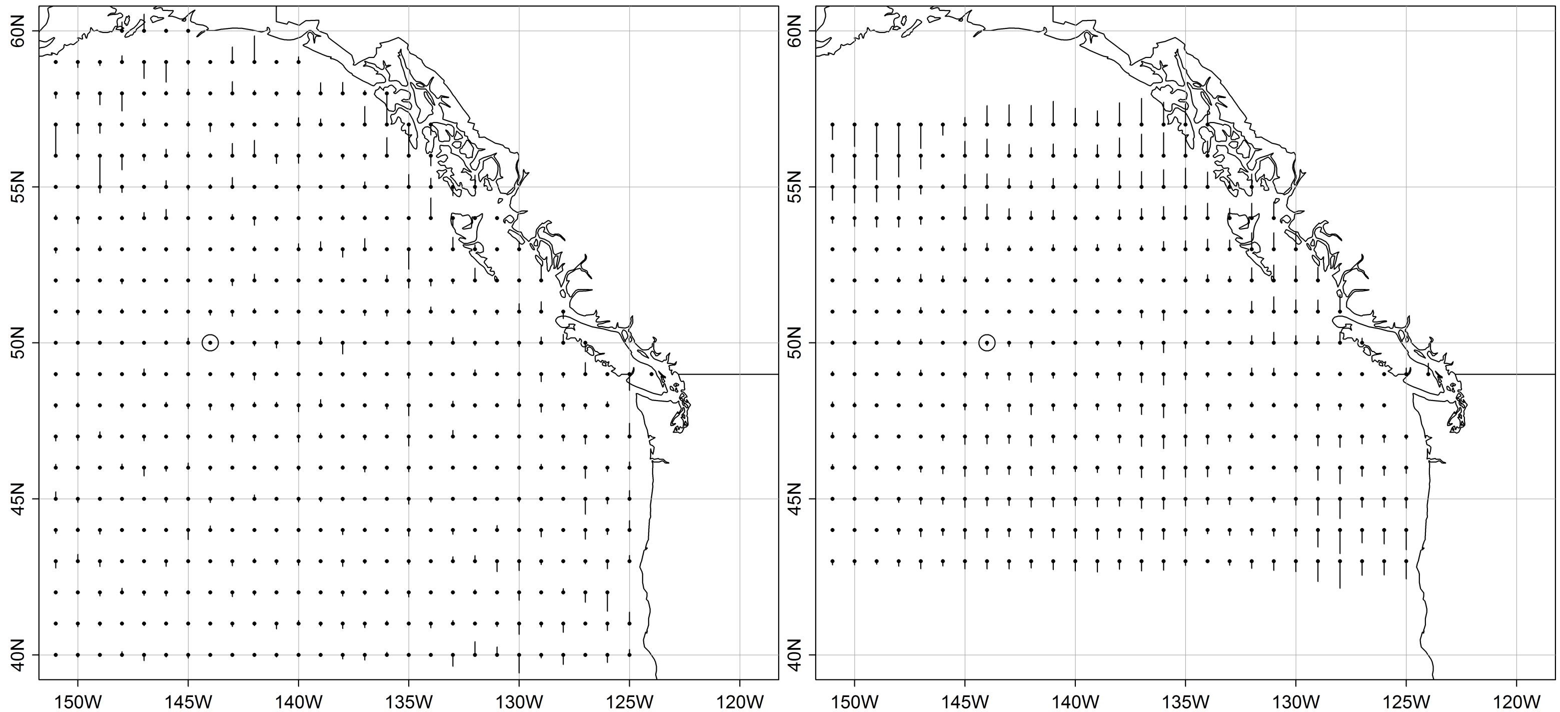


Figure 61. Magnitude of OSCAR meridional (v) data. The left panel is raw data (1/3° spatial resolution, but sub-sampled at 1° increments) and and the right panel comprises running averages based on a 5° longitude by 5° latitude window in January 2012. Each solid point is the base of each vector such that lines pointing south from their point indicate a southward current. Vector magnitudes are scaled so the largest value within each plot is 60 nautical miles (NMs) (1° latitude)—thus vector lengths are not comparable between plots. The single point with an open circle (located at 50°N, 144°W) is the only OSCAR series that ranked in the top 50 models.

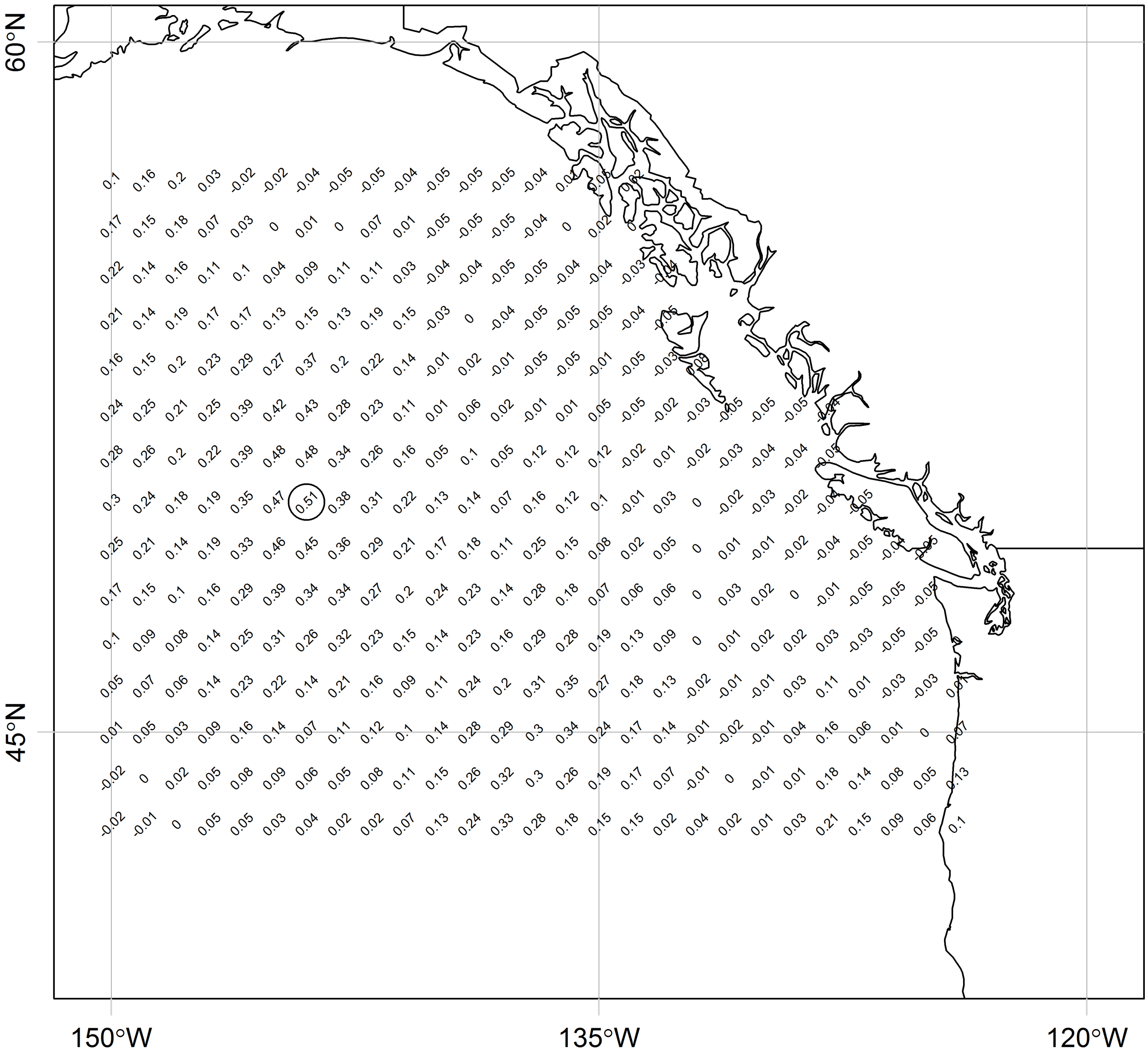


Figure 62. Adjusted R^2 values for a subset of the OSCAR meridional (v) models to predict ND rate. Note that adjusted R^2 values can be negative.[17] *The single point with an open circle (located at 50°N, 144°W) is the only OSCAR series that ranked in the top 50 models. While five of the eight neighbouring models have $R^2 \geq 0.45$, no others met the initial filter of $R^2 \geq 0.5$*

U2 using TSA benchmark: U2 values less than one indicate the *tested* model has superior performance to the naïve model. In this evaluation, we can conclude that all 89 models with rank superior to the median rank (retrospective or jackknife results) performed superior to a TSA model. The minimum U2 value is 0.39 and the maximum within the first 89 models is 0.73. These results were not included in the appendix tables.

U2 and MASE: All U2 and MASE values were less than 0.74 and 0.66 respectively (retrospective and jackknife combined) while the majority were less than 0.55 and 0.61

[17] The adjusted $\bar{R}^2$ (Theil, 1961) is defined as $\bar{R}^2 = 1 - (1 - R^2)\dfrac{n-1}{n-p-1} = R^2 - (1 - R^2)\dfrac{p}{n-p-1}$, where p is the total number of terms in the model (not including the constant term), and n is the sample size. Thus low values of R^2 can lead to negative $\bar{R}^2$.

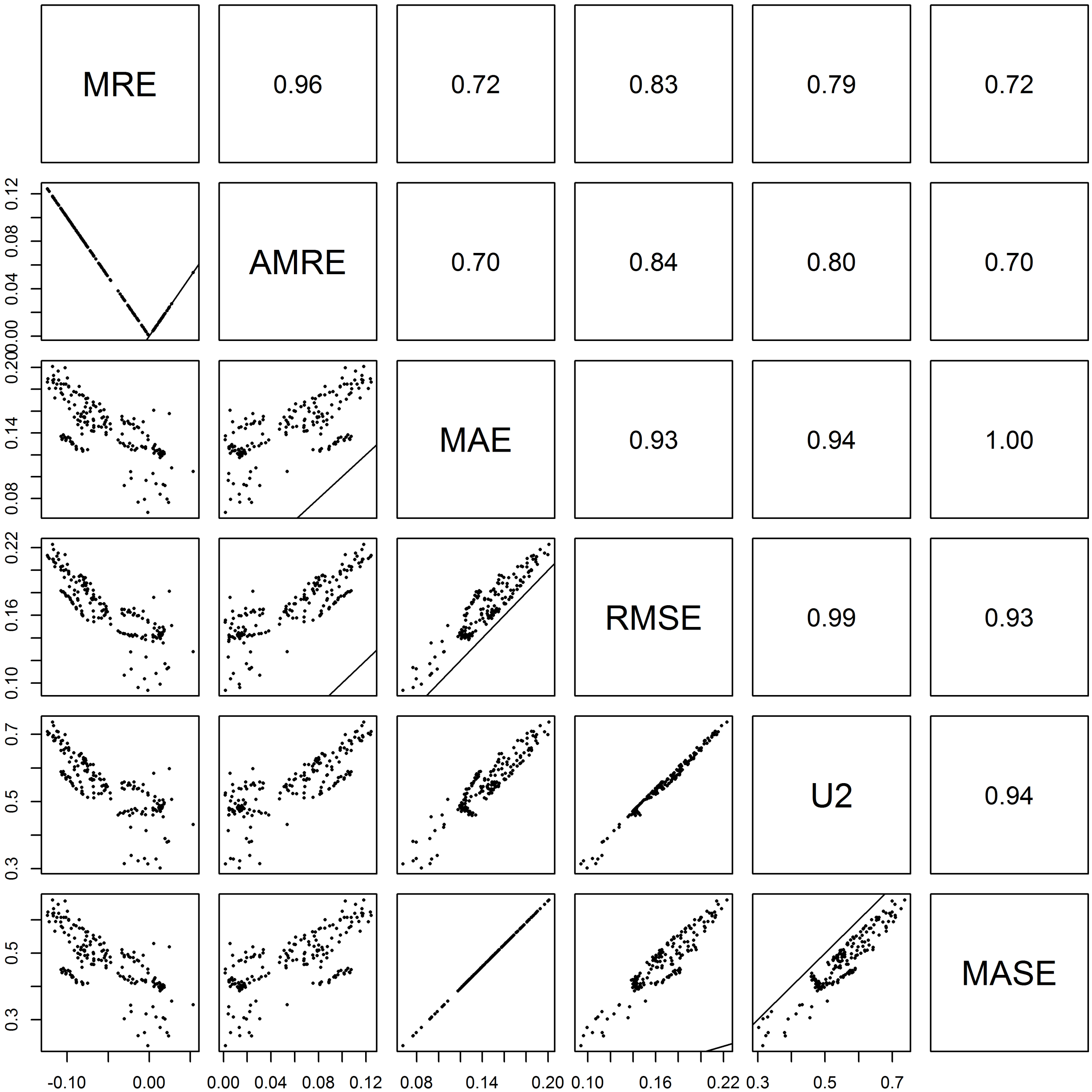


Figure 63. Pairs plot of PMs based on retrospective testing of qualifying models evaluated to forecast ND rate. The line in each panel represents a slope of 1. Values in the upper right corner represent the correlation coefficient between pairs of PMs. The PMs include: mean raw error (MRE), absolute value mean raw error (AMRE), mean absolute error (MAE), root mean squared error (RMSE), Theil's U statistic (U2), and mean absolute scaled error (MASE). The initial three PMs have units "percentage diversion". The latter two PMs are unit-less and described in the section 4.7.2.

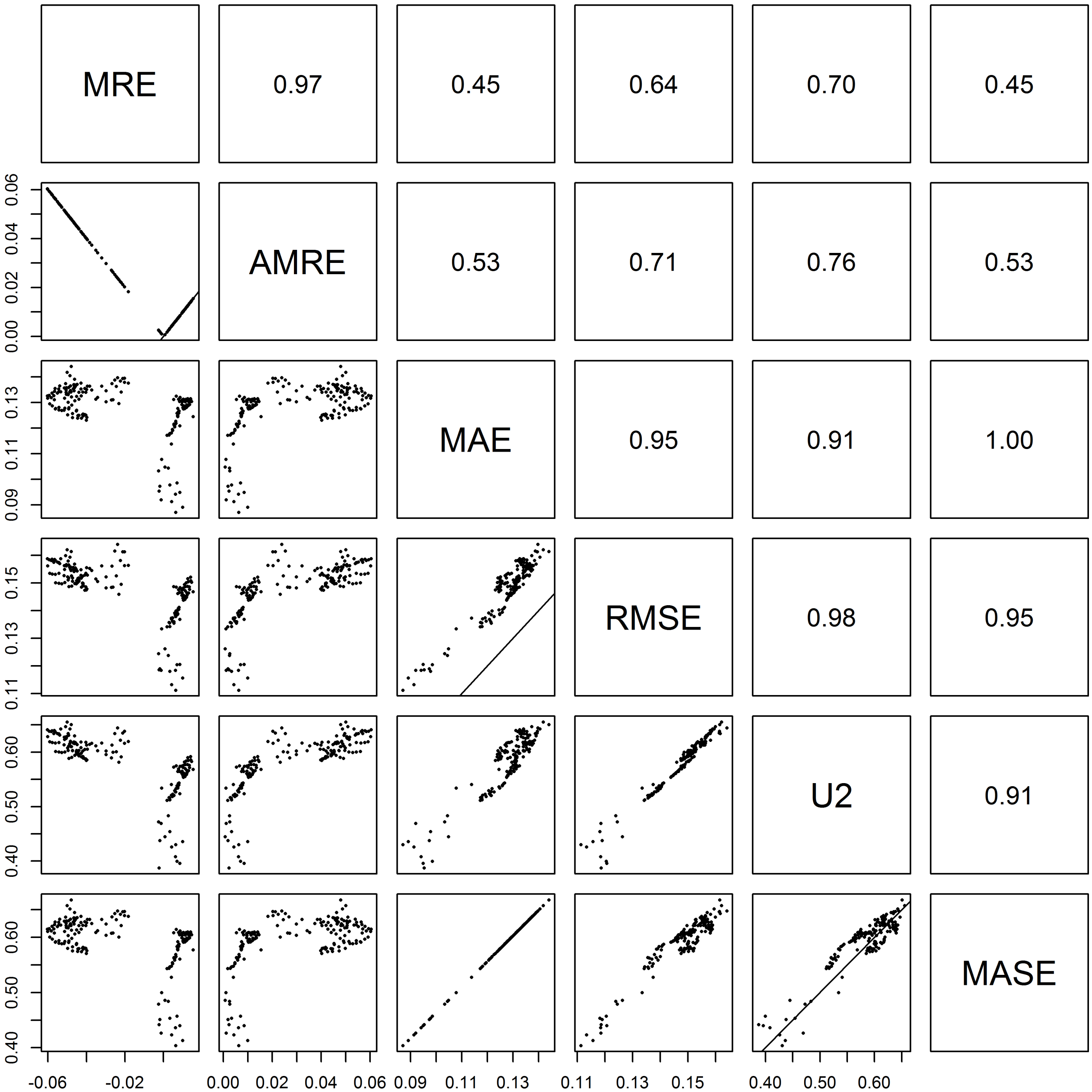


Figure 64. Pairs plot of PMs based on jackknife testing of qualifying models evaluated to forecast ND rate. The line in each panel represents a slope of 1. Values in the upper right corner represent the correlation coefficient between pairs of PMs. The PMs include: mean raw error (MRE), absolute value mean raw error (AMRE), mean absolute error (MAE), root mean squared error (RMSE), Theil's U statistic (U2), and mean absolute scaled error (MASE). The initial three PMs have units "percentage diversion". The latter two PMs are unit-less and described in the section 4.7.2.

respectively. This indicates that the PMs agree that all models have, on average, a smaller error than the benchmark approach, which was a like-last-year model. The PMs MASE and U2 are highly correlated, especially for values less than one (Figures 63 and 64), thus common results would be expected.

MRE: Pairs plots of the PMs for all qualifying models give indication of correlation between PMs, (Figures 63 and 64) . The units for MRE, MAE, and RMSE are proportion of Fraser sockeye diverting. For example if MRE is 0.02, the model tends to forecast ND two percentage points higher than the observed estimate.

The MRE column in Tables 18 and 19 is indicative of model bias. It is the mean of all the forecast errors, and not derived from the residuals of the fitted model. The retrospective estimates of MRE for the top 50 ranked ND models span -0.03–0.05 (proportion diversion), while the jackknife derived estimates of MRE spans -0.003–0.015 (proportion diversion). This suggests certain models have forecast biases as great as 5% (ND rate). Thus, focussing only on the top 50 ranked models will limit the average bias within five absolute percentage points of the true estimate. Figure 67 shows that there is not a substantial decline in MRE for the 50 top ranked models, rather the MRE rank tends to fluctuate—this is most apparent in the retrospective results. Within the retrospective results, the MRE values for NEPSTAR-MLR models have an equal share of positive and negative values within 3%, suggesting no obvious bias within that group of models. However, within jackknife results, the majority of the top 50 models have positive MRE values indicating a consistent (but insignificantly small) bias towards overestimation of ND rate. The clear grouping of results by model type is apparent in the scatter plots relating RMSE and MRE (Figure 68).

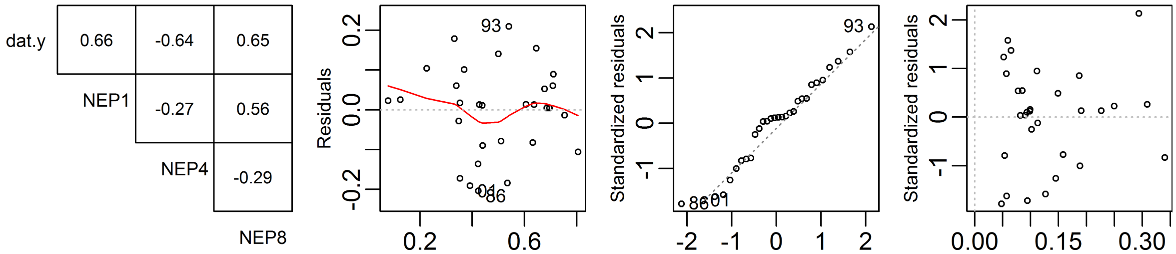
MAE: Within the retrospective results the range of MAE is 7%–20%, which is a moderate amount of contrast between models and suggests the ranking has utility for model comparison. Conversely, the range of MAE values from jackknife estimates, is somewhat narrow (9%–14%). The absolute difference in MAE between first and 50th models is less than 4%, thus ranking of jackknife MAE should be weighed carefully when comparing to other PMs (specifically MRE, U2, and MASE). Nonetheless, the MAE ranks were given equal weight when calculating the overall average rank.

RMSE: Within the first 50 models, the range of RMSE from both retrospective and jackknife is somewhat narrow (0.09–0.15). While there is a steady increase in the RMSE values from the first to the tenth model (retrospective analysis), the absolute change in values is considered small. Within the jackknife results, while the ranking (of MRE, MAE, and RMSE) suggests great differences between models, the true values indicate this is not the case (note the y-axis range in Figure 68). The similarity of RMSE values is not indicative of any weakness in the evaluation, but a confirmation that the models' forecast error is similar (based on nearly full series statistical fitting).

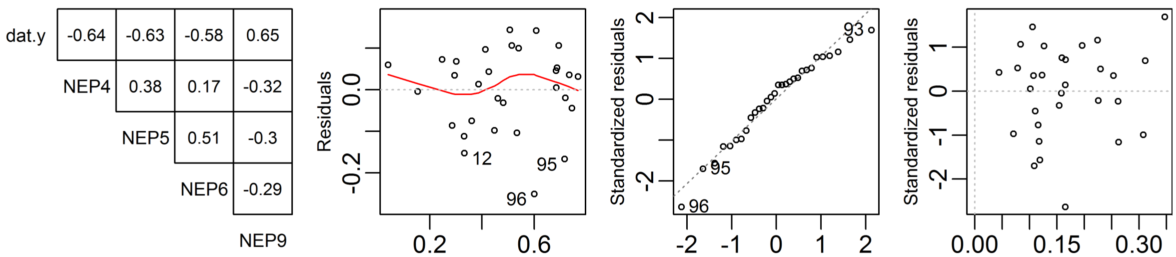
Diagnostic Plots: The diagnostic plots for the top ten models are in Figures 65 and 66. There are eight NEPSTAR-MLR models common to the top ten ranked by retrospective and jackknife analyses, thus their results are seen in each figure, and will be the same. Multicollinearity effects are likely low as most correlation coefficients are well below 0.50, and all are below 0.62 (seen in correlation matrices on each row of plots). Not all residual distributions possess a normal shape. At least three of the ten distributions are moderately, negatively skewed unimodal curves. However, transformation of the data to allow for normally shaped residuals is not necessary prior to utilization of these statistical fits (Hyndman and Athanasopoulos, 2013, Section 2.6). The modes of the residual histograms are approximately centered on zero (see the histogram panels) suggesting that these top five models lack bias. Additionally, absence of correlation between the residuals and fitted values (second column of plots) confirms that their is minimal information remaining in the residuals (that the covariates could explain).

Ranks: Figure 67 plots the rank data (MRE, RMSE, and overall average of PM ranks) for the top 50 models based on their order, 1–50. Retrospective ranks suggest a rapid decline in model performance for the first 16 models. The average rank line slope is well above the 1:1 line, suggesting that models following the first decline rapidly in their performance. This is not the case with jackknife-based ranking, which has slope close to one for the initial ten models. The MRE values fluctuate moderately along models 1–50, but there is not a substantial degrading of MRE with declining rank. This trait is revealed in scatter plot representations of the same PM data in Figure 68. This suggests there is not a noticeable increase in forecasting bias with declining model rank. Conversely, RMSE does increase with declining model rank (Figures 67 and 68) and is presumably the driver of overall model rank average. We see similar results in the jackknife analysis.

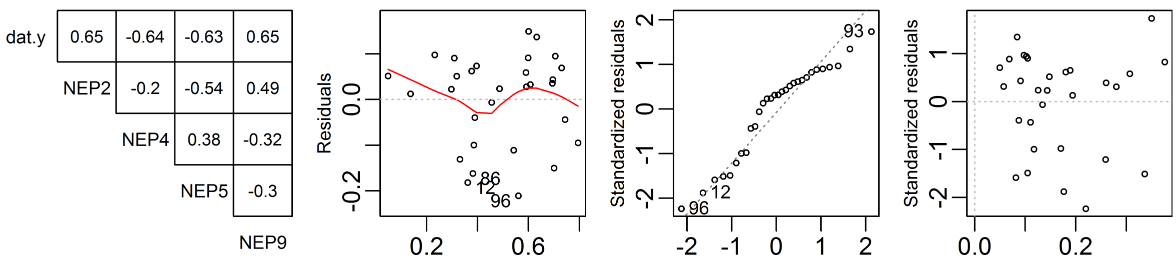
The ranks of each PM are weighted equally in the plots and in calculating the average rank. However there should be careful consideration of the range of PM values between models, which can be quite small. In both the retrospective and jackknife results, almost all models have an average bias within 2% (diversion rate units) of the true ND rate.



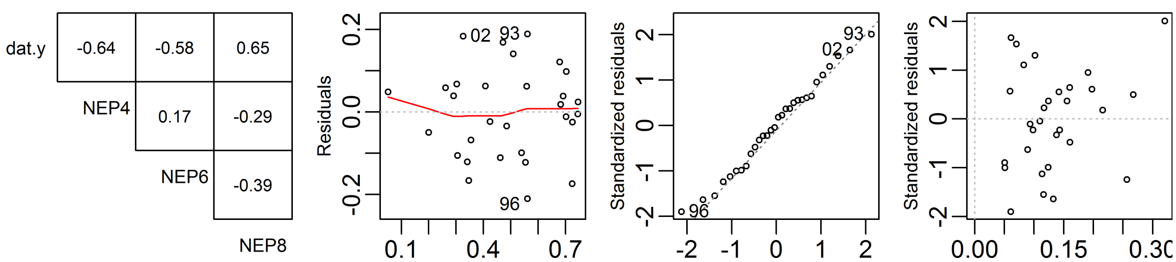
(a) nepstar7



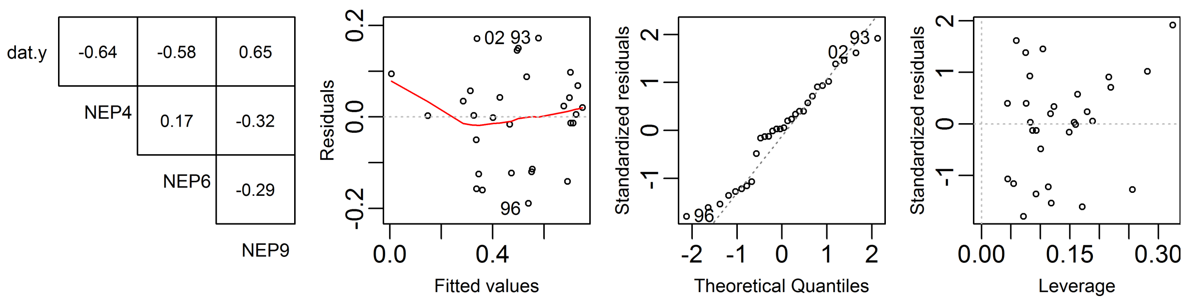
(b) nepstar3



(c) nepstar8

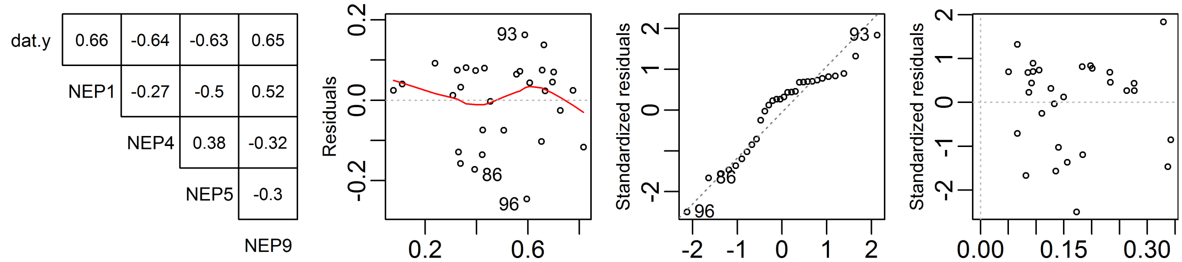


(d) nepstar10

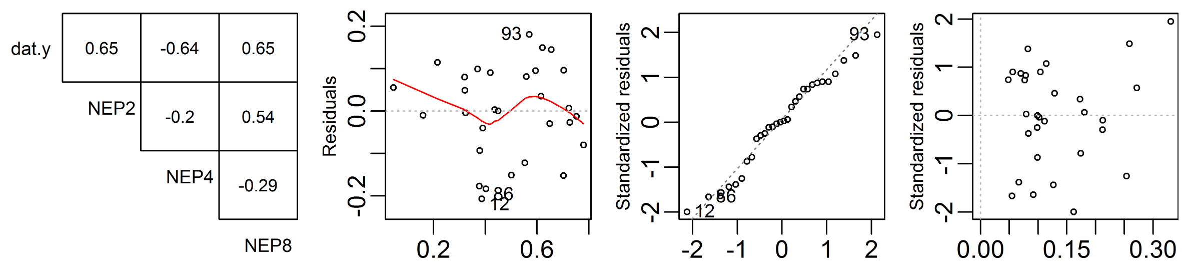


(e) nepstar1

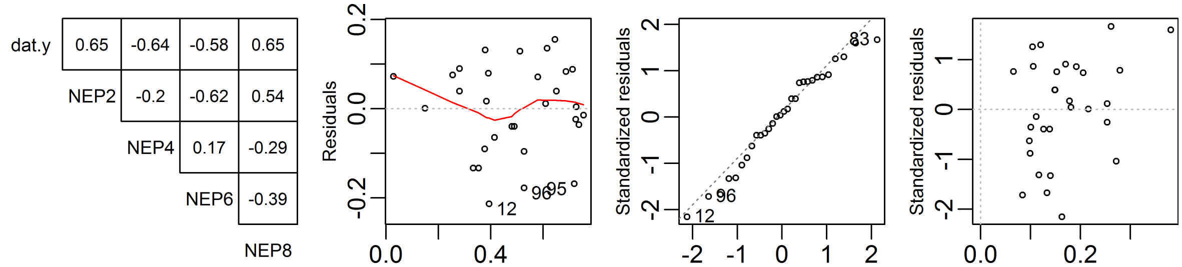
Figure 65. Diagnostic plots for statistical fits to the full data sets of the top ten performing Fraser sockeye diversion models based on retrospective evaluation. Each row of plots represents one model, which is named beneath the row. Plots are described in the beginning of the results section.



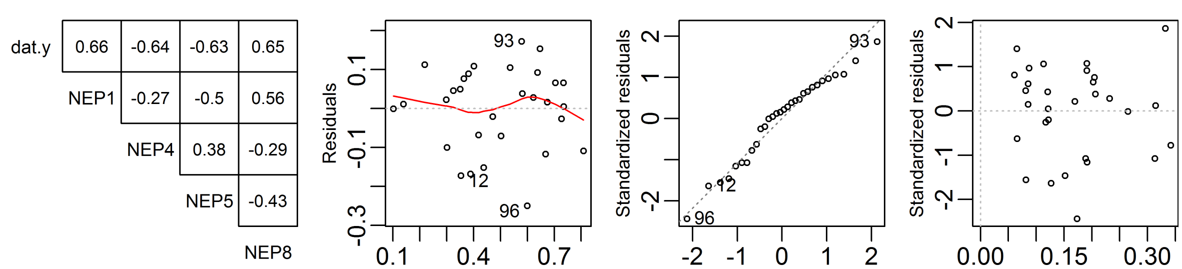
(f) nepstar5



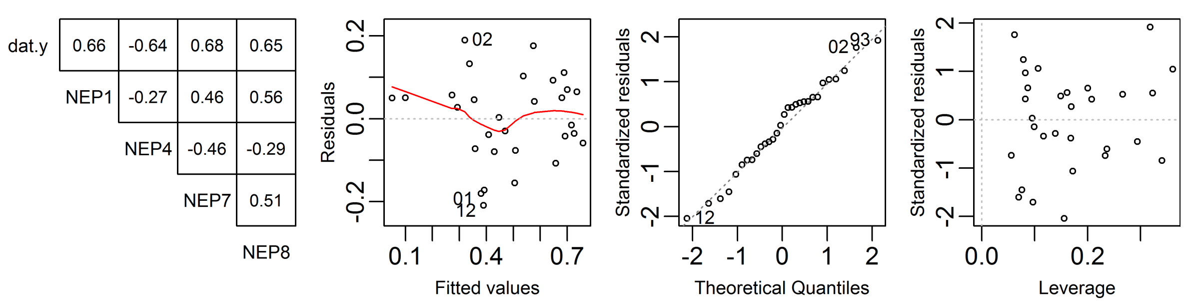
(g) nepstar4



(h) nepstar14

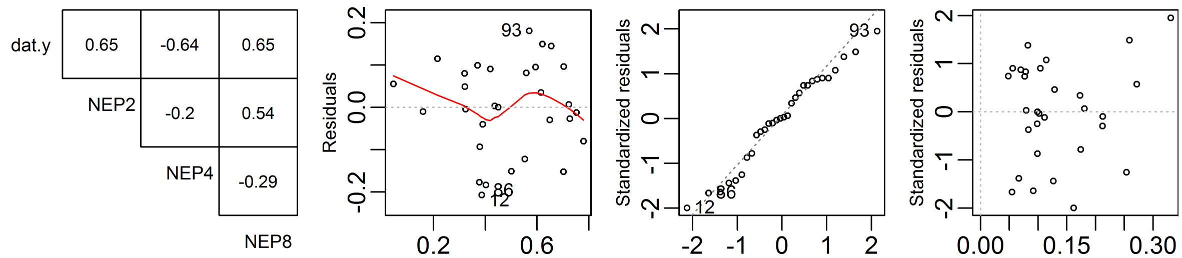


(i) nepstar12

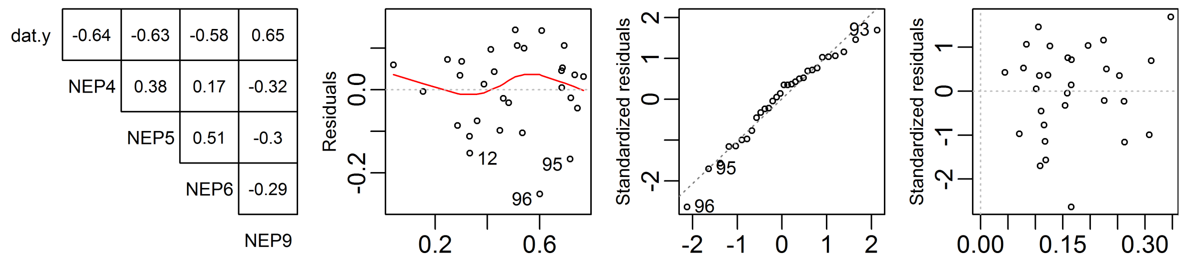


(j) nepstar13

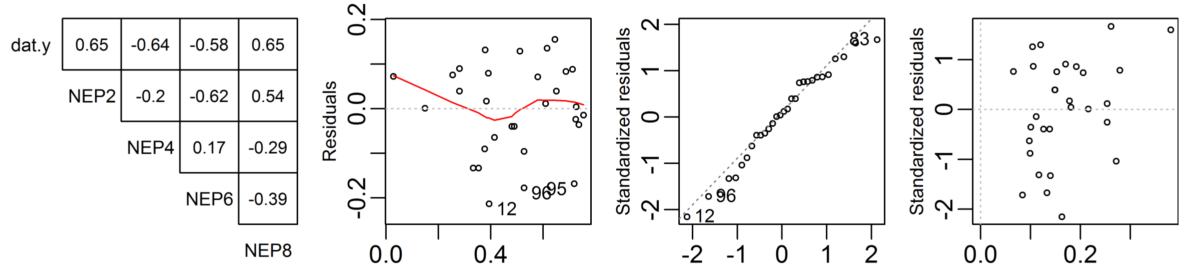
Figure 65. Continued



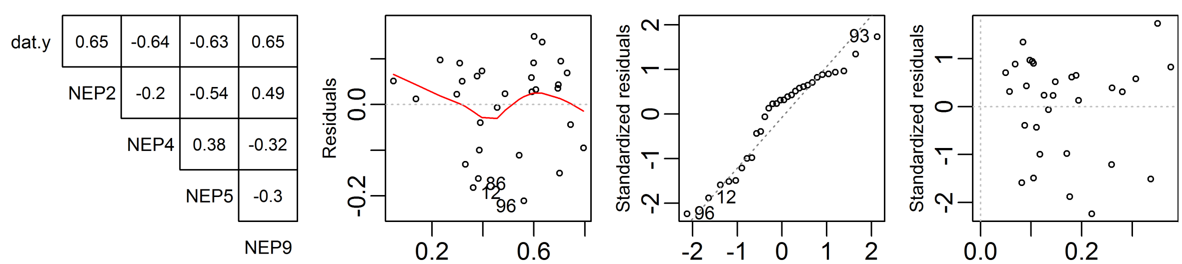
(a) nepstar4



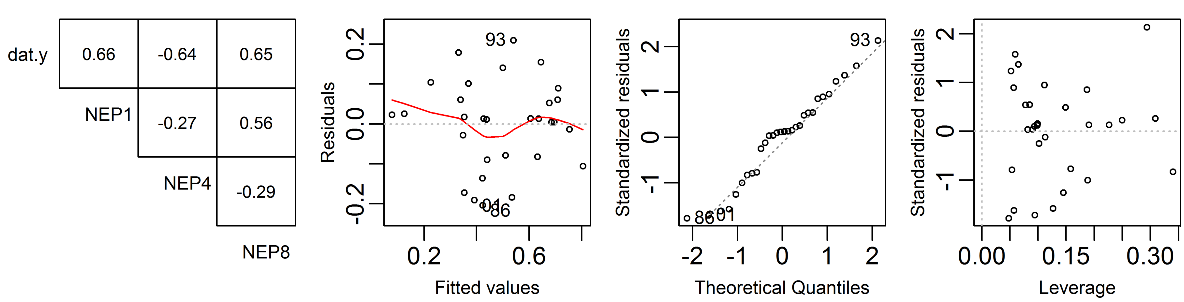
(b) nepstar3



(c) nepstar14

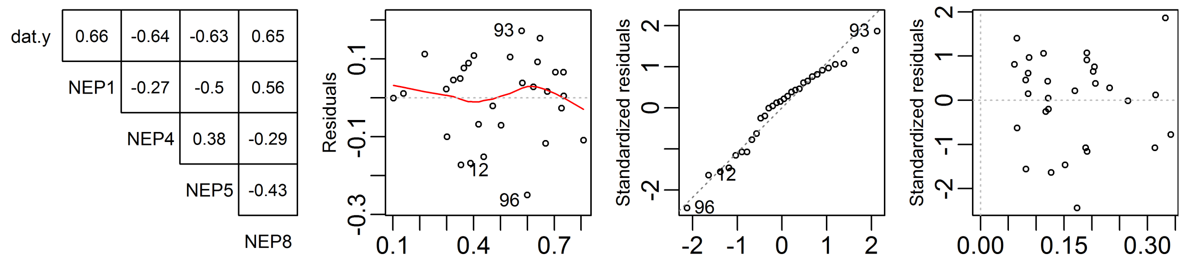


(d) nepstar8

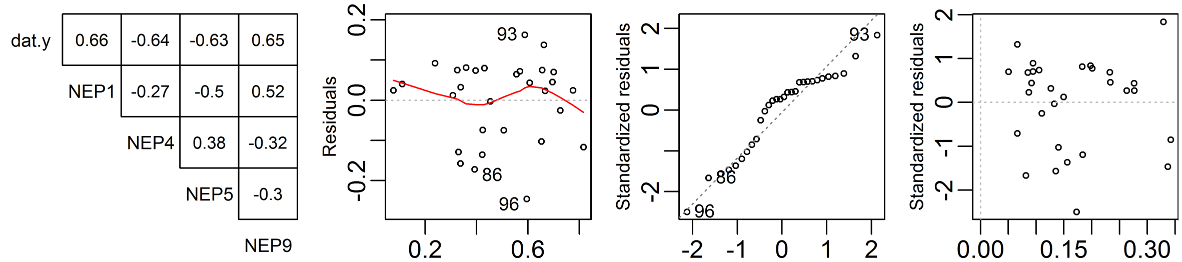


(e) nepstar7

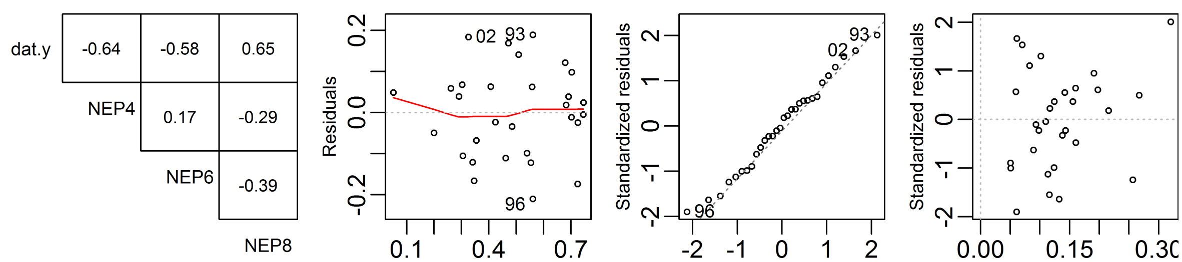
Figure 66. Diagnostic plots for statistical fits to the full data sets of the top ten performing Fraser sockeye diversion models based on jackknife evaluation. Each row of plots represents one model, which is named beneath the row. Plots are described in the beginning of the results section.



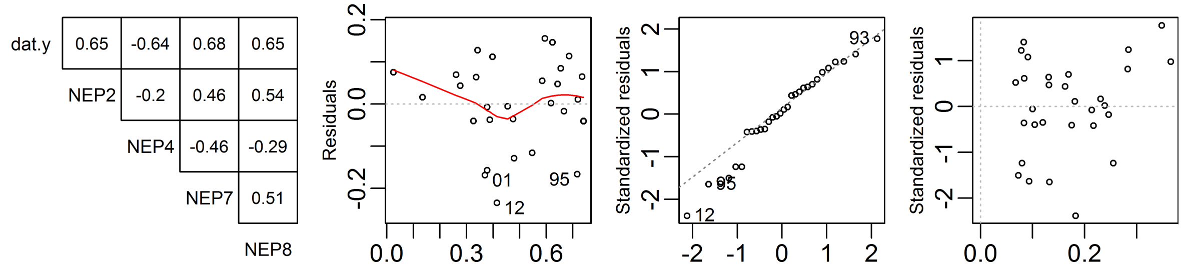
(f) nepstar12



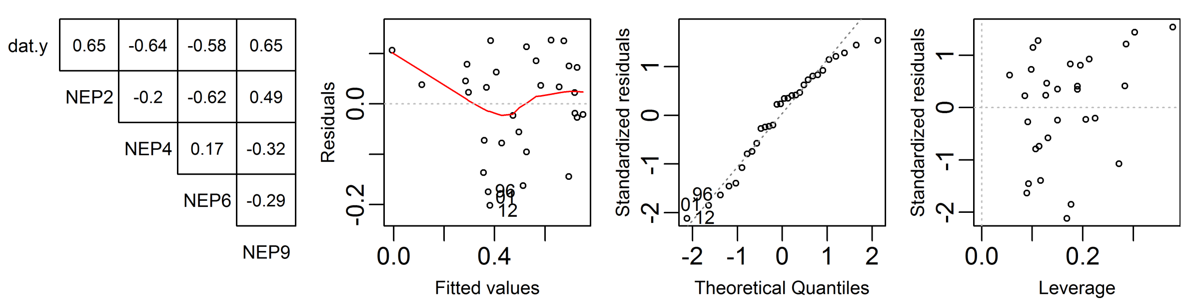
(g) nepstar5



(h) nepstar10



(i) nepstar11



(j) nepstar2

Figure 66. Continued

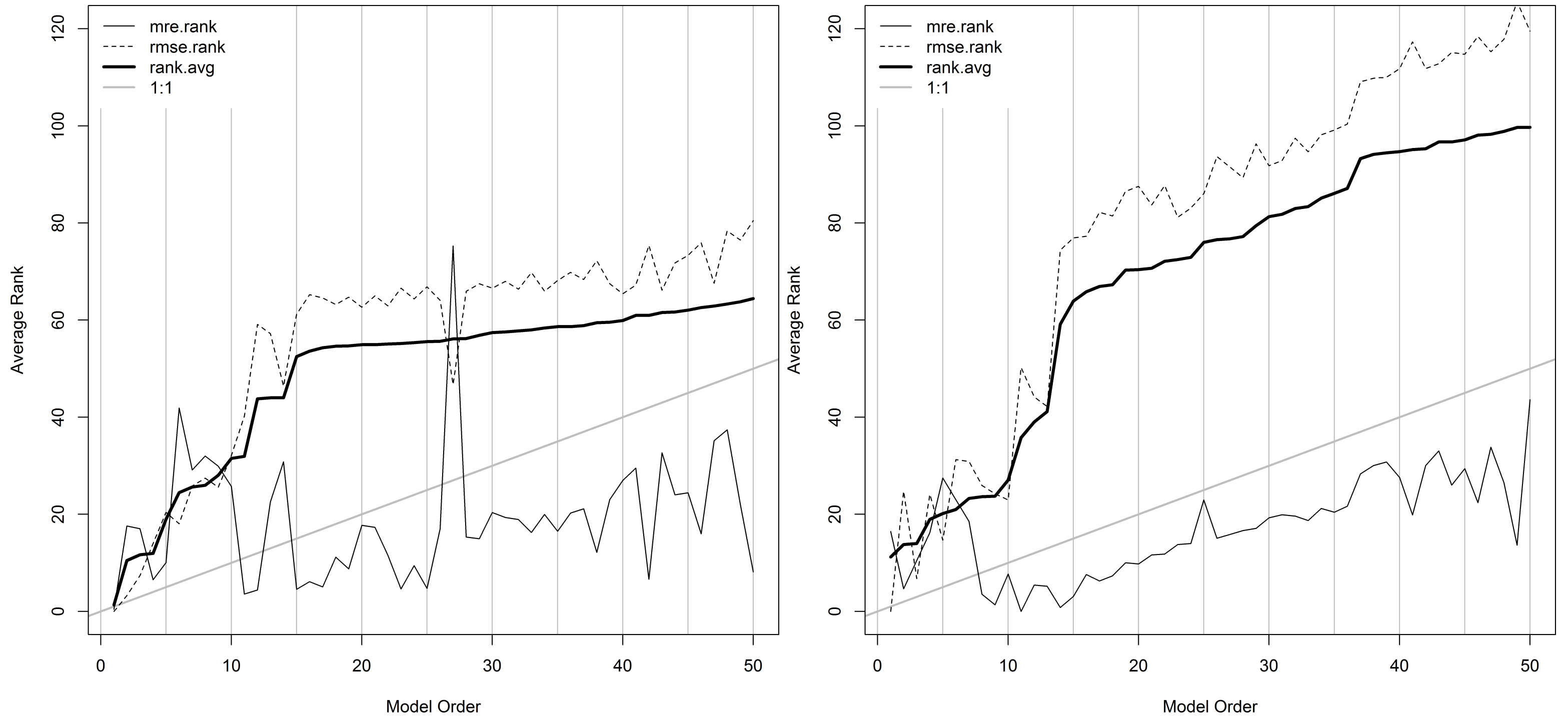


Figure 67. MRE rank, RMSE rank, and average rank for the top 50 ND forecasting models. Left panel is results for retrospective analysis, right panel is jackknife. The x-axis orders the models, by equal distance, based on their ordinal rank: 1–50. The y-axis shows the rank on an interval scale. Note that model order does not consistently match between plots, such that the tenth model of the retrospective analysis is not necessarily the same as the tenth model seen in the jackknife results. Ranks of MAE and U2 were excluded to prevent crowding. The diagonal grey line has a slope of one, which allows for comparison to the average rank line.

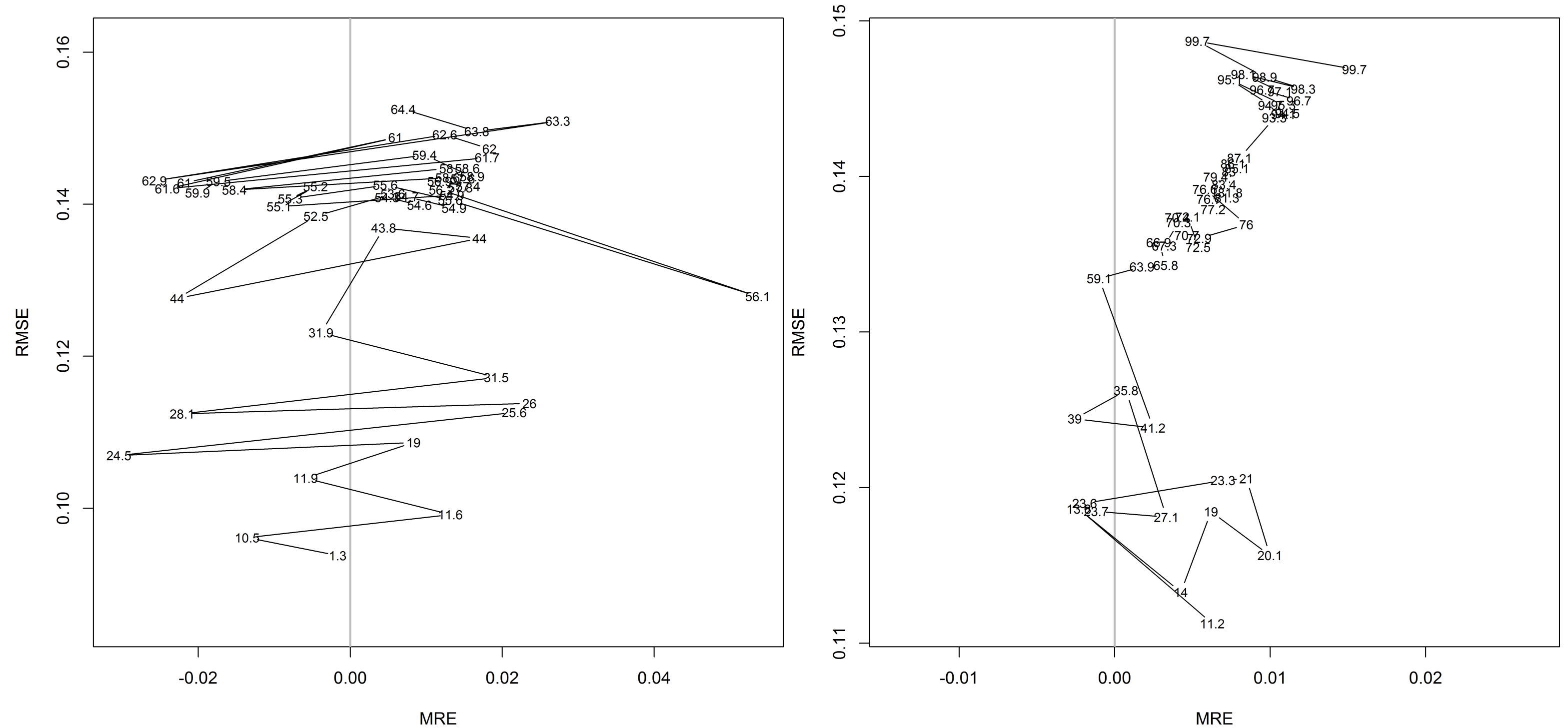


Figure 68. Relationship between PMs: RMSE and MRE for Fraser ND forecasts from retrospective (left panel) and jackknife (right panel) analysis. The number of each point corresponds to the average rank of each model. The line joins models from best ranked to worst ranked. The vertical grey line delineates models with a generally positive bias from those with a negative bias. This demonstrates how declining rank is often a process of ratcheting down between positive and negative bias (MRE).

Table 10. Summary statistics of annual forecasts, from the best performing model in each model type, for Fraser sockeye sockeye diversion based on retrospective analysis. All variables except rank have unit "proportion". The variables 'Forecast mean' and 'True mean' are "total proportion diverting". True mean and True SD are the statistics of actual post season estimates, constrained to the same period on which performance analysis was based.

Model (type #)	Rank	All Models Median Rank	Max Positive Error	Max Negative Error	Min Error	Mean Abs Error	Forecast Mean	Forecast SD	True Mean	True SD
nepstar7	1.33	95.32	0.20	-0.10	0.01	0.07	0.42	0.21	0.42	0.24
mlr57	52.49	95.32	0.17	-0.22	0.06	0.13	0.42	0.13	0.42	0.24
OSCAR213625	56.13	95.32	0.23	-0.12	0.01	0.10	0.48	0.14	0.42	0.24
OISST23405	82.63	95.32	0.13	-0.31	0.06	0.14	0.39	0.11	0.42	0.24

Table 11. Summary statistics of annual forecasts, from the best performing model in each model type, for Fraser sockeye sockeye diversion based on jackknife analysis. All variables except rank have unit "proportion". The variables 'Forecast mean' and 'True mean' are "total proportion diverting". True mean and True SD are the statistics of actual post season estimates, constrained to the same period on which performance analysis was based.

Model (type #)	Rank	All Models Median Rank	Max Positive Error	Max Negative Error	Min Error	Mean Abs Error	Forecast Mean	Forecast SD	True Mean	True SD
nepstar4	11.21	128.42	0.25	-0.16	0.00	0.09	0.51	0.18	0.51	0.21
mlr55	63.92	128.42	0.21	-0.22	0.01	0.12	0.51	0.18	0.51	0.21
OSCAR213625	99.70	128.42	0.26	-0.19	0.03	0.12	0.52	0.17	0.51	0.21
OISST23353	110.77	128.42	0.16	-0.31	0.02	0.13	0.48	0.17	0.51	0.21

Forecast Plots: Figures 69 and 70 present forecasts and observed ND by year. Models using shore station data did not qualify and are excluded. The summary statistics for data included in these plots are in Tables 10 and 11. Similar to results for the timing models, within the retrospective analysis the three lower ranked models (non-NEPSTAR-MLR, OSCAR, and OI SST) have a much lower within-model forecast variation (i.e., SD) than we see in the NEPSTAR-MLR model. It may be that these three models (non-NEPSTAR-MLR, OSCAR, and OI SST) are not representing all environmental uncertainty, and by extension not all ND variability. The greatest annual error by within model type is 0.20 (NEPSTAR), -0.22 (non-NEPSTAR-MLR), 0.23 (OSCAR), and -0.31 (OI SST). In the jackknife results the statistics of model error are much closer among model types, i.e. all four have comparable variation to that seen in the true ND. The jackknife results are calculated from 17 forecast values compared to six values in the retrospective forecasts. Appreciably just one year with a substantially erroneous forecast can influence the retrospective-based statistics—which would be less apparent in the jackknife forecast statistics.

6 DISCUSSION

Model selection and evaluation is based on three steps. All candidate models must be based on a statistically significant fitting between the dependent and independent data (adjusted $R^2 > 0.5$, Bonferonni corrected $p < 0.05$, and $n \geq 17$). Qualifying models are then appraised in performance analysis based on retrospective and jackknife procedures. Models that ranked highly in both performance analyses are then selected for use in the Proposed Operational Modelling Implementation Scheme (Section 7).

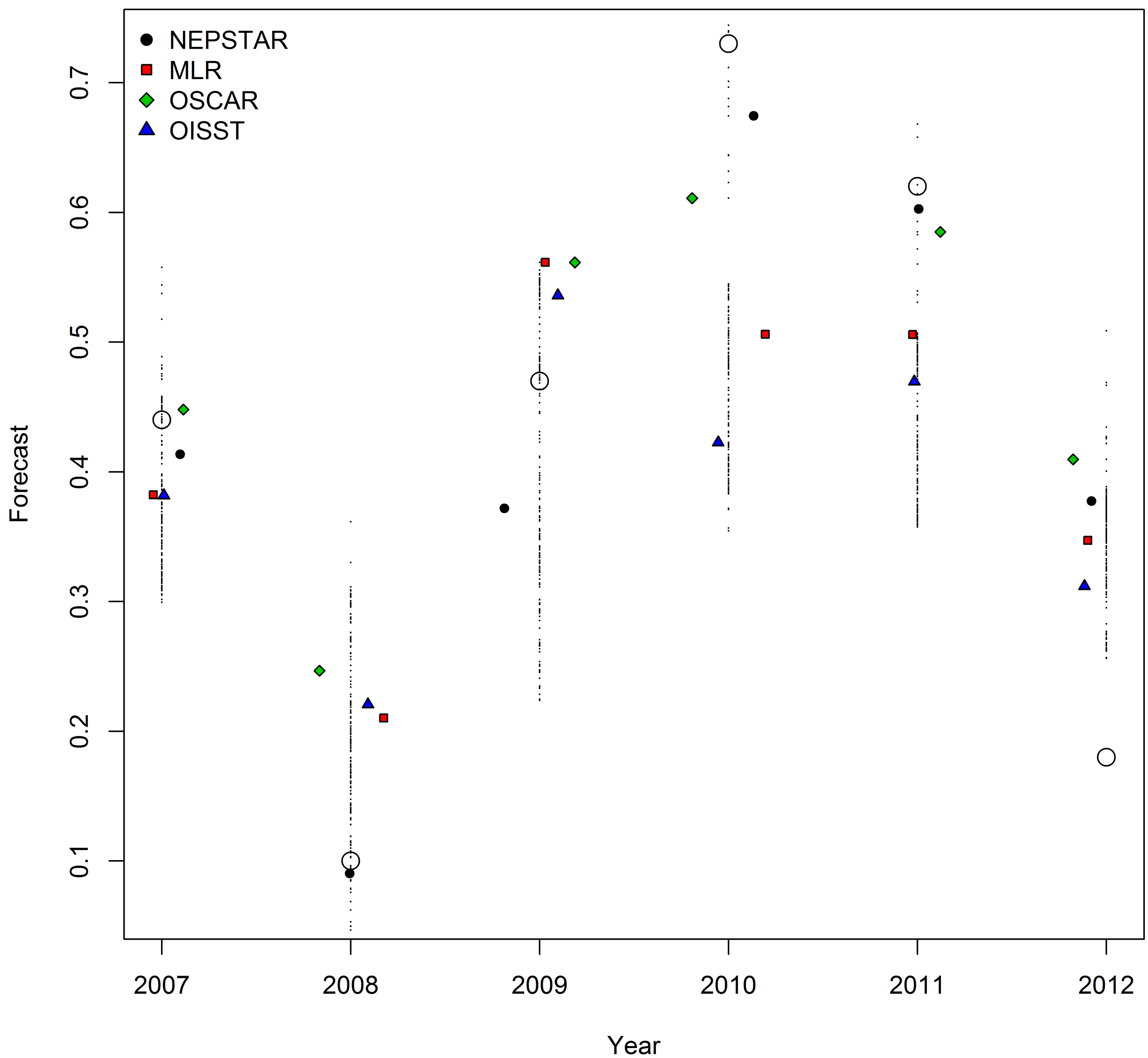


Figure 69. Annual ND rate forecasts for 2007–2012 from retrospective analysis. Data points for each year comprise approximately the 0.95 intervals of all qualifying forecast models. The black, open circle is the post-season estimate. The annual forecasts of each best ranked model, by data-origin, are given unique symbols. Models are sorted in the legend by rank.

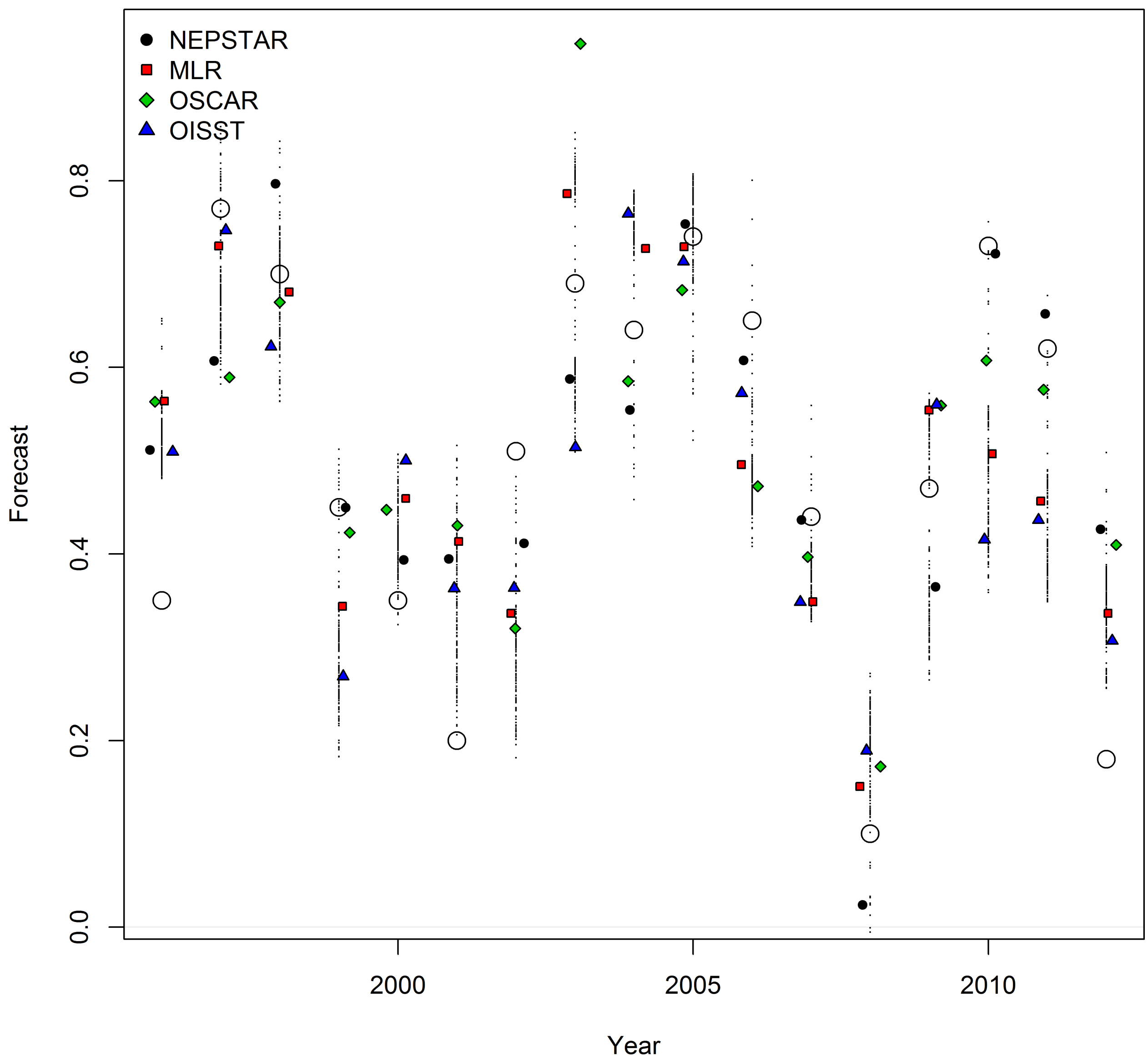


Figure 70. Annual ND forecasts for 1996–2012 from jackknife analysis. Data points for each year comprise approximately the 0.95 intervals of all qualifying forecast models. The black, open circle is the post-season estimate. The annual forecasts of each best ranked model, by data-origin, are given unique symbols. Models are sorted in the legend by rank.

6.1 THE INFLUENCE OF EL NIÑO EVENTS

Statistically significant differences in both timing (later dates) and ND rate (higher values) are found for El Niño events defined by the BEST index. The BEST index is a conservative definition of the state of El Niño/La Niña conditions than the standard ONI and SOI conditions since it depends on a substantial signal in both the ocean and atmosphere. This is in contrast to the ONI and SOI, which reflect El Niño and La Niña signals in only the ocean or atmosphere, respectively. Thus, anomalous, but less “extreme" events are excluded from El Niño/La Niña periods in the BEST index.

The consistent and protracted time periods of high correlation between El Niño events and anomalous migratory behaviour suggests a possible strong biological basis for these relationships. Return timing of the Chilko stock and ND can be linked to El Niño events during the fall and winter of their second year at sea, and spring of their final marine year (cf. Thomson et al. (2012)). The marine distribution of the Chilko stock during its final marine winter is highly uncertain due to a lack of any recent sampling. We can only speculate that there are inter-annual variations in marine distribution that are driven by various environmental factors that include the effects of El Niño. However, we can assume that during the early period of return migration, stocks in the high seas have not yet exited from their counter-clockwise cyclic path. At this time and location the fish would be under the influence of enhanced Ekman transport divergence in the surface waters due to a (typically) deeper Aleutian Low during an El Niño winter. Enhanced surface divergence could either aid or hinder salmon migration depending on its directional relation to fish migration pathways from offshore to coastal region waters. El Niño influences on Early Stuart timing appear to be limited to conditions experienced during only May and June of the return year. We assume that marine migration of Early Stuart during that period is along the coastal region. Any link between Early Stuart adult migration timing and El Niño conditions during the spring is likely related to warmer near-coastal temperatures that were established over the previous winter. Large-scale coastal region surface current anomalies may not be a factor at this time since large-scale coastal region surface wind anomalies in the spring do not appear consistent across El Niño events, although the effect of remotely forced current variations off the coast of British Columbia also need to be considered.

6.2 ON REJECTED MODELS

6.2.1 Naïve Models

In all performance analyses all naïve models ranked worse than the median rank value, except for jackknife evaluation from five (of seven) ND naïve models. However, those five models still ranked quite poorly (≥ 77). The poor ranking of all naïve models is mostly due to the greater uncertainty estimated by MAE and RMSE–relative to the environmental models. However, naïve models that are based on a statistic of the complete time series (TSA and TSMd) will also be biased if the time series is trending. We see this result looking at the MRE PMs of the TSA and TSMd models of Chilko timing and ND rate. Each of those time series are trending to increasing values. This strongly suggests that the naïve models should not be considered in any attempt to forecast return timing or ND rate.

6.2.2 Fitted Models

There has been a recent resurgence in the scientific literature on the role of geomagnetism in animal migration (Putman et al., 2013; Berdahl et al., 2014; Guerra et al., 2014; Putman et al., 2014*a*; **?**). While geomagnetic conditions may influence Fraser sockeye ND, it's role was insufficient for consideration in the multivariate models. However this exclusion was based on our criterion that an independent variable should explain the majority (i.e., greater than 50%) of the variation seen in the dependent variable. The level of this criterion could be considered somewhat subjective and is based on the majority rule concept. Future work could include the consideration of alternate R^2 levels (ranging higher or lower), which would produce fewer and more qualifying single variable models, respectively.

6.3 MODEL STRUCTURE

Variable Count: Forecast models based on three or more variables consistently showed greater forecasting performance (ranking), compared to one and two variable models—under both retrospective and jackknife testing. This appears mainly due to the inability of models based on one or two variables to capture extreme events, including the anomalous timing of 2005. The jackknife evaluation does include a forecast for 2005, while retrospective does not. The difference in model rank between retrospective and jackknife is demonstrated in Figure 71. In this figure we see that models based on one or two variables have substantially worse rank in jackknife than in retrospective. Due to the inconsistent performance of models based on one or two variables, we have excluded them from final model selection. The variables that qualified when fitted by single variable SCAMs were additionally considered in the stepwise non-NEPSTAR-MLR models, but due to limits of practicality multivariate SCAMs were not appraised.

Impacts of Stepwise Regression: An outcome from stepwise regression is the possibility that many top ranked multivariate models can include the best single variable due to it's role minimizing the AICc. Further this behaviour can also occur with the second variable. This leads to a series of top ranked models that may be based on variables that are both temporally and spatially proximate. This trait can lead to similar forecasts from top ranked models. Broadening the top variable search method within the stepwise regression (by building multivariates from more than just the top single and two variable models) has helped to avoid the risk of local AICc minima. This leads to a more heterogeneous variable mixture among the top ranked models. But it has not completely resolved the matter.

Some additional approaches exist to avoid deriving forecast models that are based on highly correlated data. Aggregation of spatially (or possibly temporally) correlated variables to a single variable that may then be used in the stepwise regression could be the simplest approach. However this may come at the risk of weakening significant information, particularly values at the extreme ranges of the probability distribution, which are of great value. While SST values are known to be temporally correlated, this is less true for current velocity. Gridded current velocity values will change on shorter time scales than is seen with SST changes. Thus (temporal) data aggregation methods may remove the "signal" in current velocity data weakening it's role in statistical models. This may be of less concern for the contribution of SST variables.

Removing the spatial or temporal correlation between like environmental variables could be explored using a "pre-whitening" procedure (Hare, 1996; Pyper and Peterman, 1998). However the latter author explains that such methods, when applied to temporal correlation, can come at a

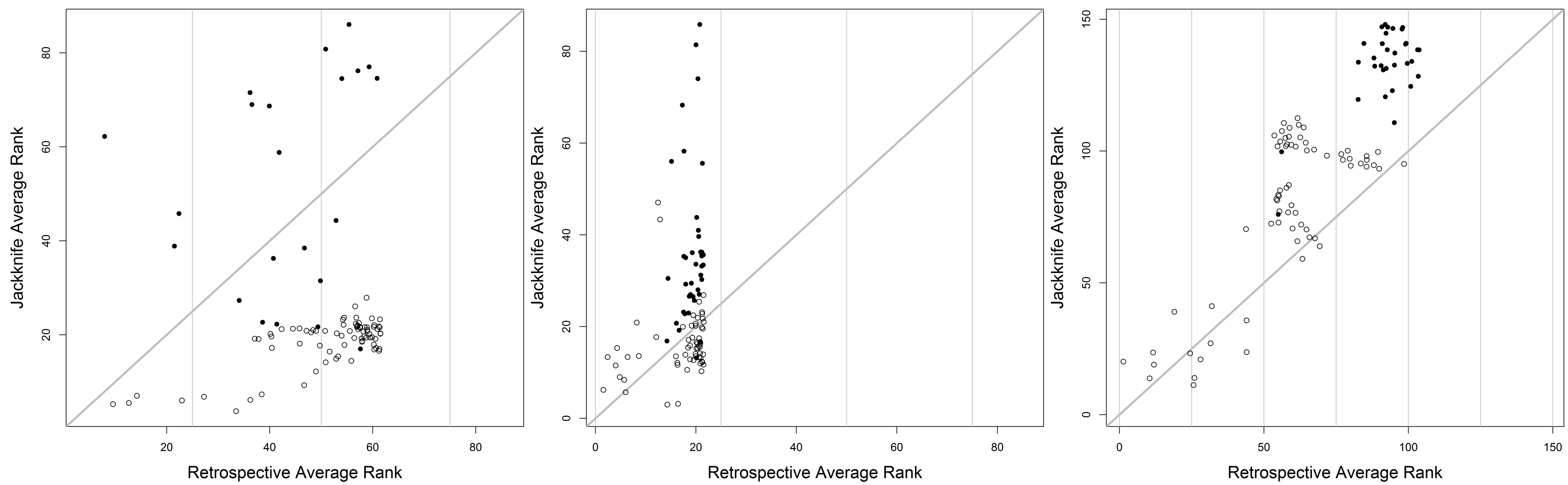


Figure 71. Comparison of model rank based on retrospective results (x-axis) to model rank based on jackknife results (y-axis) for top 100 retrospective models (left panel: Early Stuart timing; middle panel: Chilko timing; right panel: ND rate). Solid points represent models comprising one or two variables, while open points represent models with three or more variables. The diagonal line represents a slope of one, such that a point on (or near) the line represents a model with similar rank in retrospective and jackknife evaluation.

cost if “low-frequency (slowly changing) processes are important sources of covariation . . . in environmental variables”. We have not appraised the role of pre-whitening environmental variables and see this as an important next step.

On Model Over-fitting: We describe in the methods section on stepwise regression that there exist rule-of-thumb recommendations on limits to the number of coefficients a statistical model should include to avoid over-fitting. Within each forecast type (timing, ND), the top ten ranking NEPSTAR-mlr models did overstep those guidelines for at least half of the models. This occurred when the models were based on four or more variables. This does not imply that those specific models were over-fitted to the data, rather there was a greater chance over-fitting may occur for those models. The results of performance analysis strongly suggest model over-fitting was not present. Over-fitted models should not forecast well based on new, independent values that were excluded from the original fit. Poor forecast performance would be reflected in the PMs. This trait can be empirically demonstrated using random data to forecast an independently derived random data series. In this case a jackknife analysis of both an over-fitted (linear) model and a TSA model will demonstrate the former model to always have greater MRE and metrics of uncertainty (MAE and RMSE). Furthermore, those PMs of the over-fitted model will progressively increase as more covariates are added. Finally the U2 PM will demonstrate the over-fitted model to be consistently worse than other naïve models. We do not see these results with the NEPSTAR-mlr models, suggesting the likelihood they are over-fitted is minimal.

6.4 MODEL TEMPORAL AND GEOGRAPHIC DEPENDENCY

Data found to be good predictors of timing or ND should presumably have a spatial and temporal connection to sockeye distributions during their two year marine phase. The present understanding of sockeye offshore distribution and migration is based on research programs conducted over 40 years ago (French et al., 1976); see Myers et al. (1996) for summaries. There have been substantial changes to marine conditions in the ensuing 40 years (Hare and Francis, 1995; Mantua and Hare, 2002; Peterson and Schwing, 2003; Di Lorenzo et al., 2008), and fisheries scientists have no additional information to confirm whether fish distribution patterns remain similar to that prior period (Quinn, 2005). Therefore, we restrict our interpretation of environmental influences on sockeye migration to broad spatial and temporal domains, which we believe is a defensible approach.

6.4.1 Return Timing

Among the single variable models, variables from similar months also shared similar locations in the North Pacific. This temporal and spatial consistency lends more weight to the argument for these factors to be potential drivers of sockeye migratory behaviour. None of the variables considered are found in biologically unrealistic locations, in terms of historical observations, swimming energetics, and feasible migration distances. The majority of model predictors are located approximately half to two thirds of the distance between Vancouver Island and the mid-Aleutian chain (Figures 35 and 46). Figure 2 represents the marine locations of Fraser sockeye tagged by month of their return year (Myers et al., 1996), showing that there is good overlap between the distribution of tagged fish and variable locations.

The current velocity data are the primary contributors to the Early Stuart non-NEPSTAR-MLR models as they explain the majority of the interannual timing variation. These data are also the furthest offshore and represent winter months of both the early marine phase (January of first marine winter) and January of the return year. The next critical group of data are SST from July and August (year prior to return) in a zone half way between Vancouver Island and the current velocity locations. Although there appears to be geographic grouping of the non-NEPSTAR-MLR model data by its type, temporal grouping is not apparent.

During the last decade, pre-season forecasts of Early Stuart timing were based on OSCURS eastward (u) current velocity at 45°N 140°W in May of the return year, while Chilko timing was based on OSCURS eastward (u) current velocity at 57.5°N 145°W in March of the return year. This curious reversal of chronology (knowing that Early Stuart is the first stock returning to coastal waters, while Chilko arrives later with the summer aggregate) was never discussed in prior publications. The top performing Early Stuart models (non-NEPSTAR-MLR models with more than two variables) were primarily based on northward current velocity from January of the year prior to return, secondarily by January northward current velocity during the return year, and finally by some combination of SST or current velocity from the year prior to return. However, the NEPSTAR-MLR models of Early Stuart timing (which did rank comparatively well in the jackknife results) are predominantly based on eastward current velocity in May of the return year, and to a lesser degree on northward currents in the year prior to return (Figure 36).

The top performing non-NEPSTAR-MLR models of Chilko timing are primarily based on eastward current velocity in May of the return year, secondarily by eastward current velocity in December (of the prior year), and finally by one of many unique combinations of northward or eastward current velocity during the prior 18 months at sea. The most frequently used variable in the Chilko NEPSTAR-MLR models is eastward wind stress centered in March during the return year (Figure 47). Northward and eastward wind stress from May of the prior year are also frequently utilized, indicating their importance to most models. Wind stress variables—which can be used as surrogates for surface currents, wind-wave height, and mixing of the surface ocean—dominate the NEPSTAR-MLR models of Chilko timing. The fourth most utilized variable is northward current velocity in March of the return year. Considering the role of current velocities and wind stress in timing models, the NEPSTAR-MLR models for Early Stuart and Chilko timing forecasts rely on time periods consistent with those used in the original OSCURS models and these are substantially different from the time periods relevant to the non-NEPSTAR-MLR models.

Within the Early Stuart retrospective results there are four single variable models based on SST during June of the return year. The locations of these data are worth noting in that they are all are within 1–2° (grid) of each other, and situated west of Bristol Bay, Alaska. Like the OSCAR data, the SST data used in single variable models were processed through a spatial running average routine such that neighbouring data cells likely have similar values. The correlation between series ranges 0.95 to over 0.99. It is possible that the moderate correlations between SST at these locations and Early Stuart timing (+0.70 to +0.77) are spurious and should be discarded. The jackknife results place the non-NEPSTAR-MLR models with these SST data in ranks below the top 50 models, so their performance is substantially inferior when tested against all years. Figure 72 demonstrates the single variable relationship (for one of the four models) between SST data and Early Stuart timing. This single variable model is insensitive to temperatures below approximately 6.5°C, meaning the single variable model will always forecast a similar timing when the temperature is below approximately 6.5°C. It would appear that these variables play a role in the non-NEPSTAR-MLR models during higher temperature/late timing years when the salmon return migration path from the open ocean is possibly displaced further to the north than normal, but are otherwise irrelevant (when the fish possibly pass further south).

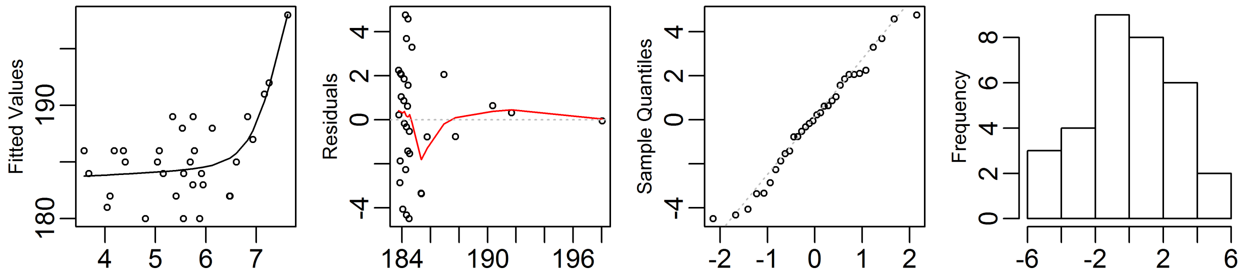


Figure 72. Diagnostic plots for one of the four single variable statistical fits (by SCAM) of Early Stuart timing to the full data set of the Bristol Bay June SST. Plots are described in the beginning of the results section.

Far fewer NEPSTAR-MLR models were evaluated compared with the non-NEPSTAR-MLR models. Thus, we also evaluate substantially fewer variables from these models. The variables used in the NEPSTAR-MLR models are spread over a substantially larger geographic area than the non-NEPSTAR model variables. However, the variables are all still within a spatial range that is biologically realistic for influencing migratory behaviour. There is a modest level of geographic grouping by data type (SST, wind, current), but within data types the time periods can span 12 months (e.g. eastward current velocity from May of return year and May of the prior year; see the jackknife panel in Figure 35). For the Chilko models, current velocity data from six unique combinations of location and time were well correlated to timing. Only one of these is based on data from the return year, and is located off Juan de Fuca Strait. Four other variables were from the year prior to return, and one variable from two years prior. We note that there is very little geographic overlap of current velocity variables used in both single and non-NEPSTAR-MLR models versus current velocity variables in the NEPSTAR-MLR models. This could be due to differences between the NEPSTAR-MLR and non-NEPSTAR variable search methods, which includes: (1) different sets of years used to find the relevant locations (i.e., variables); (2) different temporal resolution (days vs. months); or (3) the data sets are significantly different (e.g., POM vs. OSCAR currents). A quick evaluation of the current velocity data suggests the latter is unlikely. The time and place of variables relevant to Chilko timing forecasts appear to follow the assumed offshore migratory paths, while this is not the case for variables of Early Stuart timing models.

6.4.2 Northern Diversion

The top ranking models to forecast ND are the NEPSTAR-MLR models. These models are based on six different current velocity variables that span the period from January of the year prior to return up to April of the return year, plus two SST variables located in the central north Pacific. The current velocity variables are located within 400 km (200 NM) of the coast, but range from Washington State to the Alaskan pan-handle (Figure 59). Of these six current velocity variables, most are applied to five or six unique models (frequently in combination). The predominant NEPSTAR-MLR variable is an eastward current velocity located offshore at the southern edge of the Gulf of Alaska and, similar to the two central North Pacific SST variables, is estimated from the year prior to return migration. Conversely, the five remaining current velocity variables are more coastal and four of them are estimated from January to April of the return year. Of those four coastal current velocity variables representing return year conditions, three are indexes of northward vectors.

All SST data used in the single and non-NEPSTAR-MLR models are near-coastal during May and June of the return year (compared to SST for the NEPSTAR-MLR models, which is from the central North Pacific during the prior summer). And the single current velocity variable used in all the non-NEPSTAR-MLR models is from the central North Pacific (compared to the near-coastal current velocity data used in the NEPSTAR-MLR models). Thus, the non-NEPSTAR-MLR ND models rely on SST and current velocity data located geographically opposite to that of the NEPSTAR-MLR models. It is not clear why the current velocity and SST variables are differently located between the two forecasting approaches (NEPSTAR versus non-NEPSTAR-MLR). The non-NEPSTAR-MLR models rely on data that have been averaged through a moving geographic window, which is not the case for variables in the NEPSTAR-MLR models. Additionally, the non-NEPSTAR-MLR variables are averaged to monthly estimates, while NEPSTAR-MLR variables can be based on averaging windows spanning 3–89 days. We do not believe averaging window to be the critical difference between the non-NEPSTAR-MLR and NEPSTAR-MLRmodels. Finally, NEPSTAR and OSCAR current velocity data from a common spatial location will not exactly match, though there is similarity on a small geographic scale. In the ND models there may be some geographic and temporal structure to the data—related to sockeye migration behaviour—where offshore variables represent a period after the first marine winter and coastal variables represent the spring of adult return year.

6.5 RETROSPECTIVE ANALYSIS VERSUS JACKKNIFING

The relative performance of a model in both the retrospective and jackknife analyses appears to be strongly based on model structure and the ability to forecast extreme value years. Models based on either one or two variables that ranked in the top 100 retrospective results usually fail to maintain similar ranking in the jackknife evaluation (Figure 71). The retrospective PMs are calculated from forecasts of six years 2007–2012, while the jackknife PMs are calculated from forecasts of all available years over 1996–2012 (Early Stuart: 17 forecasts; Chilko: 14 forecasts—as timing estimates do not exist for 1997, 2001, 2002; ND: 17 forecasts). The range of Early Stuart observed timing values over 1996–2012 is relatively small. Most years (15 of 17) are within five days of the 1996–2012 median date. A model that tends to forecast close to the time series median (i.e., relies on environmental variables that are insensitive to observed timing changes) could forecast acceptably well during this period of the time series. However, when tested against years with extreme values (1997, 2005), the simple models' inability to forecast outside the standard deviation of the time series becomes apparent.

In both the timing and ND models, the data series used in model fitting between retrospective and jackknife analyses differ by no more than seven data points. There will be conditions when parameters of the model fits will differ between analyses. For example, the retrospective fitting will always include the anomalous timing years 1997 and 2005; jackknife fits that exclude those years produce markedly different regression parameters. Nonetheless, the majority of model fits between retrospective and jackknife analyses are mutually consistent. For example, when considering a model with 20 points available in the series, the initial fit by retrospective evaluation is derived from points 1–14, while the same model is fitted in the jackknife approach using 19 points. However, the final retrospective forecast (of point 20) is based on a model fitted using points 1–19. Thus we expect (and can confirm) that the 2012 forecasts ("point 20") from both the retrospective and jackknife evaluations are exactly the same, because the models are also exactly the same (i.e., fitted to the same data series). It must be emphasized that we rely on both retrospective and jackknife analyses not to test subtle variations of the same model (based on data length), but to test the models against differing testing periods.

On Comparing Ranks: Within a forecasting group (e.g. Early Stuart timing) the same models are analysed between performance tests (retrospective and jackknife). Thus, while the model specific ranks values may vary, the range of rank values by PM will remain equal. Therefore, PM ranks and model average ranks can be compared between performance tests.

We have indicated that there is not likely substantial variation in the range of parameters for a single model fitted to varying data lengths.[18] The varied ranking of common models between retrospective and jackknife evaluation may also be a result of data differences in the testing windows (see section 4.7.1), which comprise 6 years in retrospective and either 14 or 17 years in jackknife. To evaluate if the testing window influences results, we conducted a sensitivity of PMs to the period of the testing window. A new set of PMs were calculated from the jackknife evaluation using just the final six years of forecast results (i.e., comparable to the retrospective testing window). We call these the truncated jackknife PMs. Model specific differences in rank between jackknife PMs and truncated jackknife PMs suggests there is a substantial difference between the testing windows (Figures 73, 74, and 75, left panels). If the estimates of PMs were insensitive to testing window, we would expect points to fall on the diagonal line (left panel), indicating model rank is the same no matter the source of PM data. The similarity of model rank between retrospective and truncated jackknife results supports the assumption that fitting models to the shorter time series of the retrospective method is not resulting in inferiorly fitted models (Figures 73, 74, and 75, right panels). Thus, it is likely that it is the testing window that influences our results, not the (marginally) shorter data series utilized in the retrospective analysis. The model rank based on jackknife truncated PMs is included in the tables of jackknife results (Tables 13, 16, and 19).

Having interpreted why we see differences in model ranking between performance tests, we are now challenged with resolving the best candidate models—despite obtaining different results between the two performance tests. Ranks were recalculated for models comprising three or more variables since they generally performed better than models with fewer variables (see Section 6.3), and the results have been summarized in Rank:Order plots (Figures 76, 77, and 78). The slope of the rank line indicates how rapidly model performance is declining between neighbouring models. A steep slope indicates a rapid decline in model performance, while slopes close to horizontal suggests neighbouring models are comparable in performance. Changes to the slope of the *average rank*-line delineate a substantial shift in performance between neighbouring models. A sudden, positive increase in the slope (at an inflection point) of the average rank-line would suggest a threshold beyond which there is a rapid decline in model performance. However, a rapid increase of slope is apparent in just two of the Rank:Order plots (jackknife analyses of Early Stuart timing and ND rate, see the right panels of Figures 76 and 78). All other analyses show rank-lines with diminishing (but always positive) slopes, i.e., successive models are not substantially inferior to their predecessors. While the Rank:Order plots do help give a general overview of top ranking model groups, this approach cannot be consistently applied to all evaluations for selection of top candidate models.

[18] See section 4.3 on page 45 for our definition of a model.

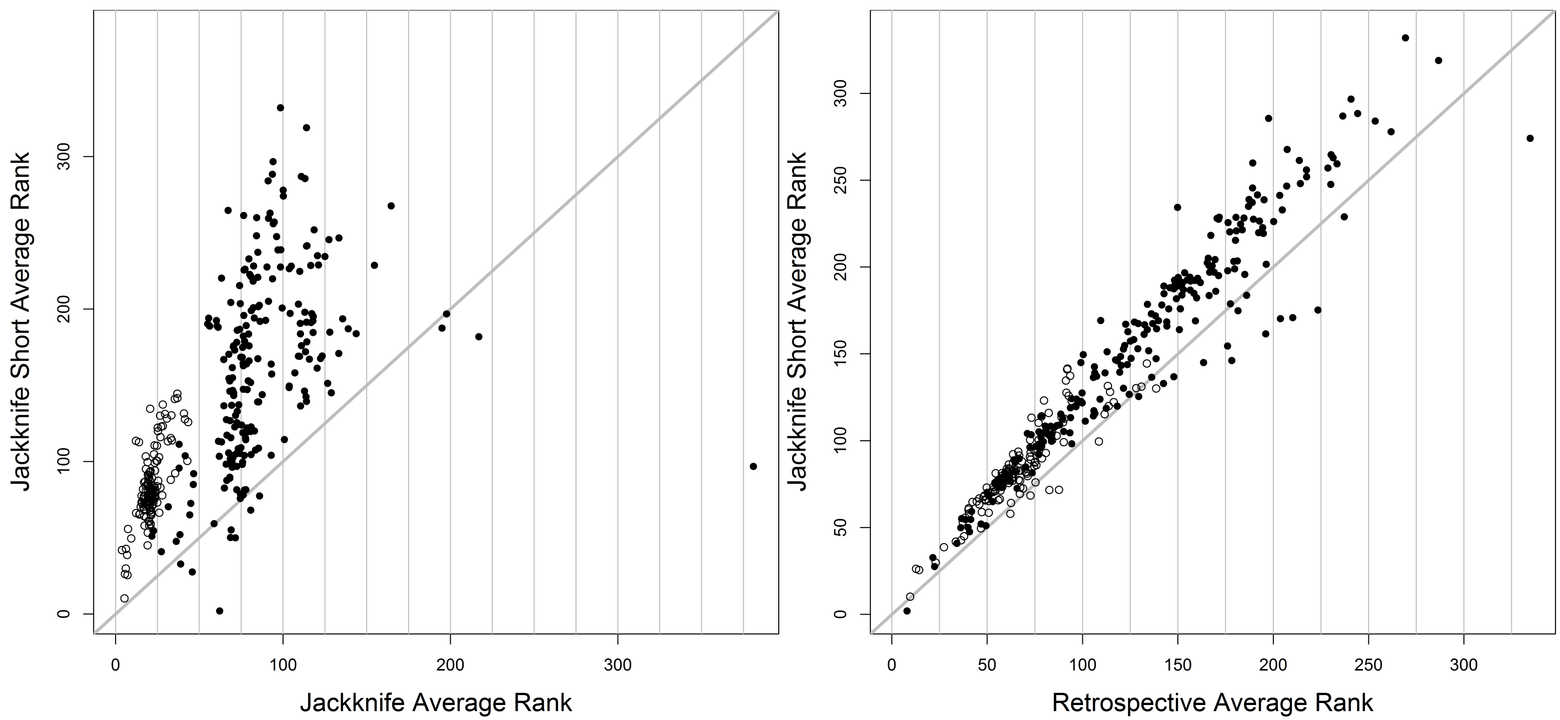


Figure 73. Comparison of ranks for all Early Stuart timing forecasting models. Left panel plots model rank calculated from the truncated jackknife results (y-axis) versus rank calculated from all jackknife results (x-axis). Right panel plots model rank calculated from the truncated jackknife results (y-axis) versus rank based on retrospective results (x-axis). Solid points represent models comprising one or two variables, while open points represent models with three or more variables. The diagonal line represents a slope of one, such that a point on (or near) the line represents a model with similar rank in retrospective and jackknife evaluation. This demonstrates the sensitivity of results to the the testing window range. Similarity between truncated jackknife results and retrospective results (right panel) would be expected as they are both calculated from forecasts of the final six years.

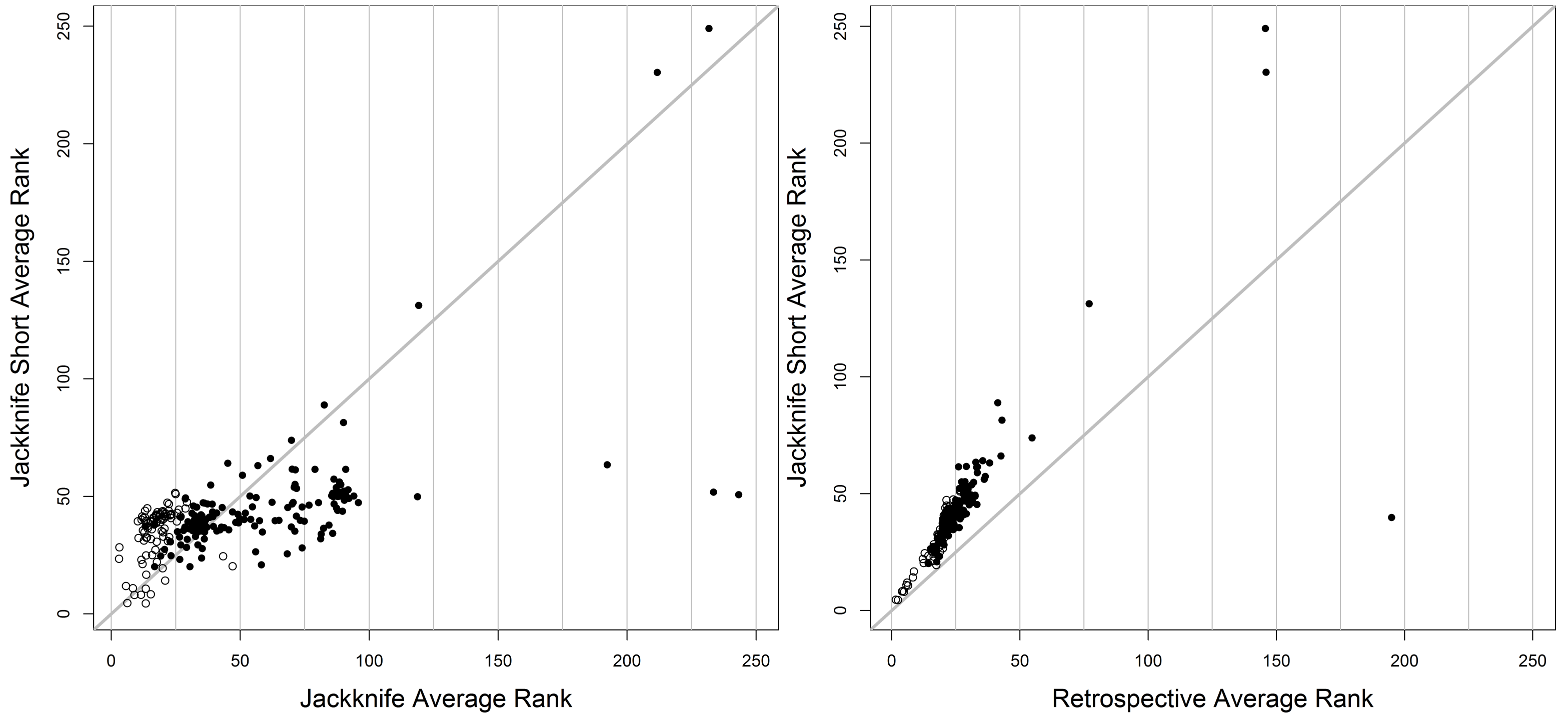


Figure 74. Comparison of ranks for all Chilko timing forecasting models. Left panel plots model rank calculated from the truncated jackknife results (y-axis) versus rank calculated from all jackknife results (x-axis). Right panel plots model rank calculated from the truncated jackknife results (y-axis) versus rank based on retrospective results (x-axis). Solid points represent models comprising one or two variables, while open points represent models with three or more variables. The diagonal line represents a slope of one, such that a point on (or near) the line represents a model with similar rank in retrospective and jackknife evaluation. This demonstrates the sensitivity of results to the the testing window range. Similarity between truncated jackknife results and retrospective results (right panel) would be expected as they are both calculated from forecasts of the final six years.

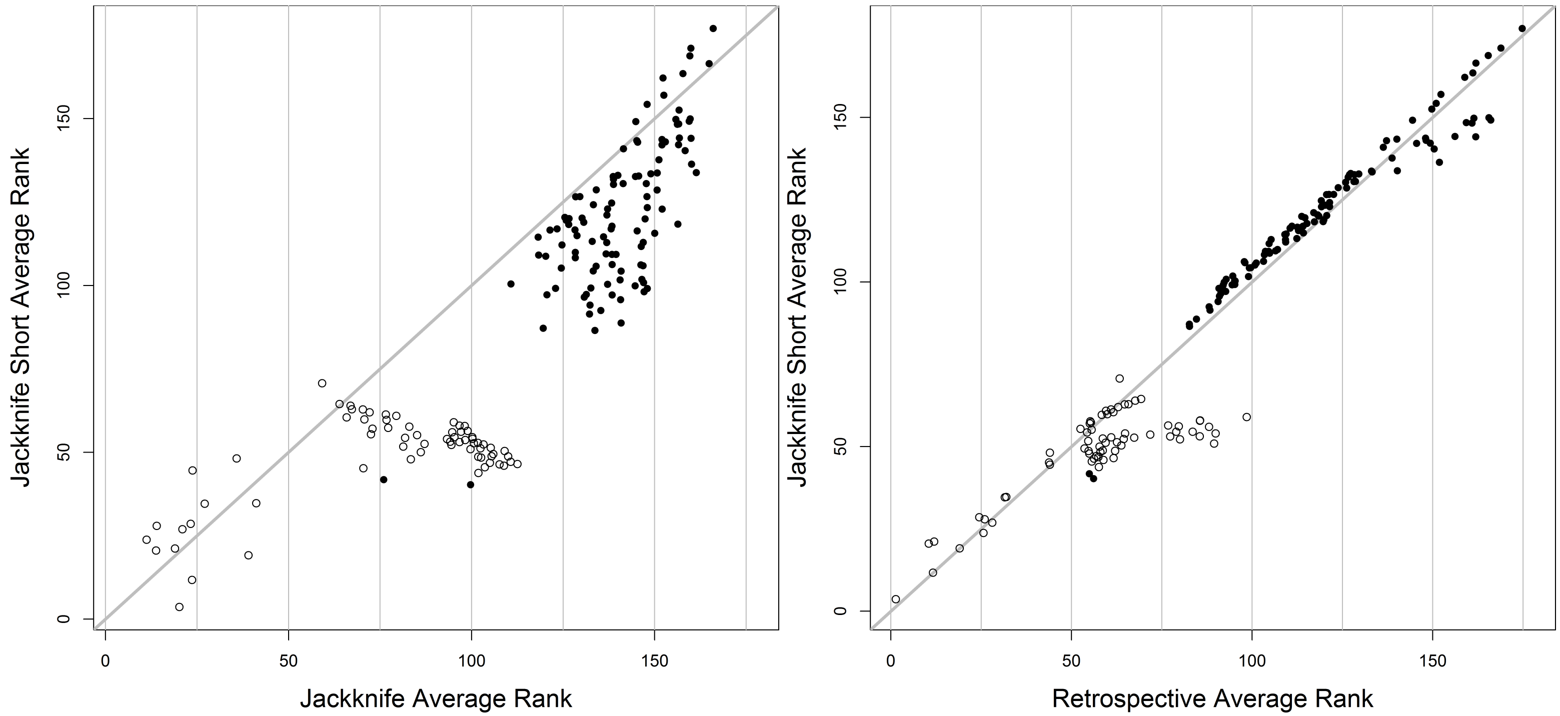


Figure 75. Comparison of ranks for all Fraser ND forecasting models. Left panel plots model rank calculated from the truncated jackknife results (y-axis) versus rank calculated from all jackknife results (x-axis). Right panel plots model rank calculated from the truncated jackknife results (y-axis) versus rank based on retrospective results (x-axis). Solid points represent models comprising one or two variables, while open points represent models with three or more variables. The diagonal grey line represents a slope of one, such that a point on (or near) the line represents a model with similar rank in retrospective and jackknife evaluation. This demonstrates the sensitivity of results to the the testing window range. Similarity between truncated jackknife results and retrospective results (right panel) would be expected as they are both calculated from forecasts of the final six years.

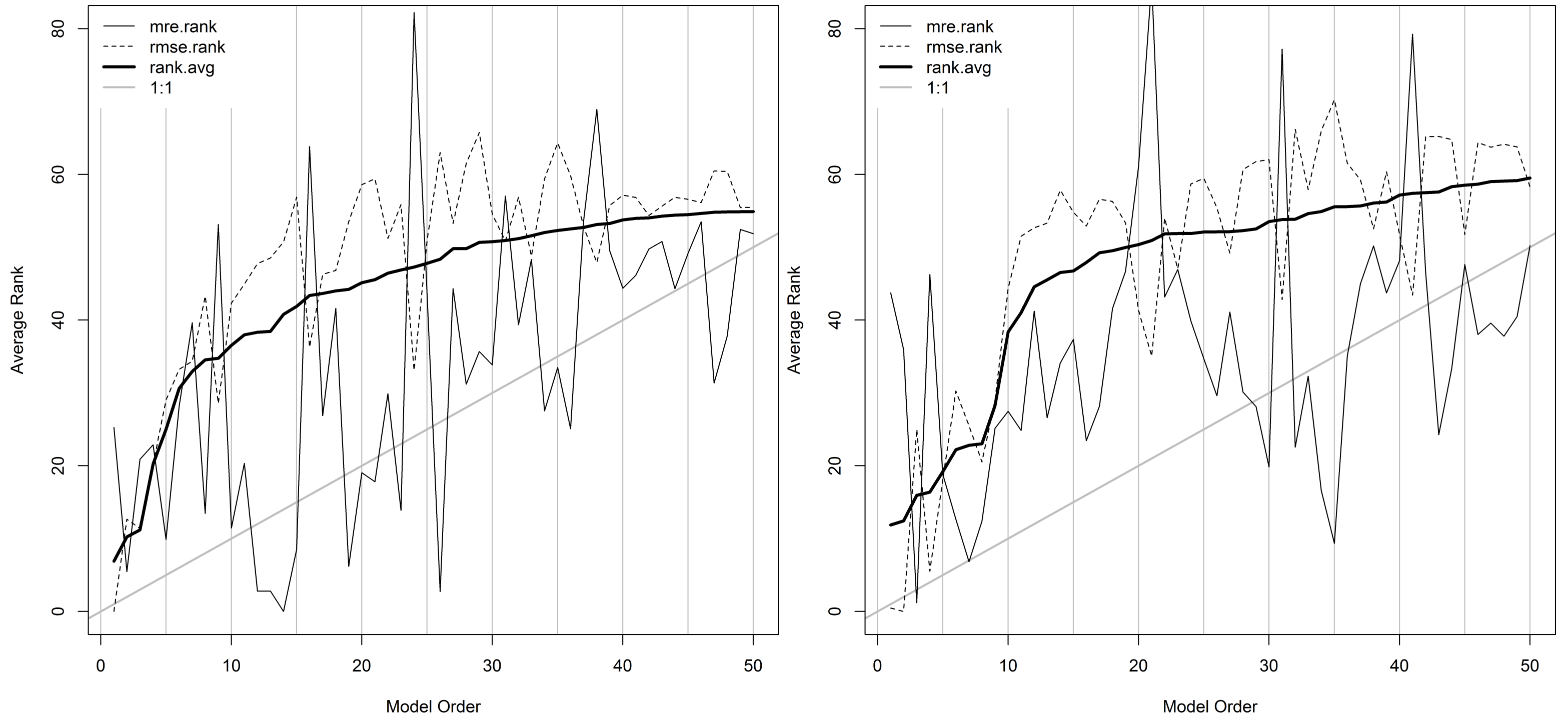
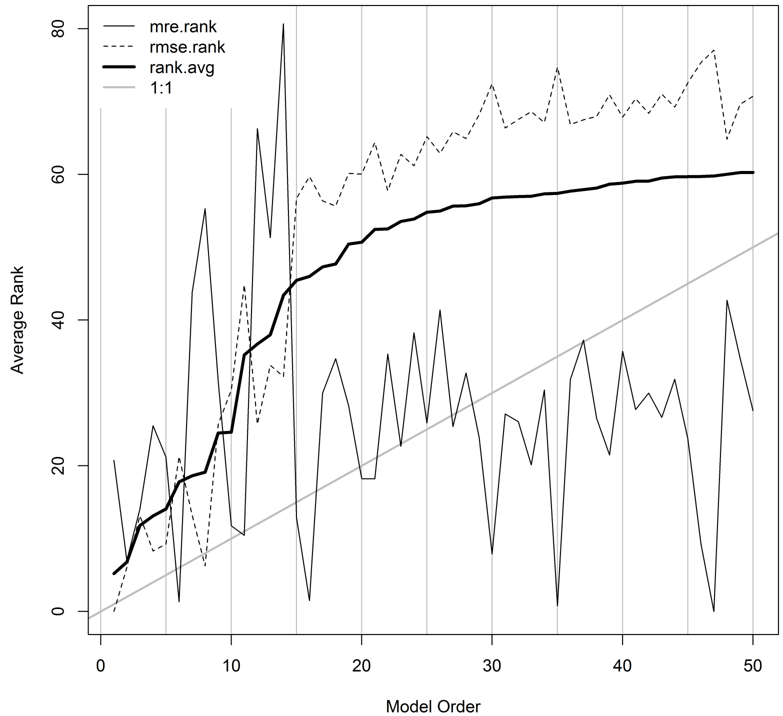


Figure 76. MRE rank, RMSE rank, and average rank for the top 50 Early Stuart timing forecast models comprising three or more variables. Left panel is results for retrospective analysis, right panel is jackknife. Note that model order does not consistently match between plots, such that the tenth model of the retrospective analysis is not necessarily the same as the tenth model seen in the jackknife results. The diagonal grey line has a slope of one, which allows for comparison to the average rank line.



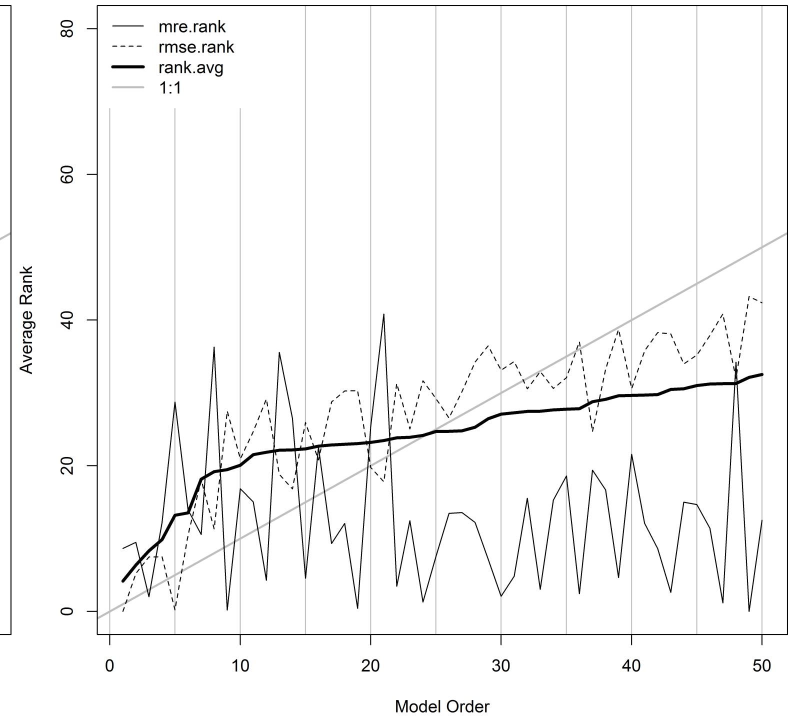


Figure 77. MRE rank, RMSE rank, and average rank for the top 50 Chilko timing forecast models comprising three or more variables. Left panel is results for retrospective analysis, right panel is jackknife. Note that model order does not consistently match between plots, such that the tenth model of the retrospective analysis is not necessarily the same as the tenth model seen in the jackknife results. The diagonal grey line has a slope of one, which allows for comparison to the average rank line.

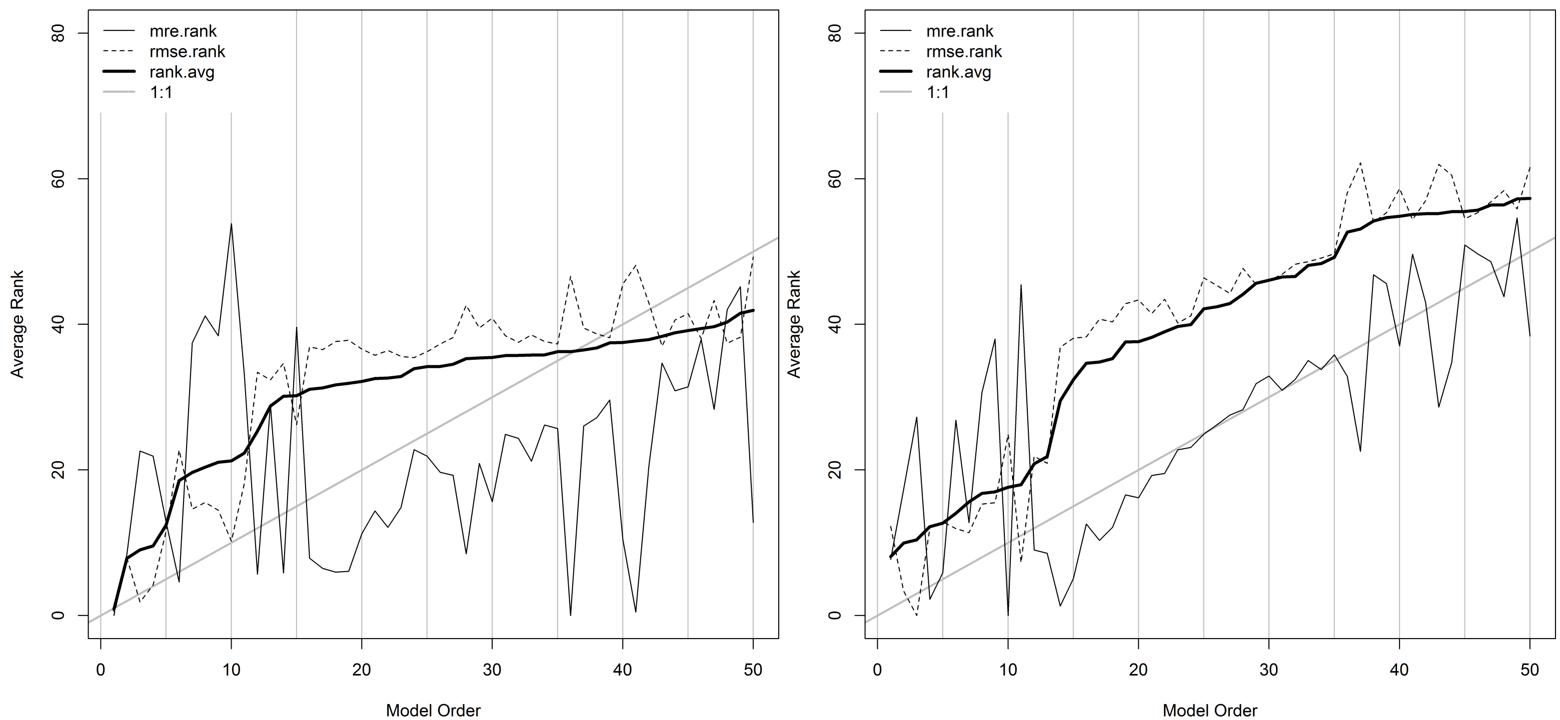


Figure 78. MRE rank, RMSE rank, and average rank for the top 50 ND rate forecast models comprising three or more variables. Left panel is results for retrospective analysis, right panel is jackknife. Note that model order does not consistently match between plots, such that the tenth model of the retrospective analysis is not necessarily the same as the tenth model seen in the jackknife results. The diagonal grey line has a slope of one, which allows for comparison to the average rank line.

6.6 MODEL SELECTION

Evaluating and reducing the large number of statistical models to a qualifying subset was achieved by filtering models on objectively defined statistical criteria (step one). While the statistics of these models (R^2, p, n) indicate they are moderately good fits; we have demonstrated, by performance analysis ranking (step 2), that they vary in bias and uncertainty and should not be treated equally. Selection from these qualifying models could be based on user tolerance of model uncertainty. User tolerance could be evaluated using graphs relating the likelihood of an event occurring and the range of outcome for that event. In this evaluation, the range of outcome for an event equates to the uncertainty of a forecast model. The model uncertainty (confidence limit) is estimated from the RMSE, which is available from both retrospective and jackknife evaluation (Haeseker et al., 2005, 2008). The RMSE equates to the forecast model SD, which has a likelihood of ≈ 0.68. The frequency distributions of forecast errors (from the jackknife results) are approximately normal in shape and do not include any extreme outliers (Figure 79). If our assumption of normal error distribution is correct, we can calculate likelihood values from a range of confidence limits with less concern of poor estimation at the extremes of the probability distribution due to skewness.

We present tolerance plots, based on contours, indicating the relationship between uncertainty of a forecast model and the likelihood of that uncertainty in Figures 80 (Early Stuart), 81 (Chilko), and 82 (ND). The relationships between retrospective and jackknife RMSE estimates, by model, is shown in Figure 83. While the plots in Figure 83 include results for one and two variable models, they are not being considered in model selection (i.e., excluded from Figures 80, 81, and 82). To estimate the contour values in Figures 80, 81, and 82 a matrix of all combinations of confidence limit (0.5–3.5 days for timing, or 0.05–0.25 for ND rate) and confidence level (0.25–0.85) was constructed. At each unique combination of these values, models that fulfilled these criteria in both the retrospective and jackknife evaluation were counted. The model count represents the z-value for these contour (i.e., x y z) plots.

Given tolerance criteria, e.g., 0.70 likelihood of a forecast being within ± 1.5 days, we note in Figure 80 that this tolerance (identified by the large circular data symbol) lies between the contour lines representing one and five models. Thus, we can conclude that there are between one to four specific models that likely fulfil this tolerance criteria.

The tolerance curves we present are based solely on model uncertainty, without consideration of the possible role of model forecast bias. Figure 84 demonstrates that estimates of forecast model bias, based on the MRE PM, are extremely small—considering just top 25 models from jackknife analysis. We suggest that due to the minimal role of bias in these top models, it need not be considered in the tolerance curves.

Model selection given specific tolerance levels is somewhat subjective but could be objectively evaluated in the pre-season fishery planning process. Estimating the ramifications of selecting models having greater uncertainty (with higher likelihood) is possible. These forecasts contribute to the early stages of pre-season fishery planning, which is evaluated in a deterministic model. Technical staff who rely on timing and ND forecasts could weigh the risks (trade-off) between uncertainty and likelihood in a dynamic version of the fisheries planning model. While such an evaluation is outside the scope of this document, output from this current research could have application to such a dynamic model.

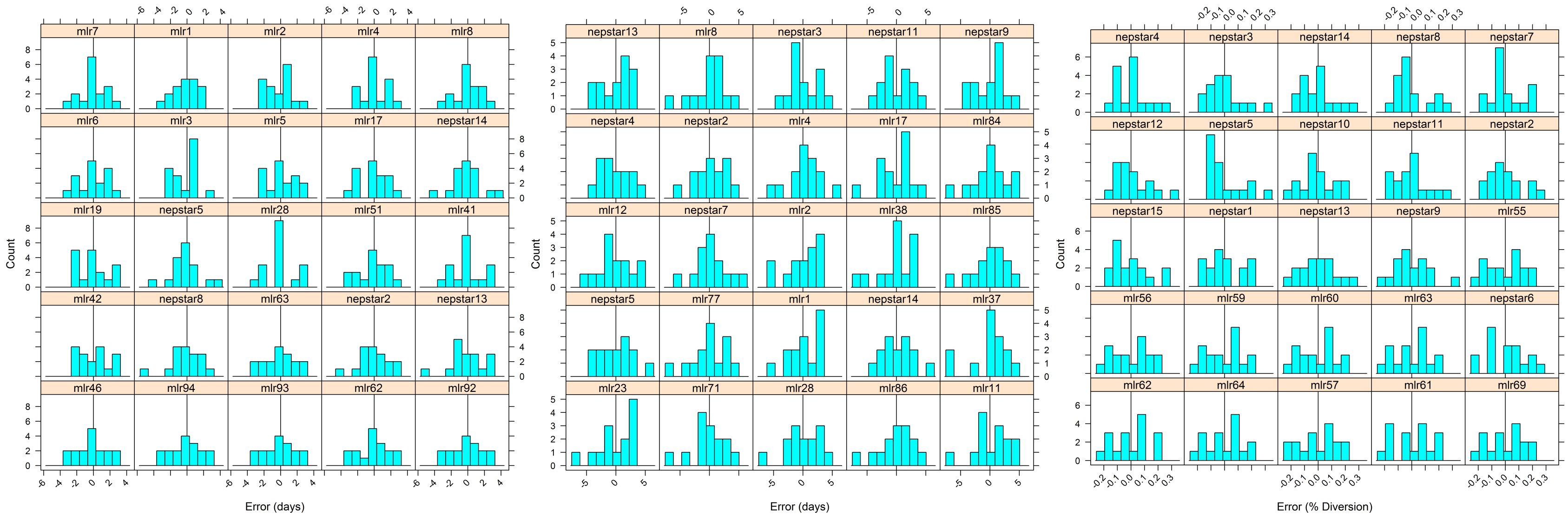


Figure 79. Frequency distributions of forecast errors (from the jackknife results) for Early Stuart timing (left panel), Chilko timing (middle panel), and ND (right panel) models. The distributions are approximately normal in shape and do not include any extreme outliers suggesting we can calculate likelihood values from a range of confidence limits with less concern of poor estimation at the extremes of the probability distribution due to skewness.

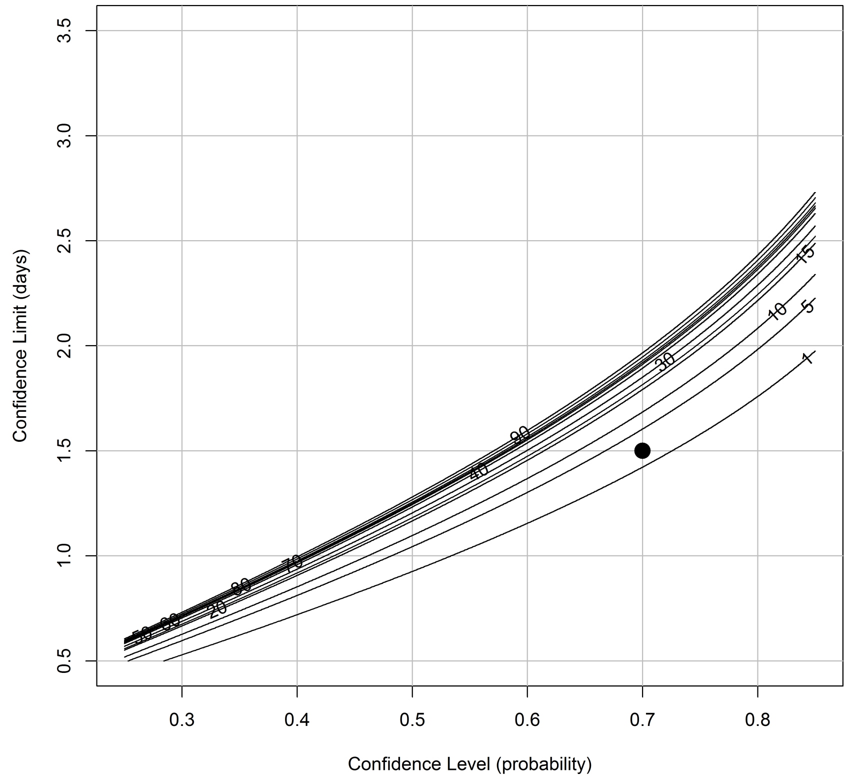


Figure 80. Contour plots relating model confidence level (i.e., likelihood, x-axis), and model confidence limit (i.e., range of error in days, y-axis), for Early Stuart timing forecast models. The confidence interval *is twice the confidence limit. For example, we could say there is a 50% likelihood (confidence level) that a model, on average, will forecast timing within a two day confidence limit. Thus, given a specific likelihood (50%), the forecast fits into a range (confidence interval) of four days. The number on each contour line defines how many models qualify under these trade-off conditions. The large point on this plot defines the 70% confidence level with a confidence limit of 1.5 days. There are between 1–4 models that fulfil these criteria. Forecast certainty (a qualitative trait represented by both confidence limit and confidence level) is relaxed with increasing values on the y-axis and decreasing x-axis values. The isopleths could define lines of common forecast certainty. We refer to these as tolerance curves.*

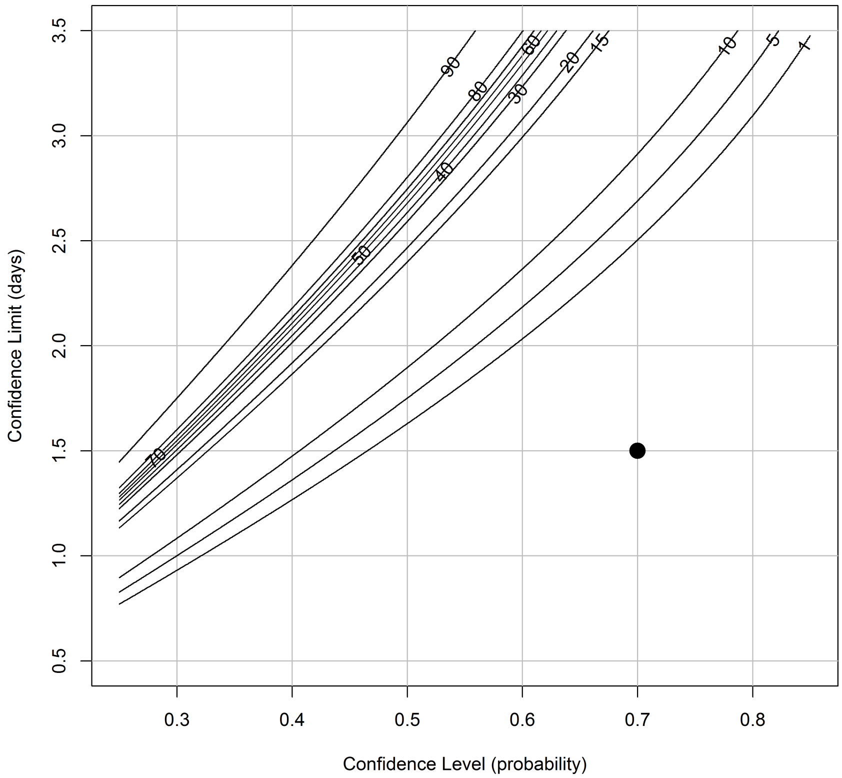


Figure 81. As per Figure 80, using Chilko timing forecast models.

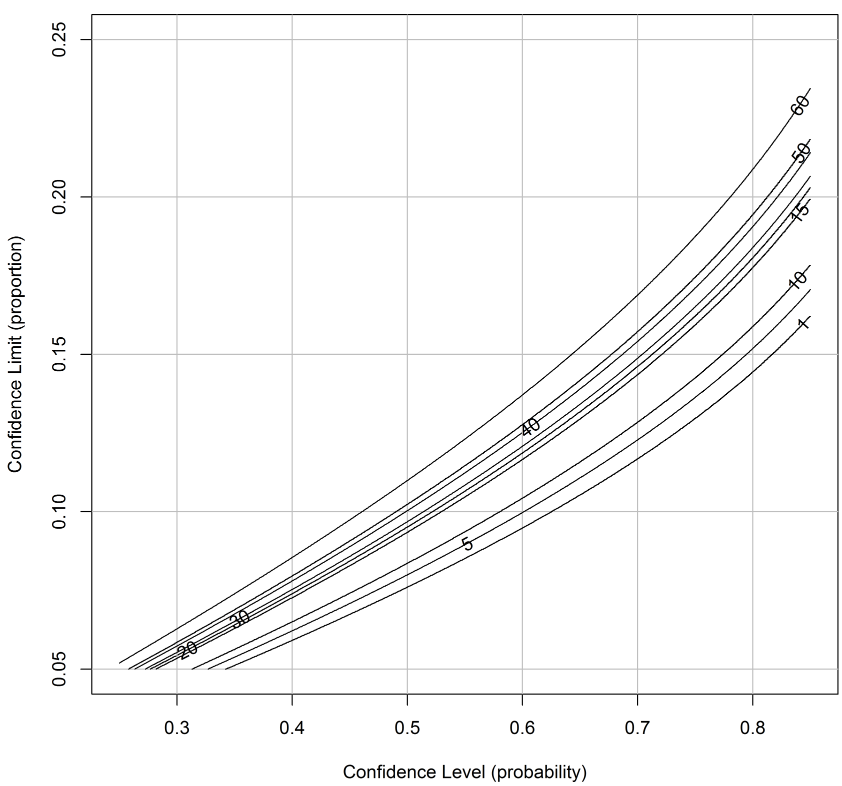


Figure 82. As per Figure 80, using ND forecast models. Unit of the y-axis is proportion *as the variable being forecasted is ND.*

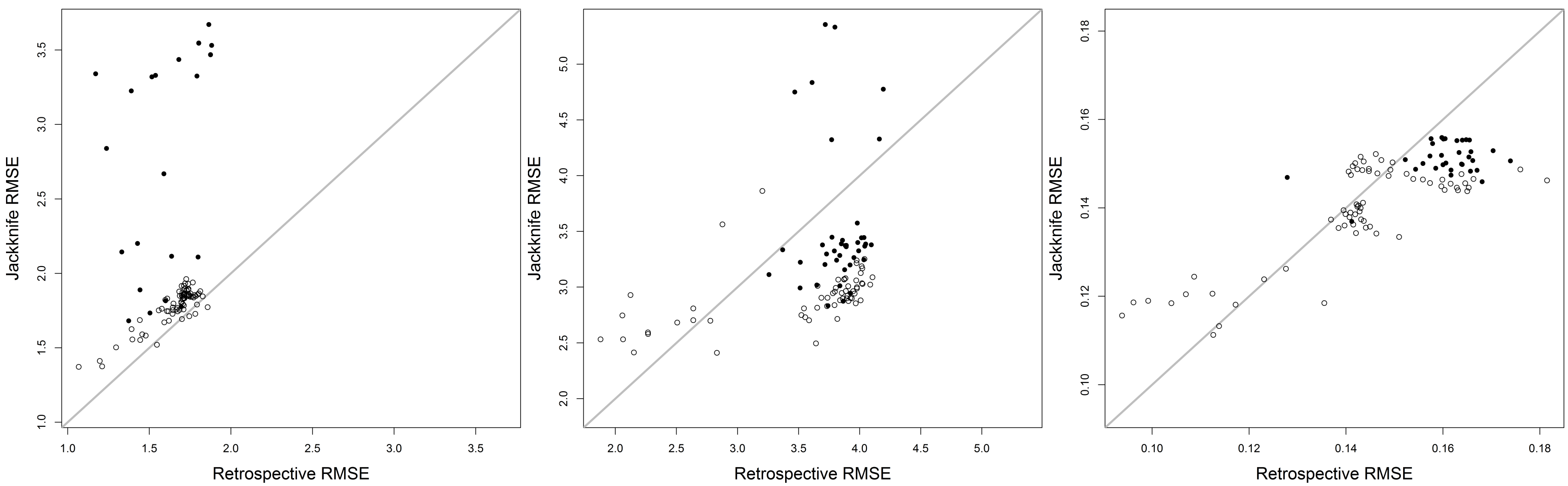


Figure 83. Comparison of model-specfic RMSE values from retrospective (x-axis) to those from jackknife results (y-axis) for top 100 models (left panel: Early Stuart timing; middle panel: Chilko timing; right panel: ND rate). Solid points represent models comprising one or two variables, while open points represent models with three or more variables. The diagonal line represents a slope of one, such that a point on (or near) the line represents a model with similar rank in retrospective and jackknife evaluation.

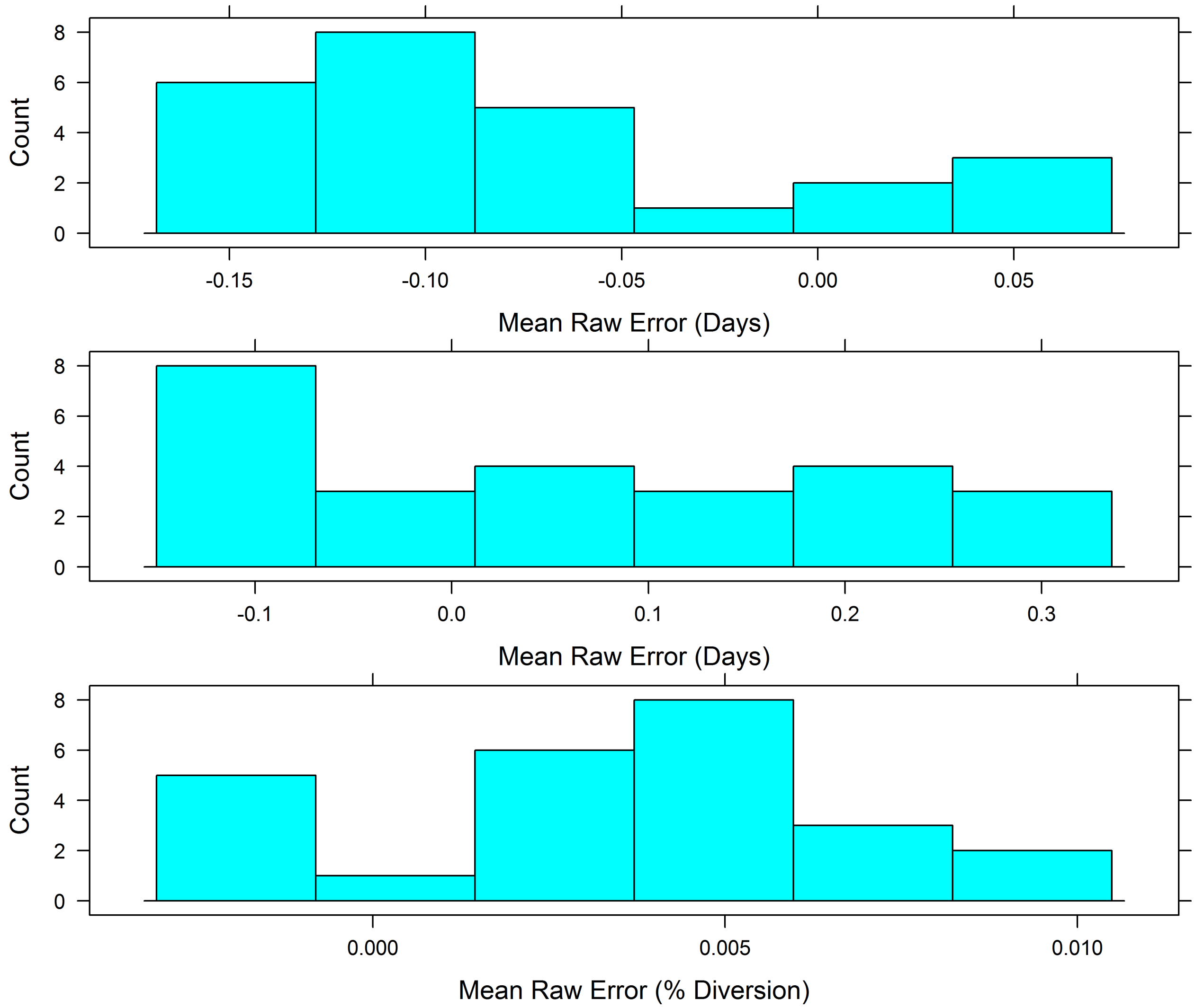


Figure 84. Frequency distributions of MRE from the top 25 ranked models based on jackknife analysis. MRE is considered a useful indicator of forecast model bias. Each histogram indicates asymmetry relative to an MRE value of zero (zero would suggest no apparent bias), thus there may be a minor bias in these models. However, it is very important to note that the values on the x*-axes fall substantially below the "working" resolution required of these models, i.e., timing forecast bias may range* ± 0.3 *days and diversion bias may range* ± 0.01*. Each plot is a forecast type, Early Stuart timing (top panel), Chilko timing (middle panel), and ND (lower panel).*

7 PROPOSED OPERATIONAL MODELLING IMPLEMENTATION SCHEME

We can summarize the modelling of timing and ND work presented here as comprised of numerous forecast models based on a suite of observed oceanic variables. The models have been evaluated using two different methods, retrospective and jackknife, and under these methods several performance measures were used to rank each model. Finally, we define groups of models that should fulfil the tolerance criteria of fishery managers. The final task is to determine how numerous independent forecasts can be summarized to one value with representative uncertainty. For operational purposes we can distil the process down to make a single prediction as follows.

- Annual appraisal of tolerance criteria from fishery management process—we consider this to be an iterative, learning process;
- Selection of models that fulfil tolerance criteria. The models must fulfil these criteria based on both retrospective and jackknife results;
- Resampling of selected model forecast probability curves (based on PIs) to estimate an overall forecast with PI values.

The time frame of pre-season forecast availability will play a role in model selection. In general, model requirements can be grouped into three time periods based on the needs of decision makers. The pre-season planning process commences in April followed by further planning in June. As in-season sampling data become available, focus turns to the in-season, Bayesian run-size model. Pre-season migration forecasts, derived from May–June data models, could inform the priors applied to the in-season run-size model. Thus, forecasts available in time for these three distinct periods will likely be based on different models, which can include data estimated up to March, May, and June, respectively, of the return year.

8 CONCLUSIONS AND RECOMMENDATIONS

We have presented a new strategy for building statistical models of Fraser River sockeye salmon migration timing and ND, and a means of evaluating the performance of those forecast models. It marks an improvement over historical methods that have also been reviewed here. This evaluation takes advantage of ocean data sources that are updated frequently enough to allow their use for pre-season forecasts.

Statistical representation of natural systems must take into account the uncertainty represented by both observational error (a by-product of imperfect sampling) and process error (the variation/uncertainty that is naturally occurring and not represented within the statistical constructs of nature). Attempts to statistically define the nature of animal behaviour (e.g., migration timing and ND rate) are challenged by these same requirements. Statistical models are imperfect representations of natural systems, and so the task is to demonstrate where on the scale of imperfection these representations lie, how quickly they are degrading, their utility for real world application, and finally when they should be discounted.

When forecasting from a statistical model that is based on assumed historical linkages between cause and effect (our means of estimating parameters and uncertainty) we are assuming the relationship is a stationary process. That is, the parameters of the relationship may have uncertainty, but neither the means nor variances of those parameters should be changing statistically with time. Simply put, we assume that the past is an indicator of the future. However, experience with failed forecasting models has demonstrated that non-stationarity is common. We should not assume that any or all of the top models will remain robust to environmental changes over extended periods of time. It has been demonstrated that forecasts derived from multiple models are less susceptible to time series outliers and conditions of non-stationarity (Kuhn and Johnson, 2013). This evidence emphasizes the value in estimating an annual forecast from multiple, independently derived forecasts.

Recommendations: We have presented an objective tool for forecast model selection given the trade-off between probability and forecast uncertainty. We are not recommending the use of a particular collection of forecast models as their selection, given the terms above, is fundamentally a subjective exercise determined by the risk tolerance of individual decision makers. The risk tolerance possessed by decision makers is not necessarily a fixed entity and may wax and wane between risk-averse, risk-neutral, to risk-seeking. If this is true, re-evaluation of tolerance and re-selection of models from the tolerance trade-off curves would be prudent. How frequently such a re-evaluation could occur is not clear, though an annual review could be a realistic initial step. Intra-annual re-evaluation of risk tolerance may not be appropriate as additional in-season information—and anticipation of particular outcomes—could confound the neutral evaluation of tolerance.

We suggest that model selection will be an iterative process. Well before the delivery time of the pre-season forecasts, decision makers should review the tolerance trade-off curves, and their feedback will determine how many (and what) models can contribute to the pre-season forecast. Science staff will then estimate an annual forecast (with PIs) from each of the selected models. These forecast probability distributions will be integrated, by re-sampling, resulting in a single annual pre-season forecast that encompasses the uncertainty of all contributing model forecasts.

We do not recommend that the model search and performance testing be rerun on an annual basis. We believe the performance testing is sufficiently rigorous to rank only robust models having a capacity to forecast with acceptable precision across multiple years.

8.1 FUTURE WORK

The timing and ND modelling approach presented herein can be implemented as it stands, but inevitably would benefit from refinement. A longer term component of the iterative review cycle could include new research. Additional work could be focussed on three areas: data, stocks, and models.

Data: There are other data available that characterize oceanic variability and may better reflect sockeye migration behaviour, but have not yet been included in the modelling. These include variables such as wind stress curl (as an index of productivity related to Ekman pumping or vertical transport), river discharge, chlorophyll (as an index of productivity), and various climate indices that generally reflect larger-scale climate variability. Reformulated versions of all variables in Table 2 could also be considered, such as the time rate of change (the slope of a linear fit to the data over a specified period) or broader evaluation of the simple difference of the data between two periods (e.g., Ruggerone (2004), winter to spring SST differences and migration timing).

The lack of sufficient spatial and temporal resolution near the coast is a concern for both numerical models and observations. The next-generation coastal models such as Regional

Ocean Modeling System (ROMS) are still under development and are years away from operational applications. Time series from current meter moorings could assist in the statistical models but these data would need to be available in quasi-realtime and for near-surface depths. This information could be sampled from the cabled observatory managed by Ocean Networks Canada, but recent financial setbacks would indicate a need for extra funding.

Stocks: Forecasts of migration timing over the past two decades have focused on two main stocks, Early Stuart and Chilko, for which the longest time series of migration timing data are available. However timing data sets do exist for other stocks and stock-groups. The quality of these estimates has improved since 2002 when genetic (i.e., DNA) replaced scale-based methods as the primary tool for stock discrimination. Those data sets should permit a more comprehensive evaluation of forecast methods that could be used to predict the timing of a larger suite of stocks. Such prediction would allow managers to anticipate the degree of overlap in migration patterns among stocks; a primary driver of fishery scheduling decisions.

PSC staff are also in the process of compiling data on stock-specific ND rates. Diversion rates typically increase over the course of each summer. The temporal trend coupled with varying run strength of different timing components likely contributes to the inter-annual variation in estimates of ND rate. Analyses of ND rate for specific stocks should help further elucidate key environmental causes (Mike Lapointe, PSC, Pers. Comm. March 30, 2015). Future collaboration between DFO Science and the PSC to evaluate such questions would have direct benefits to fishery planning.

Models: One approach to model fitting that was not evaluated was piecewise regression. Piecewise consistent linear regression models allow the relationship between variables to be broken into multiple line segments. This is also described as the “Split-and-Merge” method (Thomson and Emery, 2014). The SCAM fit might have adequately represented any benefit offered by piecewise regression negating the need for the latter.

Limits on the number of variables included in a single MLR model could be evaluated. Risks associated with model over-fitting could be tested more thoroughly, considering the general rule-of-thumb recommended by Babyak (2004) and Maindonald and Braun (2003) that there be no more than approximately one variable per 10 observed data points.

In addition to reviewing new data, different modelling strategies may perform better than those already presented. This could include alternate criteria for screening variables for inclusion in the MLR modelling such as:

1. Include only one variable per data type i.e., include only one variable each of SST, SSS, U current velocity, V current velocity, etc. as has been done in previous modelling schemes such as OSCURS (Ingraham and Miyahara, 1988);
2. Include only those variables relevant in the first (or last) year of ocean residency with the idea that the few months after ocean entry (or just before river entry) may be the most influential;
3. Include only those variables for which climate change projections are made.

Fishery managers have emphasized a value in models that are capable of accurately forecasting outlier years (possibly at the sake of accurately forecasting years that will be close to mean value). Current models could be evaluated with PMs that put weight on accurate forecasting of outlier years, and then all models re-ranked based on a new set of PMs. Or, alternatively, the model search could be re-initiated, relying on statistical models that weight their fit to outlier values. However there are fundamental statistical rules that cannot be avoided. Outlier events are, by definition, rare components of data series. The statistics of regression models compels there to be a large uncertainty at the numerical extremes of the data. This trait limits the usefulness of extreme events forecasts.

Other strategies that may improve modelling overall include using different kinds of models (e.g., neural networks), as well as different evaluation schemes and performance measures that would rate models differently.

9 ACKNOWLEDGEMENTS

Mike Lapointe (PSC) contributed substantially to documenting and improving our understanding of the return timing and ND data. We are pleased that this important information is now documented for posterity and publicly available.

Dr. Scott Tinis provided ocean currents based on the POM.

Peter Chander (DFO) kindly shared the map of B.C. shore stations. Dr. Daniel Kelley (Department of Oceanography, Dalhousie University) compiled, for use in R, the public domain Fortran code used to estimate the magnetic field data. His work is represented in the R package `oce`. Nathan Putman, (Oregon Cooperative Fish and Wildlife Research, Oregon State University) kindly shared some of his research into the role of magnetic field influences on salmon migration.

Kathleen Dohan (ESR) is responsible for preparing the OSCAR data and has been supportive with timely delivery challenges. NOAA OI SST V2, NCEP reanalysis wind stress, and GODAS temperature and salinity data provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA. Many of these data sets are stored in Unidata Network Common Data Form (NetCDF)[19]. We ben efited from the availability of the R package `ncdf` to access these large data files and spared our selves any further winzip injustices. Since the analysis was completed, itappears the `ncdf` package was replaced by `RNetCDF` or `ncdf4`.

Arlene Tompkins (DFO) and Mike Lapointe (PSC) contributed substantial feedback on both the manuscript in general and the tolerance plots in particular. Ann-Marie Huang and Sue Grant (DFO) suggested numerous helpful improvements to the document.

The open source R packages utilized in this project include: `devtools`, `gam`, `lattice`, `maptools`, `mgcv`, `ncdf`, `oce`, `ocedata`, `PBSmapping`, `plyr`, `proj4`, `scam`, `sme`, `xtable`, and any of their reverse dependency packages, which are all available from the Comprehensive R Archive Network.

The manuscript was prepared in LaTeX 2_ε.

10 REFERENCES

Anonymous. 2014. Treaty Between The Government Of Canada And The Government Of The United States Of America Concerning Pacific Salmon. Pacific Salmon Commission.

Arlot, S. and Celisse, A. 2010. A survey of cross-validation procedures for model selection. Statistical Surveys 4: 40–79.

[19] "NetCDF is a set of software libraries and self-describing, machine-independent data formats that support the creation, access, and sharing of array-oriented scientific data."

Armstrong, J.S. 1985. Long-range forecasting: from crystal ball to computer. Wiley.

Armstrong, J.S. 2001. Evaluating forecasting methods. In J. S. Armstrong, ed., Principles of forecasting, chap. 14, 443–472. Springer.

Armstrong, J.S. and Fildes, R. 1995. Correspondence on the selection of error measures for comparisons among forecasting methods. Journal of Forecasting 14(1): 67–71.

Augustin, N.H., Sauleau, E.A. and Wood, S.N. 2012. On quantile quantile plots for generalized linear models. Computational Statistics & Data Analysis 56(8): 2404–2409.

Babyak, M.A. 2004. What you see may not be what you get: A brief, nontechnical introduction to overfitting in regression-type models. Psychosomatic Medicine 66: 411–421.

Baker, R. 1978. The evolutionary ecology of animal migration. Holmes & Meier Publishers.

Beacham, T.D., Lapointe, M., Candy, J.R., McIntosh, B., MacConnachie, C., Tabata, A., Kaukinen, K., Deng, L., Miller, K.M. and Withler, R.E. 2004. Stock identification of fraser river sockeye salmon using microsatellites and major histocompatibility complex variation. Transactions of the American Fisheries Society 133(5): 1117–1137.

Benjamini, Y. 1988. Opening the box of a boxplot. The American Statistician 42(4): 257–262.

Berdahl, A., Westley, P.A.H., Levin, S.A., Couzin, I.D. and Quinn, T.P. 2014. A collective navigation hypothesis for homeward migration in anadromous salmonids. Fish and Fisheries.

Blackbourn, D.J. 1987. Sea surface temperature and the pre-season prediction of return timing in Fraser River sockeye salmon (*Oncorhynchus nerka*). Canadian Special Publication of Fisheries and Aquatic Sciences 96: 296–306.

Blumberg, A.F. and Mellor, G.L. 1987. A description of a three-dimensional coastal ocean circulation model. In N. S. Heaps, ed., Three-Dimensional Coastal Ocean Models. American Geophysical Union, Washington, D.C.

Bonjean, F. and Lagerloef, G.S.E. 2002. Diagnostic model and analysis of the surface currents in the tropical pacific ocean. Journal of Physical Oceanography 32(10): 2938–2954.

Borstad, G., Crawford, W., Hipfner, J.M., Thomson, R. and Hyatt, K. 2011. Environmental control of the breeding success of rhinoceros auklets at triangle island, british columbia. Marine Ecology Progress Series 424: 285–302.

Burnham, K.P. and Anderson, D.R. 2002. Model selection and multimodel inference - a practical information-theoretic approach. Springer, New York, second ed.

Cai, W., Borlace, S., Lengaigne, M., van Rensch, P., Collins, M., Vecchi, G., Timmermann, A., Santoso, A., McPhaden, M.J., Wu, L., England, M.H., Wang, G., Guilyardi, E. and Jin, F.F. 2014. Increasing frequency of extreme El Niño events due to greenhouse warming. Nature Clim. Change 4: 114–116.

Campbell, W.H. 2003. Introduction to Geomagnetic Fields. Cambridge University Press.

Cass, A., Folkes, M., Parken, C. and Wood, C. 2006. Pre-season run size forecasts for Fraser River sockeye for 2006. DFO Can. Sci. Advis. Sec. Res. Doc. 2006/060.

Cave, J.D. and Gazey, W.J. 1994. A preseason simulation model for fisheries on Fraser River sockeye salmon (*Oncorhynchus nerka*). Canadian Journal of Fisheries and Aquatic Sciences 51(7): 1535–1549.

Chen, Y. and Samworth, R.J. 2014. Generalised additive and index models with shape constraints. ArXiv:1404.2957.

CPC. 2014. [ENSO: Recent evolution, current status and predictions]. (Accessed April 13, 2017)

DFO, 2006. State of the Pacific Ocean 2005, DFO Sci. Ocean Status Report. 2006/001.

DFO. 2009. Revisions to official DFO commercial Pacific Salmon catch estimates for 1996–2004. DFO Can. Sci. Advis. Sec. Sci. Advis. Rep. 2009/031.

DFO. 2015. Pre-season run size forecasts for Fraser River sockeye (*Oncorhynchus nerka*) and Pink (*O. gorbuscha*) salmon in 2015. DFO Can. Sci. Advis. Sec. Sci. Resp. 2015/014.

Di Lorenzo, E., Schneider, N., Cobb, K.M., Franks, P.J.S., Chhak, K., Miller, A.J., McWilliams, J.C., Bograd, S.J., Arango, H., Curchitser, E., Powell, T.M. and Rivière, P. 2008. North Pacific gyre oscillation links ocean climate and ecosystem change. Geophysical Research Letters 35(8). L08607.

English, K.K., Koski, W.R., Sliwinski, C., Blakley, A., Cass, A. and Woodey, J.C. 2005. Migration timing and river survival of late-run fraser river sockeye salmon estimated using radiotelemetry techniques. Transactions of the American Fisheries Society 134(5): 1342–1365.

Finlay, C.C., Maus, S., Beggan, C.D., Bondar, T.N., Chambodut, A., Chernova, T.A., Chuillat, A., Golovkov, V.P., Hamilton, B., Hamoudi, M., Holme, R., Hulot, G., Kuang, W., Langlais, B., Lesur, V., Lowes, F., Lühr, H., Macmillan, S., Mandea, M., McLean, S., Manoj, C., Menvielle, M., Michaelis, I., Olsen, N., Rauberg, J., Rother, M., Sabaka, T.J., Tangborn, A., Tøffner-Clausen, L., Thébault, E., Thomson, A.W.P., Wardinksi, I., Wei, Z. and Zvereva, T.I. 2010. International Geomagnetic Reference Field: the eleventh generation. Geophysical Journal International 183(3): 1216–1230.

Frank, R.E., Massy, W.F. and Morrison, D.G. 1965. Bias in multiple discriminant analysis. Journal of Marketing Research 2: 250–258.

Fraser River Sockeye Public Review Board. 1995. Fraser river sockeye 1994 problems & discrepancies. Tech. rep., Public Works and Government Services Canada.

Freeland, H.J. 1990. Sea surface temperatures along the coast of British Columbia: regional evidence for a warming trend. Canadian Journal of Fisheries and Aquatic Sciences 47: 346–350.

Freeland, H. 2007. A short history of Ocean Station Papa and Line P. Progress in Oceanography 75(2): 120–125.

Freeland, H., Denman, K., Wong, C.S., Whitney, F. and Jacques, R. 1997. Evidence of change in the winter mixed layer in the Northeast Pacific Ocean. Deep Sea Research Part I: Oceanographic Research Papers 44(12): 2117–2129.

Freeland, H.J. 2013. Evidence of change in the winter mixed layer in the Northeast Pacific Ocean: A problem revisited. Atmosphere-Ocean 51(1): 126–133.

French, R.R., Bilton, H., Osako, M. and Hartt, A. 1976. Distribution and origin of sockeye salmon (*Oncorhynchus nerka*) in offshore waters of the North Pacific Ocean. Tech. Rep. 34, International North Pacific Fisheries Commission.

Gable, J. and Cox-Rogers, S. 1993. Stock identification of fraser river sockeye salmon:

methodology and management application. Technical Report 5, Pacific Salmon Commission.

Gelman, A. and Hill, J. 2007. Data analysis using regression and multilevel/hierarchical models. Cambridge University Press.

Gilhousen, P. 1960. Migratory behaviour of adult Fraser River sockeye. Progress Report 7, International Pacific Salmon Fisheries Commission.

Goodwin, P. and Lawton, R. 1999. On the asymmetry of the symmetric MAPE. International Journal of Forecasting 15(4): 405–408.

Green, S.B. 1991. How many subjects does it take to do a regression analysis? Multivariate Behavioral Research 26(3): 499–510.

Groot, C. and Cooke, K. 1987. Are the migrations of juvenile and adult Fraser River sockeye salmon (*Oncorhynchus nerka*) in near-shore waters related? Canadian Special Publication of Fisheries And Aquatic Sciences 96: 53–60.

Groot, C., Margolis, L. and Bailey, R. 1984. Does the route of seaward migration of Fraser River sockeye salmon (*Oncorhynchus nerka*) smolts determine the route of return migration of the adults? In J. McCleave, G. Arnold, J. Dodson and W. Neill, eds., Mechanisms of Migration In Fishes, vol. 14 of *NATO Conference Series*, 283–292. Springer US.

Groot, C. and Quinn, T.P. 1987. Homing migration of sockeye salmon, *Oncorhynchus nerka*, to the Fraser River. Fishery Bulletin 85(3): 455–469.

Guerra, P.A., Gegear, R.J. and Reppert, S.M. 2014. A magnetic compass aids monarch butterfly migration. Nature Communications 5(4164).

Gutiérrez-Estrada, J.C., Silva, C., Yáñez, E., Rodríguez, N. and Pulido-Calvo, I. 2007. Monthly catch forecasting of anchovy *Engraulis ringens* in the north area of Chile: Non-linear univariate approach. Fisheries Research 86(23): 188–200.

Haeseker, S.L., Peterman, R.M., Su, Z. and Wood, C.C. 2005. Retrospective evaluation of preseason forecasting models for pink salmon. North American Journal of Fisheries Management 25(3): 897–918.

Haeseker, S.L., Peterman, R.M., Su, Z. and Wood, C.C. 2008. Retrospective evaluation of preseason forecasting models for sockeye and chum salmon. North American Journal of Fisheries Management 28(1): 12–29.

Hamilton, K. 1985. A study of the variability of the return migration route of Fraser River sockeye salmon (*Oncorhynchus nerka*). Canadian Journal of Zoology 63(8): 1930–1943.

Hare, S.R. 1996. Low-frequency climate variability and salmon production. Ph.D. thesis, University Of Washington, Seattle.

Hare, S.R. and Francis, R.C. 1995. Climate change and salmon production in the north-east Pacific ocean. In R. J. Beamish, ed., Climate change and northern fish populations, vol. 121 of *Canadian Special Publication of Fisheries and Aquatic Sciences*, 357–372.

Harrell, F.E. 2001. Regression Modeling Strategies: With Applications to Linear Models, Logistic Regression, and Survival Analysis. Graduate Texts in Mathematics. Springer.

Hawkins, D.M. 2004. The problem of overfitting. Journal of Chemical Information and Modeling 44: 1–12.

Hirsch, R.P. 1991. Validation samples. Biometrics 47(3): 1193–1194.

Hollister, H.J. 1953. Daily seawater observations on the Pacific coast of Canada. Manuscript reports of the biological stations 549, Fisheries Research Board of Canada, Pacific Oceanographic Group.

Hollister, H.J. and Sandnes, A.M. 1972. Sea surface temperatures and salinities at shore stations on the British Columbia coast, 1914–1970. Tech. Rep. 72-13, Fisheries and Oceans, Marine Science Directorate, Pacific Region, Victoria, B.C.

Holm, S. 1979. A simple sequentially rejective multiple test procedure. Scandinavian Journal of Statistics 6(2): 65–70.

Holtby, B., Irvine, J.R., Tanasichuk, R.W. and Simpson, K.M. 1999. Forecast for southern British Columbia coho salmon in 1999. DFO Can. Sci. Advis. Sec. Res. Doc. 1999/125.

Hyndman, R.J. and Athanasopoulos, G. 2013. Forecasting: principles and practice. Otexts. Accessed 1-May-2014.

Hyndman, R.J. and Koehler, A.B. 2006. Another look at measures of forecast accuracy. International Journal of Forecasting 22(4): 679–688.

Ingraham, W.J. and Miyahara, R.K. 1988. Ocean surface current simulations in the North Pacific ocean and the Bering Sea (OSCURS–numerical model). NOAA Technical Memorandum NMFS F/NWC-130. National Oceanic And Atmospheric Administration.

IPSFC. 1939–1986. Annual reports (1937-1985) of the International Pacific Salmon Fisheries Commission. Pacific Salmon Commission, 600-1155 Robson Street, Vancouver, B.C., Canada, V6E 1B5.

Killick, S.R. 1955. The chronological order of fraser river sockeye salmon during migration, spawning and death. Bulletin VII, International Pacific Salmon Fisheries Commission.

Kistler, R., Collins, W., Saha, S., White, G., Woollen, J., Kalnay, E., Chelliah, M., Ebisuzaki, W., Kanamitsu, M., Kousky, V., van den Dool, H., Jenne, R. and Fiorino, M. 2001. The NCEP-NCAR 50-year reanalysis: Monthly means cd-rom and documentation. Bulletin of the American Meteorological Society 82(2): 247–267.

Kohavi, R. 1995. A study of cross-validation and bootstrap for accuracy estimation and model selection. In C. Mellish, ed., International Joint Conference on Artificial Intelligence, 1137–1143. Morgan Kaufmann.

Kousky, V.E. and Higgins, R.W. 2007. An alert classification system for monitoring and assessing the enso cycle. Weather and Forecasting 22(2): 353–371.

Kovach, R.P., Ellison, S.C., Pyare, S. and Tallmon, D.A. 2015. Temporal patterns in adult salmon migration timing across southeast alaska. Global Change Biology 21(5): 1821–1833.

Krzywinski, M. and Altman, N. 2014. Points of significance: Visualizing samples with box plots. Nature Methods 11(2): 119–120.

Kuhn, M. and Johnson, K. 2013. Applied predictive modeling. Springer.

Lohmann, K.J., Luschi, P. and Hays, G.C. 2008. Goal navigation and island-finding in sea turtles. Journal of Experimental Marine Biology and Ecology 356(1-2): 83–95.

MacDonald, B.L. and Grant, S.C.H. 2012. Pre-season run size forecasts for Fraser River sockeye salmon (*Oncorhynchus nerka*) in 2012. DFO Can. Sci. Advis. Sec. Res. Doc. 2012/011.

Maindonald, J. and Braun, J. 2003. Data Analysis and Graphics Using R: An Example-based Approach. Cambridge series on statistical and probabilistic mathematics. Cambridge University Press.

Mantua, N.J., Hare, S.R., Zhang, Y., Wallace, J.M. and Francis, R.C. 1997. A pacific interdecadal climate oscillation with impacts on salmon production. Bulletin of the American Meteorological Society 78(6): 1069–1079.

Mantua, N.J. and Hare, S.R. 2002. The Pacific decadal oscillation. Journal of Oceanography 58(1): 35–44.

MATLAB. 2007. Function Stepwisefit from the Statistics Toolbox, R2007b. The MathWorks Inc., Natick, Massachusetts.

McGill, R., Tukey, J.W. and Larsen, W.A. 1978. Variations of box plots. The American Statistician 32(1): 12–16.

McKinnell, S., Freeland, H.J. and Groulx, S.D. 1999. Assessing the northern diversion of sockeye salmon returning to the Fraser River, B.C. Fisheries Oceanography 8(2): 104–114.

Merkel, F.W. and Wiltschko, W. 1965. Magnetismus und richtungsfinden zugunruhiger rotkehlchen (*Erithacus rubecula*). Vogelwarte 23: 71–77.

Miller, R.G. 1974. The jackknife-a review. Biometrika 61(1): 1–15.

Minor, F.J. 1958. The prediction of turnover of clerical employees. Personnel Psychology 11: 393–409.

Mission Hydroacoustic Facility Working Group. 1994. Report of the Mission hydroacoustic facility working group. part 1: Main report. Department of Fisheries and Oceans, Canada.

Montgomery, D.B. 1975. New product distribution: An analysis of supermarket buyer decisions. Journal of Marketing Research 12: 255–264.

Mosteller, F. and Tukey, J.W. 1968. Data analysis, including statistics. In G. Lindzey and E. Aronson, eds., Handbook of social psychology, vol. 2. Addison-Wesley.

Myers, K.W., Aydin, K.Y., Walker, R.V., Fowler, S. and Dahlberg, M.L. 1996. Known ocean ranges of stocks of Pacific salmon and steelhead as shown by tagging experiments, 1956-1995. NPAFC Doc 192.

Pacific Salmon Commission, ed. 1996. Report of the Fraser River Panel to the Pacific Salmon Commission on the 1992 Fraser River sockeye salmon fishing season. Pacific Salmon Commission, Vancouver.

Pacific Salmon Commission, ed. 1999. Report of the Fraser River Panel to the Pacific Salmon Commission on the 1997 Fraser River sockeye and pink salmon fishing season. Pacific Salmon Commission, Vancouver.

Papi, F. 1992. Animal Homing. Chapman & Hall.

Pearse, P.H. and Larkin, P.A. 1992. Managing salmon in the Fraser: Report to the Minister of Fisheries and Oceans on the Fraser River salmon investigation. Tech. rep., MacDonald Printing.

Penland, C., Sun, D.Z., Capotondi, A. and Vimont, D.J. 2010. A brief introduction to El Niño and

La Niña. In D.-Z. Sun and F. Bryan, eds., Climate Dynamics: Why Does Climate Vary?, vol. 189 of *Geophysical Monographs*, chap. 3, 53–64. American Geophysical Union.

Pesaran, M.H. and Timmermann, A. 2002. Market timing and return prediction under model instability. Journal of Empirical Finance 9(5): 495–510.

Peterson, W.T. and Schwing, F.B. 2003. A new climate regime in northeast Pacific ecosystems. Geophysical Research Letters 30(17).

Putman, N.F., Jenkins, E.S., Michielsens, C.G.J. and Noakes, D.L.G. 2014*a*. Geomagnetic imprinting predicts spatio-temporal variation in homing migration of pink and sockeye salmon. Journal of The Royal Society Interface 11(99).

Putman, N., Lohmann, K., Putman, E., Quinn, T., Klimley, A. and Noakes, D.G. 2013. Evidence for geomagnetic imprinting as a homing mechanism in Pacific salmon. Current Biology 23(4): 312–316.

Putman, N., Scanlan, M., Billman, E., O'Neil, J., Couture, R., Quinn, T., Lohmann, K. and Noakes, D.G. 2014*b*. An inherited magnetic map guides ocean navigation in juvenile Pacific salmon. Current Biology 24(4): 446–450.

Pya, N. and Wood, S.N. 2015. Shape constrained additive models. Statistics and Computing 25(3): 543–559.

Pyper, B.J. and Peterman, R.M. 1998. Comparison of methods to account for autocorrelation in correlation analyses of fish data. Canadian Journal of Fisheries and Aquatic Sciences 55(9): 2127–2140.

Qin, S., Yin, H., Yang, C., Dou, Y., Liu, Z., Zhang, P., Yu, H., Huang, Y., Feng, J., Hao, J., Hao, J., Deng, L., Yan, X., Dong, X., Zhao, Z., Jiang, T., Wang, H.W., Luo, S.J. and Xie, C. 2015. A magnetic protein biocompass. Nature Materials 15: 217–226.

Quinn, T.P. 2005. The Behavior and ecology of Pacific Salmon and Trout. University Of Washington Press.

R Core Team. 2013. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.

Reynolds, R.W. and Smith, T.M. 1994. Improved global sea surface temperature analyses using optimum interpolation. Journal of Climate 7(6): 929–948.

Reynolds, R.W., Rayner, N.A., Smith, T.M., Stokes, D.C. and Wang, W. 2002. An improved in situ and satellite SST analysis for climate. J. Climate 15(13): 1609–1625.

Roach, D.E. 1971. Double cross-validation of a weighted application blank over time. Journal of Applied Psychology 55(2): 157–160.

Robichaud, D. and English, K.K. 2007. River entry timing, survival and migration behaviour of fraser river sockeye salmon in 2006. Report prepared for Pacific Salmon Commission, Vancouver, B.C.

Robichaud, D., Smith, J.J., English, K.K. and Tyerman, S.C. 2011. Survival and timing of sockeye returns to the fraser river assessed using fishwheels, radio-telemetry and additional monitoring of in-river fisheries, 2010. Report prepared for Pacific Salmon Foundation and Pacific Salmon Commission Vancouver, B.C.

Roos, J.F. 1991. Restoring Fraser River salmon: a history of the International Pacific Salmon Fisheries Commission, 1937-1985. Pacific Salmon Commission.

Rossi, B. 2013. Advances in forecasting under instability. In G. Elliott and A. Timmermann, eds., Handbook of Economic Forecasting, vol. 2, Part B of *Handbook of Economic Forecasting*, chap. 21, 1203–1324. Elsevier.

Rossi, B. and Inoue, A. 2012. Out-of-sample forecast tests robust to the choice of window size. Journal of Business & Economic Statistics 30(3): 432–453.

Royal, L.A. and Tully, J.P. 1961. Relationship of variable oceanographic factors to migration and survival of Fraser River salmon. California Cooperative Oceanic Fisheries Investigations 8: 65–68.

Ruggerone, G.T. 2004. Pre-season forecast of sockeye salmon migration timing in Bristol Bay, Alaska, based on oceanographic and biological variables. Tech. rep., Natural Resources Consultants Inc., Seattle, WA, USA.

Smith, C.A. and Sardeshmukh, P.D. 2000. The effect of ENSO on the intraseasonal variance of surface temperatures in winter. International Journal of Climatology 20(13): 1543–1557.

Smith, R.J.F. 1985. The Control of Fish Migration. Zoophysiology Series. Springer-Verlag.

Sokal, R. and Rohlf, F. 1995. Biometry. W. H. Freeman.

Starr, P. and Hilborn, R. 1988. Reconstruction of harvest rates and stock contribution in gauntlet fisheries: application to British Columbia and Washington sockeye (*Oncorhynchus nerka*). Canadian Journal of Fisheries and Aquatic Sciences 45: 2216–2229.

Steyerberg, E.W., J, E.M., Harrell, F.E.J. and D, H.J. 2001. Prognostic modeling with logistic regression analysis: in search of a sensible strategy in small data sets. Medical Decision Making 21(1): 45–56.

Stone, M. 1974. Cross-validatory choice and assessment of statistical predictions. J. Royal Stat. Soc. 36(2): 111–147.

Theil, H. 1961. Economic Forecasts and Policy. North-Holland, Amsterdam, second ed.

Theil, H. 1966. Applied economic forecasting. Rand McNally, Chicago, IL.

Thomson, R.E. 1981. Oceanography of the British Columbia coast, vol. 56 of *Canadian Special Publication of Fisheries and Aquatic Sciences*.

Thomson, R.E., Hickey, B.M. and LeBlond, P.H. 1989. The Vancouver Island coastal current: fisheries barrier and conduit. In R. Beamish and G. McFarlane, eds., Effects of Ocean Variability on Recruitment and an Evaluation of Parameters used in Stock Assessment Models, vol. 108 of *Special Publication of Fisheries And Aquatic Sciences*, 265–296. Canadian Department of Fisheries and Oceans.

Thomson, R.E., Hourston, R. and Tinis, S. 2013. OSCUR for the 21st Century: Northeast Pacific salmon tracking and research (NEPSTAR) project, year 3 interim report. 24 April 2013. Report to Pacific Salmon Commisson.

Thomson, R.E. and Hourston, R.A.S. 2011. A matter of timing: the role of ocean conditions in the initiation of spawning migration by late-run Fraser River sockeye salmon (*Oncorhynchus nerka*). Fisheries Oceanography 20(1): 47–65.

Thomson, R.E., Beamish, R.J., Beacham, T.D., Trudel, M., Whitfield, P.H. and Hourston, R.A.S. 2012. Anomalous ocean conditions may explain the recent extreme variability in fraser river sockeye salmon production. Marine and Coastal Fisheries 4(1): 415–437.

Thomson, R.E. and Emery, W.J. 2014. Data Analysis Methods in Physical Oceanography. Elsevier, third ed.

Thomson, R.E., Heesemann, M., Davis, E.E. and Hourston, R.A.S. 2014. Continental microseismic intensity delineates oceanic upwelling timing along the west coast of North America. Geophysical Research Letters .

Tucker, S., Trudel, M., Welch, D.W., Candy, J.R., Morris, J.F.T., Thiess, M.E., Wallace, C., Teel, D.J., Crawford, W., Farley, E.V. and Beacham, T.D. 2009. Seasonal stock-specific migrations of juvenile sockeye salmon along the west coast of North America: Implications for growth. Transactions of the American Fisheries Society 138(6): 1458–1480.

Tukey, J.W. 1977. Exploratory Data Analysis. Addison-Wesley series in behavioral sciences. Addison-Wesley Publishing Company.

Tully, J.P. 1937. A warmer summer. Biological Board of Canada Progress Report Pacific Biological Station 31: 16–18.

Tully, J.P., Dodimead, A.J. and Tabata, S. 1960. An anomalous increase of temperature in the ocean off the Pacific coast of Canada through 1957 and 1958. Journal of the Fisheries Research Board of Canada 17(1): 61–80.

University of Chicago Press. 2010. The Chicago Manual of Style. Chicago Manual of Style. University of Chicago Press.

Verhoeven, L.A. and Davidoff, E.B. 1962. Marine tagging of Fraser River sockeye salmon. Bulletin XIII, International Pacific Salmon Fisheries Commission.

Walters, C.J. 1997. Information requirements for salmon management. In D. J. Stouder, P. A. Bisson and R. J. Naiman, eds., Pacific Salmon & their Ecosystems, 61–68. Springer US.

Wang, C., Deser, C., Yu, J.Y., DiNezio, P. and Clement, A. 2014. El Niño-Southern Oscillation (ENSO): A review. In P. Glymn, D. Manzello and I. Enochs, eds., Coral Reefs of the Eastern Pacific. Springer Science Publisher.

Whittingham, M.J., Stephens, P.A., Bradbury, R.B. and Freckleton, R.P. 2006. Why do we still use stepwise modelling in ecology and behaviour? Journal of Animal Ecology 75(5): 1182–1189.

Wickett, W.P. 1977. Relationship of coastal oceanographic factors to the migration of Fraser River sockeye salmon (*Oncorhynchus nerka* W.). ICES CM M: 26: 18.

Wilimovsky, N.J. 1990. Misuses of the term “Julian Day”. Transactions of the American Fisheries Society 119(1): 162–162.

Williams, B. 2005. 2004 southern salmon fishery post-season review. part one: Fraser River sockeye report. Report of Canadian Minister of Fisheries and Oceans.

Wiltschko, R. and Wiltschko, W. 2006. Magnetoreception. BioEssays 28(2): 157–168.

Wiltschko, W. and Wiltschko, R. 2001. The geomagnetic field and its role in directional orientation. In F. Barth and A. Schmid, eds., Ecology of Sensing, 289–312. Springer Berlin Heidelberg.

Wiseman, F. 1972. Methodological considerations in segmentation studies. In F. C. Allvine, ed., Combined Proceedings, 306–311. American Marketing Association Chicago.

Wood, S. 2006. Generalized Additive Models: An Introduction with R. Taylor & Francis.

Xie, Y. 2002. Estimation of migratory fish abundance using river-transect sampling by a split-beam transducer. In ICES Symposium on Acoustics in Fisheries and Aquatic Ecology, Montpellier, France, 10-14, June, 2002.

Xie, Y., Cronkite, G. and Mulligan, T.J. 1997. A split-beam echosounder perspective on migratory salmon in the Fraser River: A progress report on the split-beam experiment at Mission, B.C., in 1995. Technical Report 8, Pacific Salmon Commission.

Xie, Y., Mulligan, T.J., Cronkite, G.M.W. and Gray, A.P. 2002. Assessment of potential bias in hydroacoustic estimation of Fraser River sockeye and pink salmon at Mission, B.C. Technical Report 11, Pacific Salmon Commission.

APPENDIX A: EARLY STUART TIMING MODEL PERFORMANCE RESULTS

Table 12. Performance results for all qualifying models used to forecast Early Stuart timing based on retrospective analysis. Each row represents a single model tested, some columns include: year adjust (year of environmental data same as return year [0] or prior year [-1]), month, summary statistics (P value, adjusted R squared, sample size), data name, data variables (which are sorted by their relative influence in the model). As the NEPSTAR regression models comprise more than one variable, only year-month of the latest variable is presented. Latitude and longtitude of NEPSTAR variables are excluded due to space limitations. The PMs include mean raw error, mean absolute error, root mean squared error, Thiel's U-statistic, and MASE. The initial three PMs are in day units, the latter two are unit-less. All PMs are described in the methods section. All PMs, except MASE, are given a rank. The best rank has a value of zero. The last rank equals total number of models (n). The average of the PM ranks by model (row) is included, as is the average rank for the alternate performance test method. The rows are sorted by average rank of performance method listed in caption. The first row is the best model, the last row is the worst.

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
mlr188	-1,-1	1,2	mlr	2.0e-04	0.59	20	OSCAR42; OSCAR33332	-0.16	0.92	1.17	0.39	0.46	21.1	0.0	8.1	0.0	7.3	63.4
mlr1	-1,0,-1	1,1,8	mlr	4.6e-10	0.93	20	OSCAR42; OSCAR33359; OISST177437	0.19	0.97	1.07	0.41	0.48	25.0	4.3	0.0	5.8	8.8	5.4
mlr2	-1,0,-1	1,1,7	mlr	1.5e-09	0.92	20	OSCAR42; OSCAR33359; OISST177421	-0.04	1.02	1.21	0.47	0.51	5.4	8.9	11.2	21.7	11.8	5.6
mlr3	-1,0,-1	1,1,7	mlr	2.1e-09	0.92	20	OSCAR42; OSCAR33359; OISST177416	-0.16	0.95	1.20	0.46	0.48	20.7	2.7	10.1	20.2	13.4	7.2
mlr117	-1,0	1,1	mlr	2.7e-07	0.81	20	OSCAR42; OSCAR33360	-0.05	1.22	1.33	0.48	0.61	6.8	25.6	20.5	24.0	19.2	39.6
mlr141	-1,-1	1,2	mlr	4.1e-05	0.66	20	OSCAR42; OSCAR33296	0.39	0.93	1.24	0.45	0.47	52.0	1.1	13.3	17.2	20.9	46.6
mlr4	-1,0,-1	1,1,5	mlr	6.7e-09	0.90	20	OSCAR42; OSCAR33359; OSCAR33312	0.17	1.08	1.30	0.50	0.54	22.7	13.6	17.8	30.9	21.2	6.2
mlr6	-1,0,-1	1,1,5	mlr	1.1e-08	0.90	20	OSCAR42; OSCAR33359; OSCAR33319	0.08	1.19	1.40	0.54	0.59	9.8	23.0	25.6	41.8	25.0	7.0
mlr52	-1,0	1,1	mlr	3.1e-08	0.85	20	OSCAR42; OSCAR33322	0.33	1.27	1.50	0.44	0.63	44.0	29.8	34.0	13.4	30.3	27.8
mlr7	-1,0,-1	1,1,5	mlr	1.2e-08	0.89	20	OSCAR42; OSCAR33359; OSCAR33310	0.21	1.16	1.44	0.56	0.58	27.9	20.1	29.3	46.7	31.0	3.8
mlr185	-1,-1	1,8	mlr	1.7e-04	0.60	20	OSCAR42; OISST177437	-0.01	1.37	1.68	0.55	0.69	1.0	38.3	47.7	43.2	32.6	72.9
mlr171	-1,-1	1,7	mlr	1.3e-04	0.61	20	OSCAR42; OISST177421	-0.33	1.27	1.54	0.47	0.63	43.6	29.5	36.6	21.3	32.8	70.3
mlr8	-1,0,-1	1,1,5	mlr	1.4e-08	0.89	20	OSCAR42; OSCAR33359; OSCAR33311	0.30	1.12	1.46	0.56	0.56	39.3	17.2	30.3	47.9	33.7	6.3
mlr24	-1,0,0	1,1,5	mlr	3.9e-08	0.88	20	OSCAR42; OSCAR33359; lighthouse311951	-0.10	1.23	1.56	0.60	0.62	13.3	26.5	38.2	59.3	34.3	19.5
mlr9	-1,0,0	1,1,1	mlr	1.5e-08	0.89	20	OSCAR42; OSCAR33359; OSCAR33322	0.40	1.18	1.39	0.53	0.59	52.6	22.1	25.2	38.9	34.7	19.5
mlr5	-1,0,-1	1,1,5	mlr	8.6e-09	0.90	20	OSCAR42; OSCAR33359; OSCAR33348	0.09	1.34	1.55	0.59	0.67	11.3	35.6	37.3	56.2	35.1	7.5
mlr14	-1,0	1,1	mlr	1.0e-08	0.87	20	OSCAR42; OSCAR33335	-0.30	1.18	1.60	0.53	0.59	39.7	22.0	41.4	38.3	35.4	23.1
mlr168	-1,-1	1,7	mlr	1.2e-04	0.61	20	OSCAR42; OISST177416	-0.52	1.22	1.52	0.44	0.61	69.1	25.5	34.9	13.8	35.8	69.9
mlr34	-1,0,-1	1,1,5	mlr	5.2e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116430	0.02	1.37	1.61	0.62	0.68	2.8	38.2	42.1	63.9	36.7	20.6
mlr38	-1,0,-1	1,1,5	mlr	5.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116443	-0.02	1.36	1.62	0.62	0.68	2.8	37.2	42.8	65.2	37.0	20.0
mlr121	-1,0	1,1	mlr	5.2e-07	0.80	20	OSCAR42; OSCAR33333	0.50	1.18	1.43	0.51	0.59	66.1	21.9	28.0	32.8	37.2	36.9
mlr22	-1,0,0	1,1,1	mlr	3.7e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33335	0.15	1.28	1.58	0.60	0.64	20.1	30.4	39.6	58.6	37.2	17.6
mlr21	-1,0	1,1	mlr	1.7e-08	0.86	20	OSCAR42; OSCAR33342	0.38	1.22	1.44	0.56	0.61	50.5	25.4	29.3	46.8	38.0	22.7
mlr179	-1,-1	1,2	mlr	1.5e-04	0.60	20	OSCAR42; OSCAR33344	0.53	1.14	1.39	0.53	0.57	70.7	19.1	25.1	39.1	38.5	59.9
mlr32	-1,0,0	1,1,4	mlr	4.9e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116437	-0.00	1.43	1.64	0.63	0.72	0.0	43.5	44.7	65.9	38.5	21.6
mlr48	-1,0,0	1,1,6	mlr	6.1e-08	0.87	20	OSCAR42; OSCAR33359; OISST177423	-0.06	1.28	1.71	0.66	0.64	8.4	30.7	50.1	75.9	41.3	21.7
mlr118	-1,0	1,1	mlr	2.8e-07	0.81	20	OSCAR42; OSCAR33320	0.47	1.42	1.64	0.45	0.71	63.0	42.4	44.3	16.1	41.4	39.2
mlr31	-1,0,0	1,1,4	mlr	4.8e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116447	0.05	1.45	1.67	0.63	0.73	6.1	45.4	47.2	68.2	41.7	21.8

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
mlr15	-1,0,-1	1,1,4	mlr	2.3e-08	0.89	20	OSCAR42; OSCAR33359; OSCAR33353	0.20	1.38	1.59	0.61	0.69	26.6	39.1	40.8	60.8	41.8	18.5
mlr17	-1,0,-1	1,1,2	mlr	2.6e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR45	0.48	1.23	1.48	0.57	0.62	63.2	26.6	32.0	49.7	42.9	9.5
mlr43	-1,0,0	1,1,1	mlr	5.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33360	0.31	1.25	1.60	0.62	0.63	41.2	28.2	41.3	63.6	43.6	21.2
mlr45	-1,0,0	1,1,6	mlr	5.9e-08	0.87	20	OSCAR42; OSCAR33359; OISST177422	-0.14	1.27	1.73	0.67	0.64	18.9	30.1	51.6	77.9	44.6	20.9
mlr19	-1,0,-1	1,1,1	mlr	3.2e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33351	0.10	1.42	1.70	0.66	0.71	13.7	42.2	49.2	74.4	44.9	12.4
mlr16	-1,0	1,1	mlr	1.1e-08	0.87	20	OSCAR42; OSCAR33315	0.78	1.19	1.37	0.50	0.59	104.0	22.9	23.8	29.3	45.0	22.1
mlr47	-1,0,0	1,1,6	mlr	5.9e-08	0.87	20	OSCAR42; OSCAR33359; OISST177413	-0.13	1.28	1.74	0.67	0.64	17.6	30.9	52.4	79.0	45.0	21.4
mlr57	-1,0,-1	1,1,5	mlr	6.9e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116432	0.22	1.35	1.65	0.64	0.67	29.6	36.5	45.1	68.9	45.1	21.2
mlr116	-1,0	1,1	mlr	8.8e-08	0.83	20	OSCAR42; OSCAR33356	0.06	1.49	1.80	0.63	0.74	7.9	48.4	56.9	68.0	45.3	32.1
mlr20	-1,0,-1	1,1,5	mlr	3.6e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33334	0.02	1.50	1.78	0.65	0.75	2.7	49.5	55.5	73.4	45.3	18.1
mlr201	-1,-1	1,1	mlr	2.8e-04	0.57	20	OSCAR42; OSCAR116435	-0.07	1.55	1.80	0.62	0.78	9.0	53.7	57.2	63.5	45.9	82.3
nepstar13	0,-1,0,-1,-1	5,5,5,3,7	mlr	1.8e-10	0.86	30	nepstar	0.27	1.52	1.81	0.54	0.76	35.3	50.9	58.0	40.3	46.1	16.8
mlr12	-1,0,0	1,1,1	mlr	2.2e-08	0.89	20	OSCAR42; OSCAR33359; OSCAR33315	0.61	1.26	1.44	0.56	0.63	81.5	28.8	29.2	46.4	46.5	21.2
mlr28	-1,0,-1	1,1,5	mlr	4.5e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33329	0.33	1.29	1.64	0.63	0.65	43.3	31.5	44.9	68.1	47.0	14.4
mlr127	-1,-1	1,2	mlr	1.3e-05	0.70	20	OSCAR42; OSCAR45	0.47	1.26	1.59	0.62	0.63	62.5	29.1	40.7	62.8	48.8	45.1
mlr170	-1,-1	1,5	mlr	1.2e-04	0.61	20	OSCAR42; OSCAR33311	0.09	1.57	1.80	0.64	0.79	11.9	55.6	57.2	70.7	48.8	75.9
mlr41	-1,0,-1	1,1,5	mlr	5.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33305	0.33	1.31	1.67	0.65	0.65	43.9	33.0	47.0	71.5	48.8	15.2
mlr42	-1,0,-1	1,1,1	mlr	5.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33323	0.25	1.40	1.69	0.65	0.70	33.5	40.8	48.1	73.1	48.9	15.7
mlr11	-1,0,-1	1,1,5	mlr	2.1e-08	0.89	20	OSCAR42; OSCAR33359; OSCAR99803	0.36	1.43	1.62	0.61	0.72	47.9	43.4	43.0	62.3	49.1	20.2
mlr39	-1,0,0	1,1,6	mlr	5.6e-08	0.87	20	OSCAR42; OSCAR33359; OISST177417	-0.23	1.28	1.76	0.68	0.64	30.9	30.6	54.2	81.3	49.2	20.7
mlr23	-1,0,0	1,1,4	mlr	3.9e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR66549	0.19	1.48	1.75	0.66	0.74	24.8	47.2	52.7	74.3	49.8	18.2
mlr53	-1,0,-1	1,1,1	mlr	6.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33308	0.21	1.42	1.74	0.67	0.71	27.3	42.4	52.3	78.0	50.0	24.1
mlr60	-1,0,-1	1,1,5	mlr	7.3e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116429	0.29	1.33	1.71	0.66	0.67	39.0	35.0	50.1	75.9	50.0	23.7
mlr202	-1,-1	1,1	mlr	2.9e-04	0.57	20	OSCAR42; OSCAR116442	-0.03	1.62	1.87	0.66	0.81	4.2	59.1	62.1	75.0	50.1	87.6
mlr27	-1,0,0	1,1,1	mlr	4.4e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33328	0.43	1.28	1.64	0.64	0.64	56.5	30.8	44.8	68.6	50.2	22.6
mlr190	-1,-1	1,9	mlr	2.1e-04	0.59	20	OSCAR42; OSCAR33331	-0.17	1.67	1.79	0.62	0.84	22.0	63.8	56.4	62.6	51.2	77.6
mlr51	-1,0,-1	1,1,2	mlr	6.4e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33296	0.40	1.34	1.67	0.64	0.67	53.2	35.7	46.5	70.0	51.4	14.7
mlr44	-1,0,0	1,1,6	mlr	5.7e-08	0.87	20	OSCAR42; OSCAR33359; OISST177412	-0.25	1.29	1.80	0.69	0.65	33.2	31.8	56.7	84.8	51.6	21.2
mlr80	-1,0,-1	1,1,8	mlr	8.2e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116438	0.17	1.53	1.78	0.67	0.76	21.9	51.4	55.8	78.1	51.8	24.1
mlr75	-1,0,0	1,1,2	mlr	8.1e-08	0.87	20	OSCAR42; OSCAR33359; OISST177431	0.37	1.34	1.70	0.66	0.67	49.0	35.3	49.1	74.6	52.0	19.7
mlr30	-1,0,0	1,1,1	mlr	4.7e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33320	0.51	1.31	1.61	0.62	0.65	68.3	32.8	42.2	65.0	52.1	26.5
mlr83	-1,0,-1	1,1,1	mlr	8.3e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR43	0.33	1.37	1.71	0.66	0.68	43.9	38.2	50.4	76.3	52.2	22.7
mlr102	-1,0,-1	1,1,8	mlr	8.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116434	0.24	1.47	1.75	0.67	0.73	31.1	46.4	53.3	78.2	52.3	22.4
mlr68	-1,0,0	1,1,1	mlr	7.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33337	0.37	1.38	1.68	0.65	0.69	49.3	39.3	47.9	72.6	52.3	22.1
mlr73	-1,0,0	1,1,6	mlr	8.0e-08	0.87	20	OSCAR42; OSCAR33359; OISST266113	0.35	1.37	1.71	0.66	0.68	45.7	38.0	50.1	75.9	52.4	22.3
mlr37	-1,0,-1	1,1,4	mlr	5.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33309	0.33	1.40	1.71	0.66	0.70	43.9	40.8	50.1	75.1	52.5	21.6
mlr76	-1,0,0	1,1,1	mlr	8.1e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33338	0.38	1.36	1.70	0.66	0.68	50.3	37.4	49.0	74.4	52.8	22.9
mlr10	-1,0	1,1	mlr	9.3e-09	0.87	20	OSCAR42; OSCAR33359	0.39	1.35	1.70	0.66	0.68	52.2	37.0	48.9	74.2	53.0	17.3
mlr54	-1,0,0	1,1,6	mlr	6.6e-08	0.87	20	OSCAR42; OSCAR33359; OISST266112	0.28	1.40	1.75	0.68	0.70	37.5	41.0	53.3	80.3	53.0	21.9
mlr81	-1,0,0	1,1,3	mlr	8.3e-08	0.87	20	OSCAR42; OSCAR33359; OISST177418	0.37	1.36	1.71	0.66	0.68	48.7	37.7	49.9	75.6	53.0	22.1
mlr70	-1,0,-1	1,1,6	mlr	7.9e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116448	0.40	1.34	1.70	0.66	0.67	53.0	35.8	49.5	75.1	53.3	19.6
mlr74	-1,0,0	1,1,2	mlr	8.0e-08	0.87	20	OSCAR42; OSCAR33359; OISST177428	0.39	1.37	1.70	0.66	0.69	51.4	38.7	48.9	74.1	53.3	18.9

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
mlr82	-1,0,0	1,1,2	mlr	8.3e-08	0.87	20	OSCAR42; OSCAR33359; OISST177434	0.39	1.37	1.70	0.66	0.68	52.0	38.2	48.9	74.0	53.3	19.0
mlr18	-1,0,-1	1,1,3	mlr	2.9e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33300	-0.35	1.39	1.78	0.65	0.69	45.8	39.6	55.4	72.9	53.4	21.1
mlr172	-1,-1	1,5	mlr	1.3e-04	0.61	20	OSCAR42; OSCAR33310	-0.07	1.68	1.88	0.67	0.84	9.1	64.4	63.4	77.2	53.5	78.4
mlr84	-1,0,0	1,1,6	mlr	8.3e-08	0.87	20	OSCAR42; OSCAR33359; OISST266111	0.37	1.37	1.72	0.67	0.68	49.5	38.2	50.7	76.8	53.8	22.1
mlr86	-1,0,0	1,1,2	mlr	8.4e-08	0.87	20	OSCAR42; OSCAR33359; OISST177432	0.40	1.35	1.71	0.66	0.68	52.6	36.9	49.9	75.6	53.8	20.1
mlr110	-1,0,-1	1,1,8	mlr	8.8e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116433	0.31	1.43	1.75	0.67	0.71	41.5	43.2	52.7	79.0	54.1	21.2
mlr115	-1,0,0	1,1,2	mlr	8.8e-08	0.87	20	OSCAR42; OSCAR33359; OISST177426	0.40	1.37	1.71	0.66	0.68	52.8	38.0	49.9	75.6	54.1	19.8
mlr49	-1,0,-1	1,1,1	mlr	6.2e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33324	0.38	1.41	1.70	0.66	0.70	50.5	41.4	49.5	75.0	54.1	21.5
mlr79	-1,0,-1	1,1,6	mlr	8.2e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33358	0.36	1.40	1.73	0.67	0.70	47.2	40.5	51.2	77.3	54.1	28.4
mlr95	-1,0,0	1,1,3	mlr	8.5e-08	0.87	20	OSCAR42; OSCAR33359; OISST177427	0.40	1.37	1.71	0.66	0.68	52.4	37.8	50.4	76.3	54.2	22.0
mlr109	-1,0,0	1,1,2	mlr	8.7e-08	0.87	20	OSCAR42; OSCAR33359; OISST177425	0.41	1.37	1.71	0.66	0.69	54.1	38.7	50.1	75.9	54.7	19.8
mlr65	-1,0,-1	1,1,10	mlr	7.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116439	0.44	1.35	1.71	0.66	0.67	58.1	36.2	49.6	74.9	54.7	20.5
mlr50	-1,0,-1	1,1,5	mlr	6.3e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33306	0.23	1.52	1.79	0.68	0.76	31.0	50.7	56.4	82.0	55.0	18.3
mlr105	-1,0,0	1,1,1	mlr	8.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33330	0.33	1.40	1.77	0.68	0.70	43.1	41.1	54.4	81.7	55.1	24.0
mlr106	-1,0,0	1,1,2	mlr	8.7e-08	0.87	20	OSCAR42; OSCAR33359; OISST177435	0.41	1.38	1.72	0.66	0.69	54.5	39.1	50.5	76.3	55.1	19.9
mlr114	-1,0,-1	1,1,8	mlr	8.8e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116436	0.23	1.50	1.80	0.69	0.75	30.0	49.6	57.2	83.7	55.1	22.1
mlr104	-1,0,0	1,1,3	mlr	8.7e-08	0.87	20	OSCAR42; OSCAR33359; OISST177408	0.41	1.37	1.73	0.67	0.68	54.7	38.2	51.4	77.8	55.5	22.5
OSCAR116447	0	4	scam_mpd	1.3e-04	0.51	21	u	-0.12	1.58	1.87	0.71	0.79	15.1	56.1	62.8	88.1	55.5	75.9
OSCAR66550	0	4	lm	1.6e-04	0.51	21	u	-0.12	1.58	1.87	0.71	0.79	15.1	56.1	62.8	88.1	55.5	75.9
mlr62	-1,0,-1	1,1,1	mlr	7.3e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33355	0.39	1.37	1.74	0.67	0.69	52.2	38.4	52.4	79.1	55.6	17.2
mlr56	-1,0,0	1,1,2	mlr	6.8e-08	0.87	20	OSCAR42; OSCAR33359; OISST177419	0.48	1.37	1.69	0.65	0.68	63.5	38.1	48.2	73.2	55.7	17.5
mlr13	-1,0,-1	1,1,3	mlr	2.3e-08	0.89	20	OSCAR42; OSCAR33359; OSCAR33302	-0.46	1.31	1.77	0.66	0.66	60.8	33.2	54.8	74.6	55.9	19.5
mlr33	-1,0,-1	1,1,5	mlr	5.1e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33314	0.15	1.58	1.86	0.70	0.79	20.3	56.3	61.5	85.4	55.9	17.3
mlr55	-1,0,0	1,1,1	mlr	6.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33327	0.48	1.35	1.70	0.66	0.67	63.5	36.2	49.6	75.2	56.1	21.6
mlr186	-1,-1	1,5	mlr	1.7e-04	0.60	20	OSCAR42; OSCAR116429	-0.12	1.69	1.93	0.67	0.84	15.3	65.1	66.8	77.5	56.2	76.2
mlr26	-1,0,-1	1,1,3	mlr	4.0e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33340	-0.23	1.55	1.87	0.67	0.77	30.8	53.4	62.1	78.3	56.2	25.3
mlr113	-1,0,0	1,1,3	mlr	8.8e-08	0.87	20	OSCAR42; OSCAR33359; OISST177411	0.44	1.36	1.73	0.67	0.68	58.6	37.6	51.5	77.9	56.4	22.2
mlr46	-1,0,-1	1,1,6	mlr	5.9e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR49924	0.48	1.35	1.71	0.66	0.68	63.5	36.6	50.0	75.6	56.4	16.9
mlr77	-1,0,-1	1,1,5	mlr	8.2e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33341	0.41	1.40	1.74	0.67	0.70	54.5	40.5	52.2	78.8	56.5	23.7
mlr97	-1,0,0	1,1,1	mlr	8.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33356	0.42	1.37	1.74	0.67	0.69	56.3	38.6	52.2	78.9	56.5	22.0
mlr85	-1,0,-1	1,1,1	mlr	8.3e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33321	0.42	1.38	1.74	0.68	0.69	55.3	39.2	52.6	79.4	56.6	20.7
mlr29	-1,0,-1	1,1,11	mlr	4.5e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33304	0.62	1.32	1.64	0.63	0.66	82.8	33.7	44.2	67.8	57.1	20.3
mlr35	-1,0,0	1,1,6	mlr	5.5e-08	0.87	20	OSCAR42; OSCAR33359; OISST177415	-0.37	1.30	1.83	0.70	0.65	49.3	32.4	59.1	87.5	57.1	20.6
mlr87	-1,0,0	1,1,4	mlr	8.4e-08	0.87	20	OSCAR42; OSCAR33359; OISST177424	0.39	1.39	1.78	0.69	0.69	51.0	39.9	55.8	83.6	57.6	17.3
nepstar27	0,-1,0,-1,-1,0	5,5,5,7,5,4	mlr	2.0e-09	0.85	30	nepstar	0.46	1.53	1.74	0.63	0.76	61.4	51.6	52.1	65.4	57.6	36.2
mlr111	-1,0,-1	1,1,3	mlr	8.8e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33346	0.35	1.44	1.80	0.70	0.72	45.9	44.5	56.9	85.4	58.2	20.2
mlr69	-1,0,0	1,1,5	mlr	7.7e-08	0.87	20	OSCAR42; OSCAR33359; lighthouse310799	0.46	1.44	1.73	0.67	0.72	60.9	44.5	51.3	76.6	58.3	18.5
mlr152	-1,0	1,2	mlr	6.4e-05	0.64	20	OSCAR42; OISST177428	0.16	1.61	1.87	0.72	0.81	20.6	58.7	62.6	91.7	58.4	69.5
mlr72	-1,0,0	1,1,3	mlr	7.9e-08	0.87	20	OSCAR42; OSCAR33359; OISST177436	0.50	1.40	1.71	0.66	0.70	66.6	40.5	50.2	76.0	58.4	20.8
mlr101	-1,0,-1	1,1,1	mlr	8.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33354	0.39	1.41	1.79	0.69	0.71	51.1	42.0	56.3	84.6	58.5	25.9
mlr147	-1,-1	1,1	mlr	5.2e-05	0.65	20	OSCAR42; OSCAR33324	0.22	1.66	2.02	0.64	0.83	28.8	62.6	73.9	68.8	58.5	66.2
mlr40	-1,0,0	1,1,6	mlr	5.7e-08	0.87	20	OSCAR42; OSCAR33359; OISST177414	-0.36	1.32	1.86	0.72	0.66	47.3	34.0	61.7	91.2	58.5	21.4

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
mlr88	-1,0,0	1,1,3	mlr	8.4e-08	0.87	20	OSCAR42; OSCAR33359; OISST177430	0.49	1.39	1.73	0.67	0.69	64.7	39.9	51.5	77.9	58.5	21.3
mlr123	-1,0	1,1	mlr	9.9e-07	0.78	20	OSCAR42; OSCAR33347	0.62	1.59	1.81	0.53	0.80	81.7	57.1	57.9	38.0	58.7	45.8
mlr155	-1,0	1,2	mlr	6.8e-05	0.64	20	OSCAR42; OISST177434	0.26	1.54	1.85	0.71	0.77	33.8	52.3	61.2	89.6	59.2	67.7
nepstar8	0,-1,0,-1,0,-1	5,5,5,5,4,7	mlr	1.1e-10	0.88	30	nepstar	0.44	1.72	1.83	0.57	0.86	58.9	68.3	59.0	50.9	59.3	15.8
mlr67	-1,0,-1	1,1,6	mlr	7.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116440	0.40	1.46	1.79	0.69	0.73	52.6	45.8	56.5	84.5	59.8	20.5
mlr151	-1,-1	1,5	mlr	6.2e-05	0.64	20	OSCAR42; OSCAR33312	-0.14	1.84	1.90	0.67	0.92	17.9	78.0	64.8	78.7	59.9	69.5
mlr90	-1,0,-1	1,1,2	mlr	8.4e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33344	0.47	1.41	1.79	0.69	0.71	62.7	41.7	55.8	83.9	61.0	21.3
nepstar34	-1,0,-1,-1,-1,0	5,5,7,5,3,4	mlr	4.0e-09	0.84	30	nepstar	0.95	1.37	1.69	0.50	0.68	125.7	38.0	48.8	31.5	61.0	27.2
nepstar23	0,0,-1,-1,-1	5,5,7,3,7	mlr	1.1e-09	0.84	30	nepstar	0.53	1.63	1.85	0.58	0.81	70.7	60.3	61.1	52.8	61.2	33.5
mlr64	-1,0,-1	1,1,1	mlr	7.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116442	0.48	1.39	1.80	0.70	0.69	64.0	39.6	56.7	85.1	61.4	23.8
mlr78	-1,0,0	1,1,2	mlr	8.2e-08	0.87	20	OSCAR42; OSCAR33359; OISST177429	0.51	1.41	1.77	0.68	0.71	67.1	41.9	54.6	82.1	61.4	19.7
mlr59	-1,0,-1	1,1,9	mlr	7.2e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33331	0.41	1.44	1.83	0.71	0.72	54.4	44.1	59.6	89.1	61.8	20.7
mlr99	-1,0,-1	1,1,12	mlr	8.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR49925	0.39	1.47	1.84	0.71	0.74	51.5	46.7	60.0	89.6	61.9	25.3
mlr100	-1,0,-1	1,1,5	mlr	8.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116441	0.38	1.44	1.85	0.72	0.72	50.8	44.3	61.3	91.5	62.0	22.5
nepstar9	0,-1,-2,-1,0	5,5,4,3,4	mlr	1.3e-09	0.83	30	nepstar	0.73	1.63	1.92	0.48	0.81	97.0	60.1	66.4	24.8	62.1	19.6
mlr63	-1,0,-1	1,1,8	mlr	7.4e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116431	0.60	1.48	1.73	0.65	0.74	79.6	47.6	51.4	72.5	62.8	16.1
nepstar2	0,-1,0,0,-1	5,5,5,4,7	mlr	5.6e-11	0.87	30	nepstar	0.50	1.74	1.92	0.57	0.87	65.7	69.7	66.2	50.1	62.9	16.6
nepstar12	0,-1,0,-1,0,-1	5,5,5,5,4,7	mlr	1.1e-10	0.88	30	nepstar	0.55	1.73	1.85	0.57	0.86	73.1	68.5	61.0	50.5	63.2	18.4
nepstar39	0,-1,0,-1,-1	5,3,5,7,7	mlr	2.7e-09	0.82	30	nepstar	0.85	1.52	1.71	0.55	0.76	112.8	50.6	50.1	45.2	64.7	18.0
OSCAR33308	-1	1	scam_mpi	8.3e-04	0.57	20	v	-0.07	1.74	2.05	0.76	0.87	9.2	69.6	76.8	103.2	64.7	94.7
mlr36	-1,0,0	1,1,6	mlr	5.5e-08	0.87	20	OSCAR42; OSCAR33359; OISST177433	-0.48	1.35	1.90	0.73	0.67	64.2	36.5	65.0	94.3	65.0	20.9
nepstar25	0,0,-1,-1,-1	5,5,3,7,7	mlr	5.2e-10	0.85	30	nepstar	0.80	1.54	1.85	0.54	0.77	106.2	52.9	61.0	40.4	65.1	19.8
mlr125	-1,0	1,1	mlr	8.0e-06	0.72	20	OSCAR42; OSCAR33328	0.43	1.31	2.03	0.74	0.65	56.4	32.9	75.1	96.4	65.2	47.3
mlr206	-1,0	1,5	mlr	3.5e-04	0.56	20	OSCAR42; OSCAR116445	-0.15	1.81	2.10	0.70	0.91	19.4	75.9	80.0	85.5	65.2	71.0
mlr91	-1,0,0	1,1,1	mlr	8.5e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33333	0.41	1.54	1.87	0.72	0.77	54.7	52.3	62.3	91.7	65.2	24.0
nepstar21	0,0,-1,-1,0,-1	4,5,5,3,4,7	mlr	2.3e-10	0.87	30	nepstar	-0.07	1.81	2.24	0.69	0.90	9.7	75.5	91.2	84.7	65.3	25.3
mlr66	-1,0,0	1,1,2	mlr	7.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR99806	0.43	1.57	1.86	0.72	0.78	57.0	54.9	62.0	92.4	66.6	21.0
mlr148	-1,-1	1,3	mlr	5.6e-05	0.65	20	OSCAR42; OSCAR33346	0.07	1.72	2.09	0.79	0.86	9.2	67.7	79.4	110.5	66.7	63.1
nepstar38	0,0,-1,-1,-1	5,5,3,7,7	mlr	1.1e-09	0.84	30	nepstar	0.76	1.59	1.89	0.55	0.80	101.0	57.3	64.2	44.7	66.8	18.5
mlr92	-1,0,0	1,1,4	mlr	8.5e-08	0.87	20	OSCAR42; OSCAR33359; OISST177409	0.50	1.48	1.87	0.72	0.74	65.7	47.5	62.1	92.1	66.9	17.3
OSCAR116437	0	4	scam_mpd	5.1e-05	0.55	21	u	-0.64	1.56	1.79	0.65	0.78	84.8	54.7	55.9	72.4	66.9	79.2
OSCAR66548	0	4	lm	7.1e-05	0.55	21	u	-0.64	1.56	1.79	0.65	0.78	84.8	54.7	55.9	72.4	66.9	73.7
mlr71	-1,0,-1	1,1,1	mlr	7.9e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116435	0.53	1.44	1.86	0.72	0.72	70.1	44.1	61.7	92.1	67.0	22.1
nepstar37	0,-1,0,-1,-2,0	5,5,5,5,4,4	mlr	1.4e-09	0.85	30	nepstar	0.16	1.59	2.12	0.78	0.80	21.5	57.3	82.0	108.2	67.3	31.7
nepstar1	0,-1,0,0,-1	5,5,5,4,7	mlr	5.6e-11	0.87	30	nepstar	0.63	1.75	1.95	0.56	0.87	83.9	70.1	68.3	48.2	67.6	19.7
mlr107	-1,0,-1	1,1,1	mlr	8.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33345	0.58	1.58	1.81	0.68	0.79	76.9	56.3	57.6	80.9	67.9	19.3
mlr89	-1,0,-1	1,1,1	mlr	8.4e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33352	0.57	1.61	1.82	0.68	0.81	75.2	58.7	58.2	81.5	68.4	19.9
mlr103	-1,0,0	1,1,5	mlr	8.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116445	0.55	1.53	1.84	0.71	0.76	73.6	51.5	60.1	89.1	68.6	20.9
mlr61	-1,0,0	1,1,1	mlr	7.3e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33347	0.57	1.56	1.83	0.70	0.78	76.1	54.0	59.6	85.6	68.8	24.0
OSCAR42	-1	1	lm	1.0e-04	0.55	20	v	0.24	1.65	2.15	0.74	0.82	31.7	61.6	84.0	98.1	68.8	73.7
nepstar33	0,0,-1,-1,0,-1	4,5,5,3,4,7	mlr	3.9e-10	0.87	30	nepstar	-0.01	1.94	2.33	0.71	0.97	0.9	86.2	98.4	90.3	69.0	25.1
mlr25	-1,0,-1	1,1,3	mlr	4.0e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33350	-0.47	1.52	1.94	0.73	0.76	62.1	51.3	68.2	95.7	69.3	24.0

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
mlr58	-1,0,0	1,1,5	mlr	7.0e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33326	-0.07	1.92	2.06	0.78	0.96	9.4	84.7	76.9	107.4	69.6	24.8
OSCAR33332	-1	2	scam_mpi	2.8e-03	0.53	20	v	-0.25	1.94	2.08	0.69	0.97	33.0	86.3	78.6	83.4	70.3	102.7
mlr124	-1,0	1,1	mlr	4.0e-06	0.74	20	OSCAR42; OSCAR33327	0.48	1.59	1.98	0.71	0.80	64.2	56.9	71.2	89.3	70.4	47.5
mlr120	-1,0	1,1	mlr	3.8e-07	0.80	20	OSCAR42; OSCAR33337	0.48	1.69	1.90	0.70	0.84	64.0	65.4	64.9	87.6	70.5	38.7
mlr153	-1,0	1,2	mlr	6.4e-05	0.64	20	OSCAR42; OISST177435	0.29	1.70	2.00	0.77	0.85	37.8	66.0	72.7	105.5	70.5	73.5
mlr221	-1,-1	1,1	mlr	6.4e-04	0.53	20	OSCAR42; OSCAR43	0.30	1.62	2.14	0.75	0.81	39.8	59.8	83.4	99.4	70.6	77.1
OSCAR33316	-1	1	scam_mpi	7.5e-05	0.55	20	v	0.07	1.82	2.37	0.74	0.91	8.4	76.5	101.5	98.1	71.1	388.0
mlr154	-1,0	1,2	mlr	6.5e-05	0.64	20	OSCAR42; OISST177425	0.36	1.64	1.99	0.77	0.82	48.0	61.5	71.9	104.6	71.5	71.6
nepstar40	0,-1,0,-1,-2,0	5,5,5,5,4,4	mlr	1.8e-09	0.85	30	nepstar	0.35	1.66	2.07	0.74	0.83	47.0	63.0	77.9	98.2	71.5	34.3
mlr157	-1,0	1,2	mlr	7.3e-05	0.64	20	OSCAR42; OISST177426	0.45	1.56	1.98	0.76	0.78	59.4	54.7	70.7	102.7	71.9	69.8
nepstar16	0,0,-1,0,-1	4,5,5,4,7	mlr	2.4e-10	0.86	30	nepstar	0.03	1.91	2.32	0.76	0.95	3.2	83.8	97.6	103.5	72.0	28.7
mlr98	-1,0,0	1,1,5	mlr	8.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116451	0.59	1.56	1.88	0.72	0.78	78.6	54.0	63.1	92.8	72.1	20.4
mlr165	-1,-1	1,6	mlr	1.1e-04	0.62	20	OSCAR42; OSCAR49924	-0.07	2.02	2.11	0.77	1.01	8.8	93.2	81.1	106.6	72.4	74.6
mlr198	-1,0	1,5	mlr	2.5e-04	0.58	20	OSCAR42; OSCAR116451	-0.27	1.91	2.13	0.70	0.96	35.1	84.3	82.7	87.7	72.5	68.8
nepstar24	0,0,-1,-1,0,-1	5,5,5,3,4,7	mlr	3.5e-10	0.87	30	nepstar	1.02	1.54	1.95	0.51	0.77	135.7	52.9	69.0	32.5	72.5	20.5
mlr182	-1,0	1,6	mlr	1.6e-04	0.60	20	OSCAR42; OISST266112	0.66	1.45	1.95	0.72	0.73	87.4	45.3	68.8	91.1	73.1	77.3
nepstar32	0,-1,0,0,-1	4,3,5,4,7	mlr	1.0e-09	0.84	30	nepstar	-0.02	1.92	2.47	0.75	0.96	2.9	85.0	109.0	99.4	74.1	27.3
mlr122	-1,0	1,1	mlr	5.2e-07	0.80	20	OSCAR42; OSCAR33338	0.43	1.73	2.01	0.75	0.86	56.7	68.3	73.6	99.1	74.4	42.3
mlr177	-1,-1	1,5	mlr	1.4e-04	0.61	20	OSCAR42; OSCAR33319	-0.30	1.95	2.08	0.73	0.97	40.0	87.0	78.6	94.8	75.1	74.6
nepstar35	-1,0,-1,-2,-1,0	5,5,5,4,3,4	mlr	1.8e-09	0.85	30	nepstar	0.68	1.74	2.01	0.64	0.87	90.3	69.5	73.1	68.5	75.3	18.3
mlr94	-1,0,0	1,1,4	mlr	8.5e-08	0.87	20	OSCAR42; OSCAR33359; OISST177410	0.60	1.57	1.94	0.75	0.79	80.3	55.5	67.8	99.4	75.7	17.2
mlr220	-1,-1	1,5	mlr	6.4e-04	0.53	20	OSCAR42; OSCAR33341	0.32	1.66	2.23	0.79	0.83	41.9	62.9	90.2	111.9	76.7	78.3
mlr96	-1,0,-1	1,1,9	mlr	8.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR49923	0.06	1.74	2.28	0.88	0.87	7.8	69.7	94.4	136.9	77.2	23.3
nepstar28	0,0,-1,-1,0	4,5,7,5,4	mlr	1.2e-09	0.84	30	nepstar	-0.44	1.56	2.21	0.78	0.78	57.8	54.6	89.0	107.7	77.3	43.5
mlr175	-1,-1	1,10	mlr	1.4e-04	0.61	20	OSCAR42; OSCAR116439	0.36	1.39	2.23	0.86	0.69	48.2	39.9	90.8	130.5	77.4	71.5
OSCAR33325	-1	1	scam_mpi	1.1e-04	0.54	20	v	0.67	1.42	2.03	0.76	0.71	89.5	42.2	74.5	103.5	77.4	70.9
OSCAR43	-1	1	lm	1.4e-04	0.54	20	v	0.67	1.42	2.03	0.76	0.71	89.5	42.2	74.5	103.5	77.4	70.5
mlr194	-1,-1	1,5	mlr	2.3e-04	0.58	20	OSCAR42; OSCAR116441	0.05	1.86	2.28	0.86	0.93	6.2	79.7	94.0	131.2	77.8	85.1
nepstar29	-1,-1,-2,-1	5,5,4,3	mlr	1.4e-08	0.78	30	nepstar	-0.35	1.86	2.25	0.73	0.93	45.8	79.6	91.9	95.1	78.1	26.4
mlr207	-1,-1	1,4	mlr	3.6e-04	0.56	20	OSCAR42; OSCAR33353	-0.05	1.92	2.50	0.79	0.96	6.7	84.6	111.5	110.8	78.4	86.9
mlr93	-1,0,0	1,1,4	mlr	8.5e-08	0.87	20	OSCAR42; OSCAR33359; OISST177420	0.67	1.63	1.97	0.75	0.82	88.8	60.4	70.5	101.4	80.3	17.2
mlr134	-1,-1	1,5	mlr	3.1e-05	0.67	20	OSCAR42; OSCAR99803	0.22	2.01	2.45	0.72	1.01	29.1	92.6	107.6	92.5	80.5	64.5
mlr199	-1,-1	1,5	mlr	2.8e-04	0.57	20	OSCAR42; OSCAR33305	0.12	1.83	2.36	0.86	0.92	16.2	77.4	100.5	130.3	81.1	79.1
mlr181	-1,0	1,6	mlr	1.6e-04	0.60	20	OSCAR42; OISST266113	0.73	1.50	2.02	0.77	0.75	96.5	49.3	73.9	104.9	81.2	76.3
nepstar14	0,-1,0,-1,0,-1	5,5,5,3,4,7	mlr	2.9e-10	0.87	30	nepstar	0.87	1.54	2.09	0.67	0.77	115.8	52.8	79.2	76.8	81.2	12.3
mlr193	-1,-1	1,5	mlr	2.3e-04	0.58	20	OSCAR42; OSCAR116432	-0.56	1.75	2.31	0.69	0.88	74.8	70.7	96.4	84.4	81.6	75.6
nepstar30	0,-1,0,-1,0,-1	4,5,5,3,4,7	mlr	5.1e-10	0.86	30	nepstar	0.10	2.04	2.45	0.80	1.02	12.5	94.9	107.5	114.7	82.4	21.0
nepstar41	0,-1,0,0,-1,-1	4,3,5,4,7,7	mlr	9.6e-10	0.86	30	nepstar	-0.40	1.64	2.37	0.80	0.82	52.7	61.4	101.0	114.5	82.4	23.7
nepstar5	0,-1,0,-1,0,-1	5,5,5,3,4,7	mlr	2.5e-10	0.87	30	nepstar	0.95	1.52	2.09	0.65	0.76	126.4	50.6	79.3	73.2	82.4	14.2
mlr108	-1,0,0	1,1,1	mlr	8.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33342	0.66	1.62	2.02	0.78	0.81	87.4	59.6	74.4	109.5	82.7	23.7
nepstar7	0,0,-1,-1	5,5,7,7	mlr	1.2e-09	0.82	30	nepstar	0.46	1.91	2.16	0.75	0.96	60.9	84.1	85.2	100.9	82.8	42.1
nepstar10	0,0,0,0,-1	5,4,5,4,7	mlr	4.9e-10	0.85	30	nepstar	0.09	2.03	2.48	0.81	1.02	11.8	94.2	109.8	116.7	83.1	37.5

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
nepstar26	0,0,0,0,-1	5,4,5,4,7	mlr	5.4e-10	0.85	30	nepstar	-0.02	2.05	2.50	0.83	1.02	2.4	95.5	111.7	122.9	83.1	36.0
nepstar11	0,0,-1,-1	5,5,7,7	mlr	1.1e-09	0.82	30	nepstar	0.62	1.87	2.11	0.72	0.93	82.4	80.3	80.9	91.4	83.7	44.1
nepstar19	0,0,-1,0,-1	4,5,5,4,7	mlr	4.6e-10	0.85	30	nepstar	0.08	2.12	2.46	0.80	1.06	11.1	101.7	108.4	115.3	84.1	28.7
mlr187	-1,-1	1,3	mlr	2.0e-04	0.59	20	OSCAR42; OSCAR33302	-1.02	1.76	2.27	0.52	0.88	135.4	71.1	93.6	37.3	84.3	67.2
nepstar4	0,0,-1,0,-1	4,5,3,4,7	mlr	2.7e-10	0.86	30	nepstar	-0.10	2.15	2.54	0.77	1.08	12.9	104.5	114.6	106.1	84.5	27.7
mlr126	-1,0	1,4	mlr	9.2e-06	0.71	20	OSCAR42; OSCAR66549	-0.29	1.91	2.58	0.75	0.95	38.3	83.7	117.8	99.1	84.7	62.6
mlr158	-1,0	1,5	mlr	7.4e-05	0.64	20	OSCAR42; lighthouse310799	0.06	2.17	2.45	0.81	1.09	7.4	106.1	107.9	117.7	84.8	74.7
mlr218	-1,-1	1,5	mlr	5.6e-04	0.54	20	OSCAR42; OSCAR116443	-0.44	1.80	2.37	0.77	0.90	58.2	75.1	101.1	105.3	84.9	82.5
mlr180	-1,0	1,6	mlr	1.6e-04	0.60	20	OSCAR42; OISST266111	0.70	1.59	2.10	0.80	0.79	93.2	56.9	80.6	113.9	86.1	77.4
mlr219	-1,-1	1,4	mlr	5.8e-04	0.53	20	OSCAR42; OSCAR33309	0.16	1.92	2.58	0.84	0.96	21.7	84.6	117.4	126.8	87.6	84.5
mlr210	-1,-1	1,1	mlr	4.2e-04	0.55	20	OSCAR42; OSCAR33323	-0.08	1.89	2.56	0.91	0.94	10.0	81.9	116.3	145.9	88.5	82.2
mlr156	-1,0	1,2	mlr	7.0e-05	0.64	20	OSCAR42; OISST177432	0.64	1.66	2.17	0.83	0.83	84.4	62.7	85.4	124.0	89.1	73.6
mlr161	-1,-1	1,5	mlr	8.4e-05	0.63	20	OSCAR42; OSCAR33348	-0.29	2.22	2.40	0.77	1.11	38.0	109.9	103.9	105.6	89.3	67.4
mlr215	-1,-1	1,3	mlr	4.6e-04	0.55	20	OSCAR42; OSCAR33340	-0.46	2.01	2.62	0.69	1.00	61.1	92.3	120.9	84.1	89.6	82.6
mlr159	-1,0	1,2	mlr	8.1e-05	0.63	20	OSCAR42; OISST177431	0.70	1.65	2.14	0.82	0.82	92.9	61.6	83.5	121.3	89.8	72.4
mlr204	-1,-1	1,5	mlr	3.2e-04	0.57	20	OSCAR42; OSCAR33329	0.25	1.87	2.39	0.90	0.94	33.4	81.0	102.9	141.9	89.8	80.0
mlr217	-1,-1	1,1	mlr	5.0e-04	0.54	20	OSCAR42; OSCAR33354	0.77	1.86	2.06	0.75	0.93	102.6	79.7	77.4	100.5	90.1	82.4
OSCAR116429	-1	5	scam_mpd	4.3e-04	0.62	20	u	0.23	1.92	2.41	0.91	0.96	30.0	84.5	104.3	144.5	90.8	131.2
OISST177437	-1	8	scam_mpi	4.3e-05	0.50	31	truetemp	0.55	1.92	2.28	0.79	0.96	73.6	85.1	94.4	111.3	91.1	105.7
mlr119	-1,0	1,1	mlr	3.1e-07	0.81	20	OSCAR42; OSCAR33330	1.07	1.72	1.92	0.72	0.86	142.4	67.7	66.7	92.8	92.4	38.6
mlr139	-1,-1	1,1	mlr	3.8e-05	0.66	20	OSCAR42; OSCAR33308	-0.57	2.14	2.57	0.69	1.07	75.7	103.6	116.6	82.8	94.7	67.7
mlr191	-1,-1	1,3	mlr	2.2e-04	0.58	20	OSCAR42; OSCAR33300	-0.99	1.96	2.52	0.56	0.98	131.2	88.3	113.3	46.9	94.9	70.1
OSCAR116432	-1	5	scam_mpd	8.0e-04	0.59	20	u	0.07	2.39	2.42	0.90	1.19	8.7	124.6	105.5	141.6	95.1	112.5
mlr162	-1,-1	1,6	mlr	9.7e-05	0.62	20	OSCAR42; OSCAR33358	-0.07	2.23	2.87	0.83	1.12	9.5	111.2	140.1	121.8	95.7	86.5
mlr203	-1,-1	1,5	mlr	3.1e-04	0.57	20	OSCAR42; OSCAR116430	-0.74	1.87	2.45	0.74	0.93	98.0	80.3	107.7	97.3	95.8	79.2
OSCAR116430	-1	5	scam_mpd	9.9e-04	0.60	20	u	-0.11	2.38	2.42	0.91	1.19	14.3	123.7	104.9	144.0	96.7	74.9
OSCAR116438	-1	8	scam_mpd	2.6e-03	0.54	20	u	0.10	2.14	2.49	0.96	1.07	12.9	103.8	110.6	160.1	96.8	115.9
mlr209	-1,-1	1,3	mlr	3.9e-04	0.56	20	OSCAR42; OSCAR33350	-0.77	2.06	2.40	0.71	1.03	102.5	97.0	103.3	89.5	98.1	76.7
OSCAR116443	-1	5	scam_mpd	5.1e-03	0.52	20	u	-0.02	2.47	2.49	0.93	1.23	2.2	131.0	110.9	149.8	98.5	125.7
mlr112	-1,0,-1	1,1,2	mlr	8.8e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33332	0.60	1.88	2.33	0.89	0.94	79.0	81.3	98.1	139.5	99.5	19.5
mlr214	-1,-1	1,1	mlr	4.6e-04	0.55	20	OSCAR42; OSCAR33345	-0.46	2.07	3.07	0.72	1.03	60.7	97.1	155.5	90.6	101.0	79.3
mlr212	-1,-1	1,1	mlr	4.4e-04	0.55	20	OSCAR42; OSCAR33321	0.60	2.13	2.40	0.82	1.06	79.2	102.5	103.6	119.0	101.1	87.0
OSCAR33345	-1	1	scam_mpi	2.2e-03	0.51	20	v	-0.25	2.39	2.57	0.86	1.20	33.0	124.8	116.9	130.7	101.4	129.0
median.all	0	0	median.all	NA			median.all	0.67	2.33	2.52	0.71	1.17	88.5	119.8	112.7	88.3	102.4	181.1
nepstar18	0,0,-1,-1,-1	4,5,7,3,7	mlr	2.0e-09	0.83	30	nepstar	-0.63	1.76	2.54	0.90	0.88	83.7	71.5	114.4	140.9	102.6	33.5
nepstar20	0,0,-1,-1,-1	4,5,3,7,7	mlr	6.3e-10	0.84	30	nepstar	-0.53	2.01	2.56	0.88	1.00	70.2	92.1	115.8	136.2	103.6	25.7
nepstar36	0,0,-1,-1,0,-1	4,5,7,5,4,7	mlr	1.9e-09	0.85	30	nepstar	-0.56	1.81	2.55	0.93	0.90	74.2	75.3	115.6	151.9	104.2	41.5
mlr128	-1,0	1,3	mlr	2.2e-05	0.68	20	OSCAR42; OISST177427	-0.35	2.38	2.50	0.90	1.19	46.7	123.7	111.6	141.0	105.8	71.2
nepstar17	0,-1,0,-1,-1	4,3,5,7,7	mlr	6.8e-09	0.81	30	nepstar	-0.64	1.66	2.62	0.94	0.83	84.9	62.8	121.2	154.7	105.9	31.2
mlr216	-1,-1	1,1	mlr	4.6e-04	0.55	20	OSCAR42; OSCAR33352	-0.50	2.14	3.14	0.73	1.07	66.6	103.3	161.1	93.4	106.1	79.6
nepstar3	0,0,-1,-1,-1	4,5,3,7,7	mlr	2.7e-10	0.86	30	nepstar	-0.63	1.95	2.54	0.89	0.98	83.6	87.6	114.2	139.8	106.3	25.6
mlr129	-1,0	1,3	mlr	2.2e-05	0.68	20	OSCAR42; OISST177418	-0.44	2.35	2.48	0.88	1.18	58.1	121.5	109.6	137.1	106.6	69.5

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
OSCAR33324	-1	1	scam_mpi	1.6e-03	0.54	20	v	1.19	1.99	2.09	0.77	0.99	157.6	90.5	79.9	105.2	108.3	116.1
mlr130	-1,0	1,4	mlr	2.5e-05	0.68	20	OSCAR42; OSCAR116447	-0.90	2.22	2.60	0.70	1.11	119.1	110.1	119.6	86.2	108.7	73.0
OSCAR116434	-1	8	scam_mpd	2.2e-04	0.59	20	u	-0.28	2.29	2.56	0.99	1.15	36.8	116.2	115.9	167.6	109.1	105.6
mlr133	-1,0	1,3	mlr	2.9e-05	0.67	20	OSCAR42; OISST177408	-0.24	2.45	2.62	0.95	1.23	31.3	129.9	121.1	156.3	109.7	69.5
mlr132	-1,0	1,3	mlr	2.8e-05	0.67	20	OSCAR42; OISST177411	-0.15	2.49	2.67	0.97	1.24	20.1	133.0	124.9	162.9	110.2	71.2
OSCAR116431	-1	8	scam_mpd	1.0e-04	0.60	20	u	0.25	2.45	2.59	0.97	1.22	32.6	129.4	118.3	163.2	110.9	117.9
OSCAR116444	0	4	scam_mpd	1.1e-04	0.52	21	u	0.92	1.70	2.41	0.93	0.85	122.8	66.6	104.4	150.7	111.1	71.8
OSCAR66549	0	4	lm	1.4e-04	0.52	21	u	0.92	1.70	2.41	0.93	0.85	122.8	66.6	104.4	150.7	111.1	71.8
mlr131	-1,0	1,4	mlr	2.6e-05	0.68	20	OSCAR42; OSCAR116437	-1.09	2.25	2.48	0.67	1.13	144.7	113.0	110.1	77.0	111.2	69.7
mlr211	-1,-1	1,12	mlr	4.3e-04	0.55	20	OSCAR42; OSCAR49925	0.44	2.33	2.65	0.91	1.17	57.7	119.7	123.2	146.3	111.7	89.2
mlr197	-1,-1	1,6	mlr	2.5e-04	0.58	20	OSCAR42; OSCAR116448	-0.50	2.35	2.94	0.81	1.18	65.9	121.5	145.5	117.8	112.7	77.7
OSCAR33302	-1	3	scam_mpi	1.4e-04	0.59	20	v	-0.93	1.97	2.33	0.90	0.99	123.7	89.2	97.9	141.9	113.2	77.7
OSCAR33296	-1	2	scam_mpi	5.4e-04	0.64	20	v	0.86	2.40	2.67	0.71	1.20	113.8	125.2	124.7	90.1	113.4	77.1
OSCAR33323	-1	1	scam_mpi	1.8e-03	0.54	20	v	0.90	2.08	2.37	0.88	1.04	119.7	98.1	101.5	136.1	113.8	95.0
OISST177416	-1	7	scam_mpi	7.7e-05	0.53	31	truetemp	0.95	2.10	2.43	0.85	1.05	126.2	100.4	105.8	128.2	115.2	109.0
mlr196	-1,-1	1,5	mlr	2.4e-04	0.58	20	OSCAR42; OSCAR33306	-0.30	2.52	2.97	0.89	1.26	40.2	135.6	148.2	139.3	115.8	80.7
OSCAR33352	-1	1	scam_mpi	3.2e-03	0.51	20	v	-0.11	2.67	2.83	0.98	1.34	14.6	148.7	137.1	163.8	116.1	124.7
mlr146	-1,0	1,6	mlr	5.1e-05	0.65	20	OSCAR42; OISST177423	-1.63	1.87	2.14	0.71	0.93	216.9	80.6	83.6	88.5	117.4	73.8
nepstar15	0,0,-1,-1,-1	4,5,7,3,7	mlr	5.8e-10	0.85	30	nepstar	-0.80	1.90	2.65	0.96	0.95	106.6	83.0	122.9	158.4	117.7	34.0
OSCAR44	-1	2	lm	2.0e-04	0.52	20	v	1.13	2.35	2.65	0.68	1.17	149.7	121.0	122.9	79.6	118.3	65.8
OSCAR33346	-1	3	scam_mpi	3.2e-03	0.51	20	v	0.80	2.33	2.55	0.88	1.17	106.5	120.0	115.5	136.1	119.5	122.7
nepstar22	0,-1,0,-1,-1	4,3,5,7,7	mlr	1.4e-09	0.83	30	nepstar	-0.87	1.80	2.69	0.99	0.90	115.7	74.7	126.0	166.7	120.8	30.1
OISST177418	0	3	scam_mpi	1.1e-05	0.53	32	truetemp	0.15	2.62	2.80	1.06	1.31	19.4	144.1	134.8	187.2	121.4	116.4
OSCAR33353	-1	4	scam_mpi	3.0e-03	0.51	20	v	0.76	2.33	2.54	0.93	1.16	100.5	119.4	114.9	151.0	121.4	94.6
mlr200	-1,-1	1,8	mlr	2.8e-04	0.57	20	OSCAR42; OSCAR116438	-0.71	2.41	3.38	0.70	1.21	94.6	126.6	179.8	86.8	121.9	86.6
mean.all	0	0	mean.all	NA			mean.all	1.03	2.39	2.68	0.75	1.20	136.7	125.0	125.7	101.4	122.2	157.1
mlr208	-1,-1	1,6	mlr	3.9e-04	0.56	20	OSCAR42; OSCAR116440	-0.19	2.38	3.20	1.02	1.19	24.7	123.4	166.1	175.3	122.4	82.2
mlr142	-1,0	1,3	mlr	4.1e-05	0.66	20	OSCAR42; OISST177430	0.17	2.56	2.88	1.07	1.28	22.9	139.3	141.0	190.8	123.5	72.5
nepstar31	0,0,-1,-1,-1	4,5,7,5,7	mlr	2.4e-09	0.83	30	nepstar	-0.77	1.85	2.78	1.04	0.92	101.7	78.7	133.1	180.7	123.5	37.5
mlr143	-1,0	1,5	mlr	4.1e-05	0.66	20	OSCAR42; lighthouse311951	-1.68	1.87	2.24	0.75	0.94	223.2	80.8	91.1	100.7	124.0	65.9
OSCAR49924	-1	6	scam_mpd	4.8e-04	0.53	20	v	0.88	2.40	2.51	0.91	1.20	117.2	125.7	112.4	144.5	124.9	115.6
mlr213	-1,-1	1,11	mlr	4.5e-04	0.55	20	OSCAR42; OSCAR33304	0.15	2.48	3.06	1.10	1.24	19.3	132.5	154.7	198.2	126.2	80.1
OSCAR33300	-1	3	scam_mpi	9.9e-05	0.60	20	v	-1.06	2.10	2.47	0.96	1.05	140.3	100.0	109.3	158.1	126.9	77.6
OISST177421	-1	7	scam_mpi	6.1e-05	0.53	31	truetemp	1.06	2.20	2.56	0.90	1.10	141.4	108.5	116.3	141.9	127.0	111.2
nepstar6	0,-1,0,-1	4,3,5,7	mlr	4.4e-10	0.83	30	nepstar	-1.13	1.82	2.60	0.98	0.91	149.6	76.4	119.3	165.6	127.7	27.1
mlr140	-1,0	1,3	mlr	4.0e-05	0.66	20	OSCAR42; OISST177436	0.26	2.57	2.92	1.10	1.28	33.8	139.7	144.1	197.0	128.7	73.7
mlr183	-1,-1	1,5	mlr	1.6e-04	0.60	20	OSCAR42; OSCAR33334	-0.70	2.63	3.16	0.80	1.32	92.6	145.2	163.1	113.8	128.7	76.2
mlr192	-1,-1	1,8	mlr	2.3e-04	0.58	20	OSCAR42; OSCAR116434	-0.87	2.49	3.32	0.72	1.24	115.1	132.7	175.4	91.6	128.7	81.2
OISST177417	0	6	scam_mpi	1.1e-05	0.53	32	truetemp	0.51	2.63	2.77	1.00	1.32	67.8	145.4	132.5	169.2	128.7	57.1
mlr150	-1,0	1,6	mlr	5.9e-05	0.64	20	OSCAR42; OISST177422	-1.80	1.94	2.26	0.74	0.97	239.7	86.8	92.5	98.1	129.3	74.0
OISST177427	0	3	scam_mpi	2.0e-05	0.51	32	truetemp	0.22	2.68	2.89	1.10	1.34	28.7	149.5	141.9	197.3	129.3	120.1
OISST177422	0	6	scam_mpi	1.8e-05	0.53	32	truetemp	0.60	2.63	2.77	1.00	1.31	79.9	144.8	132.7	169.3	131.7	62.4

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
mlr163	-1,0	1,2	mlr	1.0e-04	0.62	20	OSCAR42; OSCAR99806	0.40	2.30	3.05	1.14	1.15	53.0	116.7	153.9	209.1	133.2	71.7
OISST177415	0	6	scam_mpi	1.2e-05	0.54	32	truetemp	0.62	2.65	2.80	1.00	1.33	81.9	146.9	134.8	171.7	133.8	61.4
OISST177408	0	3	scam_mpi	2.7e-07	0.59	32	truetemp	0.20	2.77	2.96	1.13	1.38	26.2	156.4	147.4	205.5	133.9	198.6
OISST177423	0	6	scam_mpi	2.1e-05	0.52	32	truetemp	0.68	2.61	2.78	1.00	1.31	89.8	143.7	132.9	169.1	133.9	79.5
mlr137	-1,0	1,6	mlr	3.8e-05	0.66	20	OSCAR42; OISST177413	-1.86	1.96	2.30	0.77	0.98	247.3	88.0	95.7	106.7	134.4	70.7
OISST177433	0	6	scam_mpi	1.5e-05	0.51	32	truetemp	0.61	2.66	2.82	1.01	1.33	81.4	147.3	136.2	174.0	134.7	61.7
mlr195	-1,-1	1,8	mlr	2.4e-04	0.58	20	OSCAR42; OSCAR116433	-0.92	2.52	3.31	0.77	1.26	122.6	136.0	174.4	106.7	134.9	79.7
OSCAR33348	-1	5	scam_mpi	2.0e-04	0.51	20	v	0.89	2.50	2.71	0.96	1.25	118.5	134.3	127.6	159.6	135.0	220.9
OSCAR33341	-1	5	scam_mpi	1.7e-04	0.52	20	v	0.75	2.59	2.75	1.00	1.29	99.5	141.4	131.2	169.7	135.5	127.3
OISST177412	0	6	scam_mpi	9.7e-06	0.55	32	truetemp	0.71	2.62	2.79	1.00	1.31	94.8	144.4	134.0	169.5	135.7	56.6
OISST177413	0	6	scam_mpi	8.1e-06	0.54	32	truetemp	0.69	2.64	2.80	1.00	1.32	91.7	145.6	134.7	171.6	135.9	56.0
OISST177414	0	6	scam_mpi	3.2e-06	0.54	32	truetemp	0.80	2.58	2.78	0.99	1.29	106.7	140.9	133.0	168.1	137.2	57.2
OSCAR33309	-1	4	scam_mpi	1.3e-03	0.57	20	v	0.85	2.55	2.74	0.99	1.28	113.5	138.5	130.5	166.5	137.2	116.1
OSCAR33329	-1	5	scam_mpi	1.3e-04	0.53	20	v	1.17	2.30	2.66	0.94	1.15	155.7	117.0	124.2	152.9	137.4	113.0
OSCAR33331	-1	9	scam_mpi	1.4e-04	0.53	20	v	0.89	2.55	2.75	0.98	1.27	117.7	137.8	130.9	164.0	137.6	146.4
OSCAR116448	-1	6	scam_mpd	2.4e-03	0.51	20	u	0.67	2.66	2.83	1.03	1.33	88.8	147.7	136.7	177.7	137.7	112.3
OSCAR116442	-1	1	scam_mpd	6.8e-04	0.53	20	u	0.81	2.61	2.79	0.99	1.30	107.6	142.9	133.8	168.6	138.2	141.5
mlr205	-1,-1	1,1	mlr	3.3e-04	0.56	20	OSCAR42; OSCAR33355	1.15	2.20	2.63	1.00	1.10	153.3	108.3	121.8	169.7	138.3	81.2
lly	0	0	lly	NA			lly	0.33	2.67	3.56	1.00	1.33	44.1	148.1	193.8	170.3	139.1	121.5
OISST177411	0	3	scam_mpi	9.2e-06	0.55	32	truetemp	0.32	2.74	3.00	1.14	1.37	42.5	154.1	150.5	210.3	139.3	201.3
OISST177428	0	2	scam_mpi	2.5e-05	0.51	32	truetemp	0.85	2.60	2.81	1.00	1.30	113.1	142.3	135.8	169.1	140.1	91.3
OISST177434	0	2	scam_mpi	3.1e-05	0.51	32	truetemp	0.99	2.54	2.79	0.98	1.27	131.0	137.3	133.9	165.0	141.8	87.9
shore310799	0	5	scam_mpi	2.7e-04	0.52	26	temperature.c.	0.76	2.47	2.87	1.09	1.24	101.6	131.5	140.2	196.6	142.4	84.4
mlr176	-1,-1	1,5	mlr	1.4e-04	0.61	20	OSCAR42; OSCAR33314	-0.41	2.96	3.35	0.99	1.48	54.7	173.0	177.2	168.1	143.2	77.7
shore311951	0	5	scam_mpi	3.2e-05	0.59	26	temperature.c.	-1.08	2.24	2.77	1.05	1.12	143.3	112.0	132.1	185.3	143.2	75.6
OSCAR33310	-1	5	scam_mpi	2.5e-04	0.56	20	v	1.00	2.56	2.81	0.99	1.28	132.5	139.4	135.3	168.1	143.8	120.1
OSCAR33312	-1	5	scam_mpi	2.7e-04	0.56	20	v	1.30	2.35	2.68	0.94	1.18	173.4	121.7	125.6	154.7	143.9	130.3
OSCAR116433	-1	8	scam_mpd	1.7e-04	0.59	20	u	-0.41	2.83	3.01	1.14	1.42	54.2	162.1	151.3	209.3	144.2	111.9
OSCAR33311	-1	5	scam_mpi	6.3e-05	0.56	20	v	1.03	2.56	2.82	0.99	1.28	136.5	139.4	136.2	168.8	145.2	138.2
OSCAR33305	-1	5	scam_mpi	4.2e-05	0.58	20	v	1.02	2.61	2.85	0.99	1.31	136.1	143.3	138.5	167.4	146.3	118.9
mlr145	-1,0	1,6	mlr	4.9e-05	0.65	20	OSCAR42; OISST177417	-2.06	2.06	2.45	0.81	1.03	273.6	96.5	107.8	116.7	148.6	71.9
OISST177425	0	2	scam_mpi	5.0e-05	0.52	32	truetemp	1.03	2.59	2.89	1.03	1.29	137.3	141.3	141.6	180.0	150.1	87.5
OISST177435	0	2	scam_mpi	7.7e-05	0.50	32	truetemp	0.95	2.63	2.93	1.05	1.31	126.6	144.9	144.9	185.7	150.5	93.0
OSCAR33319	-1	5	scam_mpi	1.2e-03	0.55	20	v	1.04	2.65	2.91	1.02	1.32	138.4	146.6	143.5	174.6	150.8	119.4
OISST177426	0	2	scam_mpi	4.2e-05	0.51	32	truetemp	1.14	2.53	2.86	1.02	1.27	152.2	136.9	139.5	175.3	151.0	83.8
OSCAR33334	-1	5	scam_mpi	1.0e-03	0.52	20	v	0.61	2.75	3.08	1.17	1.37	80.5	154.9	156.3	216.6	152.1	83.7
OSCAR33350	-1	3	scam_mpi	2.1e-04	0.51	20	v	-1.27	2.33	2.75	1.07	1.16	169.3	119.4	131.0	188.6	152.1	80.9
OSCAR33351	-1	1	scam_mpi	8.1e-04	0.51	20	v	0.44	3.15	3.53	1.00	1.57	58.4	189.0	191.3	171.0	152.4	106.9
OSCAR33328	0	1	scam_mpi	2.0e-03	0.53	21	v	1.51	2.38	2.83	0.94	1.19	200.4	123.8	136.9	152.6	153.4	106.1
OSCAR45	-1	2	lm	2.2e-04	0.51	20	v	1.48	2.41	2.89	0.92	1.20	197.3	126.3	141.8	149.3	153.7	70.1
mlr173	-1,-1	1,9	mlr	1.3e-04	0.61	20	OSCAR42; OSCAR49923	-0.37	2.86	3.31	1.21	1.43	49.6	164.3	174.5	228.5	154.2	74.0
OSCAR116451	0	5	scam_mpd	5.9e-04	0.50	21	u	-0.35	2.57	3.35	1.29	1.28	46.9	139.8	177.8	252.1	154.2	101.4

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
OSCAR33358	-1	6	scam_mpi	2.9e-03	0.50	20	v	0.90	2.72	2.99	1.11	1.36	119.8	153.0	149.3	199.8	155.5	120.3
OSCAR33301	-1	2	scam_mpi	2.0e-04	0.60	20	v	1.10	2.56	3.05	1.05	1.28	146.7	138.9	153.9	183.0	155.6	92.1
OSCAR33306	-1	5	scam_mpi	4.2e-05	0.58	20	v	0.39	2.72	3.32	1.28	1.36	51.7	152.2	174.9	249.0	156.9	157.4
mlr178	-1,-1	1,8	mlr	1.4e-04	0.60	20	OSCAR42; OSCAR116436	-1.25	2.69	3.56	0.85	1.34	166.4	150.0	194.2	127.0	159.4	78.6
mlr135	-1,0	1,6	mlr	3.4e-05	0.67	20	OSCAR42; OISST177412	-2.15	2.15	2.57	0.87	1.08	286.0	104.3	116.6	134.0	160.2	68.9
OSCAR33320	0	1	scam_mpi	1.2e-03	0.55	21	v	1.70	2.38	2.72	0.97	1.19	225.5	124.1	128.8	162.4	160.2	115.2
OISST266111	0	6	scam_mpi	7.2e-06	0.51	32	winterdiff	1.30	2.55	2.96	1.06	1.28	172.5	138.5	147.5	185.9	161.1	64.5
mlr160	-1,0	1,2	mlr	8.3e-05	0.63	20	OSCAR42; OISST177429	0.90	2.37	3.23	1.24	1.19	120.1	123.2	167.9	237.4	162.2	78.1
OSCAR33327	0	1	scam_mpi	1.4e-03	0.53	21	v	1.75	2.47	2.77	0.94	1.23	233.2	131.3	132.5	153.5	162.6	111.2
OSCAR33333	0	1	scam_mpi	3.8e-04	0.52	21	v	1.32	2.65	3.04	1.02	1.32	174.9	146.5	153.7	176.5	162.9	82.5
OISST177430	0	3	scam_mpi	6.3e-05	0.51	32	truetemp	0.44	2.98	3.33	1.27	1.49	58.2	174.7	176.1	247.1	164.0	118.7
OISST177431	0	2	scam_mpi	1.3e-05	0.51	32	truetemp	1.32	2.56	2.99	1.08	1.28	175.7	139.0	149.8	191.3	164.0	75.4
OISST266113	0	6	scam_mpi	2.2e-06	0.50	32	winterdiff	1.32	2.59	3.00	1.07	1.29	175.0	141.2	150.6	190.1	164.2	86.6
OSCAR99803	-1	5	scam_mpi	4.8e-04	0.58	20	u	1.89	1.89	2.78	1.07	0.95	251.8	82.6	133.0	190.7	164.5	114.9
mlr169	-1,-1	1,8	mlr	1.2e-04	0.61	20	OSCAR42; OSCAR116431	-1.20	2.96	3.75	0.82	1.48	159.7	172.6	208.4	119.9	165.1	78.0
OSCAR116441	-1	5	scam_mpd	5.8e-02	0.53	20	u	1.46	2.59	3.12	0.99	1.29	194.3	141.4	159.7	167.5	165.7	112.1
mlr189	-1,-1	1,1	mlr	2.0e-04	0.59	20	OSCAR42; OSCAR33351	-0.46	2.82	3.42	1.32	1.41	61.2	160.8	182.6	258.8	165.9	77.2
mlr164	-1,0	1,4	mlr	1.0e-04	0.62	20	OSCAR42; OISST177424	-1.79	2.14	2.85	1.05	1.07	237.6	103.5	138.4	185.4	166.2	75.9
OISST177432	0	2	scam_mpi	1.1e-05	0.51	32	truetemp	1.28	2.62	3.06	1.11	1.31	169.6	143.8	155.0	200.4	167.2	82.3
OSCAR33326	0	5	scam_mpi	3.8e-04	0.54	21	v	0.90	2.90	3.18	1.17	1.45	120.2	167.6	164.2	218.1	167.5	84.0
OSCAR116436	-1	8	scam_mpd	2.6e-03	0.56	20	u	-1.04	2.95	3.18	1.10	1.48	138.2	172.3	164.2	197.5	168.0	112.5
OISST177436	0	3	scam_mpi	7.5e-05	0.50	32	truetemp	0.53	3.02	3.38	1.29	1.51	70.4	177.8	180.0	252.1	170.1	122.8
OSCAR33344	-1	2	scam_mpi	7.3e-04	0.51	20	v	0.84	3.01	3.47	1.14	1.51	111.8	177.4	186.7	208.1	171.0	85.8
OISST177424	0	4	scam_mpi	9.2e-05	0.52	32	truetemp	-0.96	2.59	3.30	1.26	1.29	127.1	141.5	173.8	244.0	171.6	100.5
OISST266112	0	6	scam_mpi	8.2e-06	0.51	32	winterdiff	1.39	2.64	3.10	1.11	1.32	184.2	145.8	158.2	201.9	172.5	100.3
OSCAR33321	-1	1	scam_mpi	2.2e-03	0.54	20	v	1.47	2.45	3.01	1.17	1.22	195.3	129.4	151.4	216.8	173.2	129.8
OISST177409	0	4	scam_mpi	1.3e-06	0.58	32	truetemp	-1.01	2.54	3.31	1.27	1.27	134.5	137.7	174.1	247.1	173.3	86.5
OSCAR33322	0	1	scam_mpi	1.4e-03	0.54	21	v	1.73	2.65	2.91	1.03	1.32	230.5	146.6	143.3	177.6	174.5	95.5
OISST177429	0	2	scam_mpi	1.3e-04	0.51	32	truetemp	0.65	2.75	3.52	1.36	1.38	86.2	155.4	190.7	270.3	175.7	116.4
OSCAR33360	0	1	scam_mpi	6.4e-04	0.50	21	v	1.33	2.92	3.27	1.06	1.46	176.6	169.1	171.2	187.2	176.0	84.0
OSCAR116439	-1	10	scam_mpd	1.4e-03	0.53	21	u	1.83	2.16	3.27	1.06	1.08	243.5	105.4	171.4	186.5	176.7	105.6
OSCAR33335	0	1	scam_mpi	1.7e-03	0.52	21	v	1.25	2.78	3.27	1.16	1.39	166.4	157.8	171.2	214.3	177.5	98.8
mlr144	-1,0	1,6	mlr	4.8e-05	0.65	20	OSCAR42; OISST177415	-2.37	2.37	2.76	0.90	1.19	315.4	123.0	131.4	142.2	178.0	71.0
mlr184	-1,0	1,4	mlr	1.7e-04	0.60	20	OSCAR42; OISST177420	-1.81	2.29	3.12	1.09	1.15	241.0	116.5	159.8	195.0	178.1	81.6
OSCAR33304	-1	11	scam_mpi	2.4e-05	0.58	21	v	0.95	2.95	3.32	1.25	1.48	125.7	172.2	175.4	240.9	178.6	86.7
OSCAR116440	-1	6	scam_mpd	2.5e-04	0.53	20	u	1.13	2.94	3.28	1.19	1.47	150.5	171.6	171.9	223.1	179.3	115.3
mlr166	-1,0	1,4	mlr	1.1e-04	0.62	20	OSCAR42; OISST177409	-1.89	2.24	3.11	1.16	1.12	251.0	112.2	158.7	214.0	184.0	78.8
OSCAR49923	-1	9	scam_mpd	7.6e-04	0.56	20	v	1.50	2.93	3.12	1.14	1.46	198.8	170.1	159.5	209.1	184.4	116.2
mlr136	-1,0	1,6	mlr	3.6e-05	0.66	20	OSCAR42; OISST177414	-2.41	2.41	2.84	0.95	1.20	320.2	126.1	137.9	157.2	185.3	68.8
mlr174	-1,0	1,4	mlr	1.3e-04	0.61	20	OSCAR42; OISST177410	-1.90	2.30	3.19	1.16	1.15	253.2	117.0	165.3	216.2	187.9	81.1
OSCAR33314	-1	5	scam_mpi	3.0e-04	0.56	20	v	1.24	2.90	3.39	1.25	1.45	164.9	167.4	180.6	241.3	188.6	135.8
OSCAR116435	-1	1	scam_mpd	2.5e-04	0.56	20	u	1.16	3.25	3.54	1.16	1.62	153.7	197.1	192.1	215.8	189.7	135.7

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
OISST177419	0	2	scam_mpi	1.1e-05	0.53	32	truetemp	0.57	3.00	3.77	1.45	1.50	76.1	176.2	209.9	296.9	189.8	167.6
OSCAR33342	0	1	scam_mpi	2.2e-03	0.52	21	v	1.73	2.91	3.49	1.06	1.45	230.5	168.3	188.6	187.8	193.8	85.8
mlr167	-1,0	1,2	mlr	1.1e-04	0.62	20	OSCAR42; OISST177419	1.25	2.59	3.61	1.40	1.29	166.2	141.5	198.0	281.2	196.7	77.9
OSCAR33347	0	1	scam_mpi	2.2e-03	0.51	21	v	1.97	2.84	3.12	1.13	1.42	261.7	163.1	159.8	205.6	197.6	120.7
OSCAR33356	0	1	scam_mpi	2.4e-03	0.50	21	v	1.51	2.89	3.47	1.24	1.44	200.6	166.8	187.0	237.7	198.0	95.9
mlr149	-1,0	1,6	mlr	5.7e-05	0.65	20	OSCAR42; OISST177433	-2.63	2.63	3.06	0.97	1.31	349.7	144.8	155.1	160.8	202.6	71.6
OSCAR33337	0	1	scam_mpi	2.0e-03	0.52	21	v	1.75	3.04	3.46	1.22	1.52	232.3	179.6	186.0	232.9	207.7	96.5
OSCAR33315	0	1	scam_mpi	9.6e-04	0.56	21	v	2.12	2.98	3.30	1.14	1.49	282.1	174.5	174.0	208.7	209.8	94.0
OSCAR99806	0	2	scam_mpi	2.3e-03	0.51	21	u	1.60	2.88	3.59	1.35	1.44	212.3	166.0	196.0	267.5	210.5	98.0
mlr138	-1,0	1,5	mlr	3.8e-05	0.66	20	OSCAR42; OSCAR33326	-0.91	3.11	4.07	1.47	1.55	121.5	185.5	233.5	302.0	210.6	68.5
OSCAR33338	0	1	scam_mpi	4.1e-04	0.52	21	v	1.52	3.12	3.71	1.30	1.56	202.3	186.4	205.4	255.1	212.3	93.1
OSCAR33355	-1	1	scam_mpi	1.8e-03	0.50	20	v	1.98	2.65	3.50	1.35	1.33	263.1	146.9	189.2	269.1	217.1	112.9
OSCAR49925	-1	12	scam_mpd	8.2e-04	0.50	21	v	2.16	2.59	3.48	1.30	1.29	286.8	141.5	187.8	254.5	217.7	123.5
OSCAR33340	-1	3	scam_mpi	2.0e-03	0.52	20	v	-2.39	3.13	3.59	1.03	1.56	318.1	187.0	196.5	179.9	220.4	95.4
OISST177420	0	4	scam_mpi	1.2e-05	0.53	32	truetemp	-1.26	2.70	4.10	1.59	1.35	167.3	151.2	236.2	334.8	222.4	95.8
median8	0	0	median8	NA			median8	2.67	2.83	3.64	1.02	1.42	354.7	162.2	200.1	176.7	223.4	130.4
OSCAR33330	0	1	scam_mpi	4.1e-04	0.53	21	v	2.21	3.23	3.53	1.24	1.61	294.5	195.4	191.2	238.6	229.9	92.8
OSCAR33359	0	1	scam_mpi	3.2e-03	0.50	21	v	2.06	3.48	4.11	1.16	1.74	274.2	217.0	236.7	216.1	236.0	101.9
mean8	0	0	mean8	NA			mean8	2.92	2.92	3.80	1.07	1.46	388.0	169.2	212.2	188.9	239.6	132.3
OISST177410	0	4	scam_mpi	2.8e-06	0.57	32	truetemp	-1.42	2.98	4.42	1.71	1.49	189.0	174.2	261.1	369.2	248.4	100.3
OSCAR33354	-1	1	scam_mpi	2.2e-03	0.51	20	v	2.52	3.16	3.91	1.47	1.58	335.3	189.5	221.0	302.8	262.2	116.1
median4	0	0	median4	NA			median4	1.33	5.00	5.24	1.47	2.50	177.2	345.7	324.9	302.7	287.6	150.7
OSCAR116445	0	5	scam_mpd	1.2e-04	0.52	21	u	-1.35	4.46	5.51	1.78	2.23	179.8	300.3	345.8	388.0	303.5	102.0
mean4	0	0	mean4	NA			mean4	2.50	5.50	6.06	1.70	2.75	332.5	388.0	388.0	366.5	368.8	152.7

Table 13. Performance results for all qualifying models used to forecast Early Stuart timing based on jackknife analysis. Each row represents a single model tested, some columns include: year adjust (year of environmental data same as return year [0] or prior year [-1]), month, summary statistics (P value, adjusted R squared, sample size), data name, data variables (which are sorted by their relative influence in the model). As the NEPSTAR regression models comprise more than one variable, only year-month of the latest variable is presented. Latitude and longtitude of NEPSTAR variables are excluded due to space limitations. The PMs include mean raw error, mean absolute error, root mean squared error, Thiel's U-statistic, and MASE. The initial three PMs are in day units, the latter two are unit-less. All PMs are described in the methods section. All PMs, except MASE, are given a rank. The best rank has a value of zero. The last rank equals total number of models (n). The average of the PM ranks by model (row) is included, as is the average rank for the alternate performance test method. The rows are sorted by average rank of performance method listed in caption. The first row is the best model, the last row is the worst.

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr7	-1,0,-1	1,1,5	mlr	1.2e-08	0.89	20	OSCAR42; OSCAR33359; OSCAR33310	0.01	1.17	1.55	0.32	0.31	0.6	0.0	5.5	9.4	3.8	40.3
mlr1	-1,0,-1	1,1,8	mlr	4.6e-10	0.93	20	OSCAR42; OSCAR33359; OISST177437	-0.12	1.19	1.37	0.27	0.32	17.3	1.8	0.0	2.4	5.4	8.7
mlr2	-1,0,-1	1,1,7	mlr	1.5e-09	0.92	20	OSCAR42; OSCAR33359; OISST177421	-0.15	1.19	1.38	0.25	0.32	21.0	1.4	0.1	0.0	5.6	24.7
mlr4	-1,0,-1	1,1,5	mlr	6.7e-09	0.90	20	OSCAR42; OSCAR33359; OSCAR33312	0.07	1.22	1.50	0.30	0.32	9.0	4.1	3.9	7.5	6.2	28.4
mlr8	-1,0,-1	1,1,5	mlr	1.4e-08	0.89	20	OSCAR42; OSCAR33359; OSCAR33311	0.05	1.20	1.59	0.32	0.32	6.1	2.3	6.6	10.1	6.3	40.9
mlr6	-1,0,-1	1,1,5	mlr	1.1e-08	0.90	20	OSCAR42; OSCAR33359; OSCAR33319	0.03	1.29	1.56	0.31	0.34	3.3	10.4	5.6	8.7	7.0	37.4
mlr3	-1,0,-1	1,1,7	mlr	2.1e-09	0.92	20	OSCAR42; OSCAR33359; OISST177416	-0.16	1.22	1.41	0.26	0.33	22.2	4.6	1.2	0.8	7.2	24.0
mlr5	-1,0,-1	1,1,5	mlr	8.6e-09	0.90	20	OSCAR42; OSCAR33359; OSCAR33348	0.04	1.30	1.52	0.31	0.35	5.9	11.5	4.5	8.1	7.5	55.9
mlr17	-1,0,-1	1,1,2	mlr	2.6e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR45	-0.09	1.30	1.58	0.31	0.35	12.1	11.4	6.3	8.1	9.5	47.3
nepstar14	0,-1,0,-1,0,-1	5,5,5,3,4,7	mlr	2.9e-10	0.87	30	nepstar	-0.09	1.29	1.74	0.36	0.34	11.9	10.2	11.2	16.0	12.3	119.5
mlr19	-1,0,-1	1,1,1	mlr	3.2e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33351	-0.10	1.35	1.69	0.33	0.36	13.2	15.7	9.7	11.2	12.4	64.4
nepstar5	0,-1,0,-1,0,-1	5,5,5,3,4,7	mlr	2.5e-10	0.87	30	nepstar	-0.12	1.29	1.79	0.37	0.34	16.4	10.6	12.6	17.3	14.2	119.4
mlr28	-1,0,-1	1,1,5	mlr	4.5e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33329	-0.14	1.32	1.75	0.35	0.35	19.8	13.0	11.5	13.4	14.4	63.2
mlr51	-1,0,-1	1,1,2	mlr	6.4e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33296	-0.09	1.42	1.76	0.34	0.38	12.8	21.8	11.6	12.8	14.7	63.5
mlr41	-1,0,-1	1,1,5	mlr	5.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33305	-0.13	1.37	1.77	0.35	0.36	17.9	17.3	12.0	13.6	15.2	68.5
mlr42	-1,0,-1	1,1,1	mlr	5.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33323	-0.08	1.48	1.75	0.34	0.39	11.2	27.0	11.5	13.0	15.7	71.6
nepstar8	0,-1,0,-1,0,-1	5,5,5,5,4,7	mlr	1.1e-10	0.88	30	nepstar	-0.14	1.33	1.78	0.37	0.35	20.0	14.0	12.3	16.9	15.8	81.8
mlr63	-1,0,-1	1,1,8	mlr	7.4e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116431	-0.10	1.46	1.78	0.35	0.39	13.5	25.2	12.3	13.3	16.1	70.0
nepstar2	0,-1,0,0,-1	5,5,5,4,7	mlr	5.6e-11	0.87	30	nepstar	-0.07	1.46	1.82	0.38	0.39	9.5	25.0	13.5	18.4	16.6	88.7
nepstar13	0,-1,0,-1,-1	5,5,5,3,7	mlr	1.8e-10	0.86	30	nepstar	-0.03	1.49	1.88	0.39	0.40	4.5	27.8	15.3	19.4	16.8	79.1
mlr46	-1,0,-1	1,1,6	mlr	5.9e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR49924	-0.16	1.41	1.76	0.34	0.38	22.4	20.9	11.6	12.7	16.9	73.6
mlr62	-1,0,-1	1,1,1	mlr	7.3e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33355	-0.08	1.50	1.85	0.36	0.40	10.8	28.6	14.4	15.0	17.2	75.2
mlr93	-1,0,0	1,1,4	mlr	8.5e-08	0.87	20	OSCAR42; OSCAR33359; OISST177420	-0.10	1.49	1.82	0.35	0.40	13.5	28.3	13.5	13.5	17.2	70.1
mlr94	-1,0,0	1,1,4	mlr	8.5e-08	0.87	20	OSCAR42; OSCAR33359; OISST177410	-0.10	1.49	1.81	0.35	0.40	14.5	27.7	13.2	13.4	17.2	69.9
mlr10	-1,0	1,1	mlr	9.3e-09	0.87	20	OSCAR42; OSCAR33359	-0.12	1.47	1.78	0.34	0.39	17.4	26.6	12.2	13.1	17.3	71.1
mlr33	-1,0,-1	1,1,5	mlr	5.1e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33314	-0.10	1.50	1.77	0.35	0.40	14.2	29.2	12.1	13.8	17.3	86.7
mlr87	-1,0,0	1,1,4	mlr	8.4e-08	0.87	20	OSCAR42; OSCAR33359; OISST177424	-0.14	1.45	1.80	0.34	0.39	19.1	24.5	12.8	12.9	17.3	62.6
mlr92	-1,0,0	1,1,4	mlr	8.5e-08	0.87	20	OSCAR42; OSCAR33359; OISST177409	-0.12	1.47	1.80	0.34	0.39	16.7	26.3	13.0	13.2	17.3	66.8
mlr56	-1,0,0	1,1,2	mlr	6.8e-08	0.87	20	OSCAR42; OSCAR33359; OISST177419	-0.06	1.54	1.85	0.36	0.41	8.0	32.3	14.4	15.4	17.5	74.7
mlr22	-1,0,0	1,1,1	mlr	3.7e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33335	-0.15	1.45	1.76	0.34	0.39	20.7	24.7	11.8	13.1	17.6	60.1
nepstar39	0,-1,0,-1,-1	5,3,5,7,7	mlr	2.7e-09	0.82	30	nepstar	0.01	1.54	1.93	0.40	0.41	1.4	32.6	16.8	21.1	18.0	89.6

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr20	-1,0,-1	1,1,5	mlr	3.6e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33334	-0.14	1.51	1.73	0.34	0.40	19.7	29.4	10.7	12.4	18.1	75.8
mlr23	-1,0,0	1,1,4	mlr	3.9e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR66549	-0.16	1.49	1.71	0.34	0.40	22.5	27.8	10.3	12.1	18.2	76.1
mlr50	-1,0,-1	1,1,5	mlr	6.3e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33306	-0.11	1.52	1.79	0.35	0.41	15.5	30.9	12.6	14.1	18.3	83.5
nepstar35	-1,0,-1,-2,-1,0	5,5,5,4,3,4	mlr	1.8e-09	0.85	30	nepstar	-0.12	1.37	1.96	0.41	0.36	16.1	17.2	17.7	22.1	18.3	110.5
nepstar12	0,-1,0,-1,0,-1	5,5,5,5,4,7	mlr	1.1e-10	0.88	30	nepstar	-0.16	1.38	1.84	0.38	0.37	22.3	18.5	14.2	18.8	18.4	85.7
mlr15	-1,0,-1	1,1,4	mlr	2.3e-08	0.89	20	OSCAR42; OSCAR33359; OSCAR33353	-0.21	1.47	1.67	0.32	0.39	29.3	26.0	9.0	9.6	18.5	63.4
mlr69	-1,0,0	1,1,5	mlr	7.7e-08	0.87	20	OSCAR42; OSCAR33359; lighthouse310799	-0.12	1.50	1.82	0.35	0.40	16.8	29.3	13.4	14.3	18.5	78.6
nepstar38	0,0,-1,-1,-1	5,5,3,7,7	mlr	1.1e-09	0.84	30	nepstar	-0.08	1.52	1.84	0.37	0.41	11.6	30.7	14.2	17.3	18.5	102.6
mlr74	-1,0,0	1,1,2	mlr	8.0e-08	0.87	20	OSCAR42; OSCAR33359; OISST177428	-0.15	1.48	1.80	0.35	0.40	21.6	27.5	12.9	13.5	18.9	71.9
mlr82	-1,0,0	1,1,2	mlr	8.3e-08	0.87	20	OSCAR42; OSCAR33359; OISST177434	-0.15	1.49	1.81	0.35	0.40	21.0	28.2	13.2	13.7	19.0	71.9
mlr107	-1,0,-1	1,1,1	mlr	8.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33345	-0.11	1.53	1.84	0.36	0.41	16.0	31.9	14.1	15.2	19.3	83.2
mlr112	-1,0,-1	1,1,2	mlr	8.8e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33332	-0.07	1.57	1.90	0.37	0.42	10.1	35.4	15.8	16.7	19.5	97.2
mlr13	-1,0,-1	1,1,3	mlr	2.3e-08	0.89	20	OSCAR42; OSCAR33359; OSCAR33302	-0.13	1.52	1.84	0.36	0.41	18.2	30.6	14.0	15.2	19.5	80.3
mlr24	-1,0,0	1,1,5	mlr	3.9e-08	0.88	20	OSCAR42; OSCAR33359; lighthouse311951	-0.17	1.51	1.75	0.34	0.40	24.1	29.4	11.5	13.2	19.5	52.0
mlr9	-1,0,0	1,1,1	mlr	1.5e-08	0.89	20	OSCAR42; OSCAR33359; OSCAR33322	-0.29	1.40	1.63	0.31	0.37	41.5	19.8	7.6	9.0	19.5	47.5
mlr70	-1,0,-1	1,1,6	mlr	7.9e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116448	-0.08	1.59	1.87	0.36	0.42	11.0	36.7	15.1	15.7	19.6	71.2
nepstar9	0,-1,-2,-1,0	5,5,4,3,4	mlr	1.3e-09	0.83	30	nepstar	-0.25	1.23	1.93	0.40	0.33	35.6	5.0	16.8	21.1	19.6	98.2
mlr75	-1,0,0	1,1,2	mlr	8.1e-08	0.87	20	OSCAR42; OSCAR33359; OISST177431	-0.11	1.55	1.85	0.36	0.41	15.0	33.8	14.4	15.6	19.7	73.7
mlr78	-1,0,0	1,1,2	mlr	8.2e-08	0.87	20	OSCAR42; OSCAR33359; OISST177429	-0.07	1.58	1.90	0.37	0.42	9.5	36.0	16.1	17.2	19.7	89.0
nepstar1	0,-1,0,0,-1	5,5,5,4,7	mlr	5.6e-11	0.87	30	nepstar	-0.09	1.52	1.90	0.40	0.40	11.9	30.3	16.0	20.8	19.7	93.3
mlr109	-1,0,0	1,1,2	mlr	8.7e-08	0.87	20	OSCAR42; OSCAR33359; OISST177425	-0.14	1.53	1.83	0.36	0.41	19.0	31.6	13.9	14.7	19.8	75.6
mlr115	-1,0,0	1,1,2	mlr	8.8e-08	0.87	20	OSCAR42; OSCAR33359; OISST177426	-0.13	1.54	1.84	0.36	0.41	18.1	32.1	14.0	14.8	19.8	74.8
nepstar25	0,0,-1,-1,-1	5,5,3,7,7	mlr	5.2e-10	0.85	30	nepstar	-0.14	1.50	1.83	0.37	0.40	19.5	29.0	13.7	17.0	19.8	98.3
mlr106	-1,0,0	1,1,2	mlr	8.7e-08	0.87	20	OSCAR42; OSCAR33359; OISST177435	-0.14	1.53	1.83	0.36	0.41	19.4	31.4	13.9	14.8	19.9	76.6
mlr89	-1,0,-1	1,1,1	mlr	8.4e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33352	-0.12	1.54	1.86	0.36	0.41	16.1	32.9	14.8	15.9	19.9	85.5
mlr38	-1,0,-1	1,1,5	mlr	5.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116443	-0.16	1.54	1.75	0.35	0.41	23.1	32.4	11.3	13.3	20.0	60.0
mlr86	-1,0,0	1,1,2	mlr	8.4e-08	0.87	20	OSCAR42; OSCAR33359; OISST177432	-0.12	1.55	1.85	0.36	0.41	16.4	33.7	14.6	15.7	20.1	75.9
mlr11	-1,0,-1	1,1,5	mlr	2.1e-08	0.89	20	OSCAR42; OSCAR33359; OSCAR99803	-0.26	1.46	1.68	0.32	0.39	37.1	25.2	9.3	9.1	20.2	71.8
mlr111	-1,0,-1	1,1,3	mlr	8.8e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33346	-0.15	1.53	1.85	0.36	0.41	20.6	31.2	14.3	14.7	20.2	75.1
mlr29	-1,0,-1	1,1,11	mlr	4.5e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33304	-0.10	1.60	1.87	0.36	0.43	13.3	37.5	15.0	15.6	20.3	55.6
mlr98	-1,0,0	1,1,5	mlr	8.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116451	-0.05	1.62	1.98	0.36	0.43	7.1	39.9	18.5	16.0	20.4	87.5
mlr65	-1,0,-1	1,1,10	mlr	7.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116439	-0.17	1.53	1.79	0.35	0.41	24.1	31.2	12.7	14.1	20.5	74.6
mlr67	-1,0,-1	1,1,6	mlr	7.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116440	-0.07	1.61	1.92	0.37	0.43	10.2	38.8	16.5	16.6	20.5	80.8
nepstar24	0,0,-1,-1,0,-1	5,5,5,3,4,7	mlr	3.5e-10	0.87	30	nepstar	-0.26	1.31	1.84	0.38	0.35	37.4	12.0	14.0	18.8	20.5	103.1
mlr34	-1,0,-1	1,1,5	mlr	5.2e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116430	-0.16	1.57	1.75	0.35	0.42	22.9	34.9	11.3	13.3	20.6	59.7
mlr35	-1,0,0	1,1,6	mlr	5.5e-08	0.87	20	OSCAR42; OSCAR33359; OISST177415	-0.18	1.47	1.85	0.36	0.39	25.7	26.6	14.3	15.9	20.6	75.8
mlr39	-1,0,0	1,1,6	mlr	5.6e-08	0.87	20	OSCAR42; OSCAR33359; OISST177417	-0.19	1.47	1.84	0.36	0.39	26.3	26.5	14.2	15.8	20.7	70.3
mlr59	-1,0,-1	1,1,9	mlr	7.2e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33331	-0.18	1.51	1.81	0.35	0.40	25.0	30.0	13.2	14.4	20.7	67.6
mlr85	-1,0,-1	1,1,1	mlr	8.3e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33321	-0.14	1.55	1.86	0.36	0.41	19.8	33.1	14.6	15.3	20.7	76.9
mlr72	-1,0,0	1,1,3	mlr	7.9e-08	0.87	20	OSCAR42; OSCAR33359; OISST177436	-0.12	1.57	1.88	0.37	0.42	16.2	35.2	15.3	16.5	20.8	76.5
mlr103	-1,0,0	1,1,5	mlr	8.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116445	-0.00	1.69	2.11	0.36	0.45	0.0	45.4	22.3	16.0	20.9	85.1
mlr36	-1,0,0	1,1,6	mlr	5.5e-08	0.87	20	OSCAR42; OSCAR33359; OISST177433	-0.18	1.48	1.86	0.37	0.40	25.3	27.4	14.6	16.2	20.9	80.7

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr45	-1,0,0	1,1,6	mlr	5.9e-08	0.87	20	OSCAR42; OSCAR33359; OISST177422	-0.19	1.48	1.85	0.36	0.39	26.7	26.8	14.4	15.9	20.9	66.4
mlr66	-1,0,0	1,1,2	mlr	7.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR99806	-0.12	1.57	1.88	0.37	0.42	16.6	35.3	15.3	16.7	21.0	91.0
nepstar30	0,-1,0,-1,0,-1	4,5,5,3,4,7	mlr	5.1e-10	0.86	30	nepstar	-0.06	1.46	2.13	0.45	0.39	8.6	25.0	22.8	27.6	21.0	144.3
mlr18	-1,0,-1	1,1,3	mlr	2.9e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33300	-0.16	1.53	1.86	0.36	0.41	22.5	31.4	14.6	15.8	21.1	79.4
mlr110	-1,0,-1	1,1,8	mlr	8.8e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116433	-0.16	1.54	1.85	0.36	0.41	22.6	32.5	14.3	15.3	21.2	75.7
mlr12	-1,0,0	1,1,1	mlr	2.2e-08	0.89	20	OSCAR42; OSCAR33359; OSCAR33315	-0.27	1.46	1.69	0.33	0.39	38.0	25.8	9.5	11.7	21.2	58.6
mlr43	-1,0,0	1,1,1	mlr	5.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33360	-0.20	1.50	1.82	0.35	0.40	28.4	28.5	13.6	14.5	21.2	57.5
mlr44	-1,0,0	1,1,6	mlr	5.7e-08	0.87	20	OSCAR42; OSCAR33359; OISST177412	-0.20	1.47	1.86	0.37	0.39	27.6	26.4	14.6	16.2	21.2	72.3
mlr57	-1,0,-1	1,1,5	mlr	6.9e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116432	-0.16	1.57	1.80	0.35	0.42	22.6	35.5	12.8	14.1	21.2	64.6
mlr88	-1,0,0	1,1,3	mlr	8.4e-08	0.87	20	OSCAR42; OSCAR33359; OISST177430	-0.13	1.57	1.89	0.37	0.42	17.7	35.1	15.6	16.8	21.3	78.8
mlr90	-1,0,-1	1,1,2	mlr	8.4e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33344	-0.08	1.60	1.96	0.38	0.43	11.3	37.5	17.6	18.8	21.3	91.3
mlr40	-1,0,0	1,1,6	mlr	5.7e-08	0.87	20	OSCAR42; OSCAR33359; OISST177414	-0.19	1.48	1.86	0.37	0.39	27.2	27.2	14.8	16.4	21.4	77.1
mlr47	-1,0,0	1,1,6	mlr	5.9e-08	0.87	20	OSCAR42; OSCAR33359; OISST177413	-0.20	1.47	1.86	0.37	0.39	28.2	26.7	14.7	16.2	21.4	67.0
mlr49	-1,0,-1	1,1,1	mlr	6.2e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33324	-0.13	1.60	1.85	0.36	0.43	18.1	37.9	14.3	15.7	21.5	76.0
mlr32	-1,0,0	1,1,4	mlr	4.9e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116437	-0.23	1.53	1.73	0.34	0.41	31.9	31.6	10.7	12.3	21.6	64.4
mlr37	-1,0,-1	1,1,4	mlr	5.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33309	-0.22	1.51	1.78	0.35	0.40	30.4	29.8	12.4	13.6	21.6	77.4
mlr55	-1,0,0	1,1,1	mlr	6.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33327	-0.16	1.58	1.83	0.36	0.42	21.8	36.1	13.7	14.9	21.6	77.2
mlr48	-1,0,0	1,1,6	mlr	6.1e-08	0.87	20	OSCAR42; OSCAR33359; OISST177423	-0.20	1.48	1.86	0.37	0.39	28.5	27.2	14.8	16.3	21.7	63.8
mlr31	-1,0,0	1,1,4	mlr	4.8e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116447	-0.22	1.54	1.74	0.34	0.41	31.2	32.1	11.2	12.6	21.8	66.9
mlr54	-1,0,0	1,1,6	mlr	6.6e-08	0.87	20	OSCAR42; OSCAR33359; OISST266112	-0.17	1.55	1.86	0.36	0.41	24.4	33.4	14.9	15.0	21.9	79.3
mlr95	-1,0,0	1,1,3	mlr	8.5e-08	0.87	20	OSCAR42; OSCAR33359; OISST177427	-0.18	1.54	1.87	0.36	0.41	24.6	32.7	14.9	15.9	22.0	77.4
mlr97	-1,0,0	1,1,1	mlr	8.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33356	-0.15	1.57	1.89	0.37	0.42	20.4	35.2	15.6	16.8	22.0	82.8
mlr114	-1,0,-1	1,1,8	mlr	8.8e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116436	-0.17	1.55	1.87	0.36	0.41	24.1	33.6	14.9	16.0	22.1	80.6
mlr16	-1,0	1,1	mlr	1.1e-08	0.87	20	OSCAR42; OSCAR33315	-0.35	1.34	1.68	0.35	0.36	50.2	15.2	9.3	13.7	22.1	55.0
mlr68	-1,0,0	1,1,1	mlr	7.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33337	-0.18	1.55	1.88	0.36	0.41	24.8	33.0	15.3	15.4	22.1	69.1
mlr71	-1,0,-1	1,1,1	mlr	7.9e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116435	-0.15	1.56	1.90	0.37	0.42	20.7	34.4	16.0	17.3	22.1	87.0
mlr81	-1,0,0	1,1,3	mlr	8.3e-08	0.87	20	OSCAR42; OSCAR33359; OISST177418	-0.19	1.53	1.86	0.36	0.41	26.2	31.7	14.6	15.7	22.1	76.0
mlr84	-1,0,0	1,1,6	mlr	8.3e-08	0.87	20	OSCAR42; OSCAR33359; OISST266111	-0.13	1.59	1.93	0.36	0.42	18.6	36.8	16.9	16.0	22.1	78.3
mlr113	-1,0,0	1,1,3	mlr	8.8e-08	0.87	20	OSCAR42; OSCAR33359; OISST177411	-0.16	1.57	1.89	0.37	0.42	21.8	34.8	15.5	16.7	22.2	79.8
mlr73	-1,0,0	1,1,6	mlr	8.0e-08	0.87	20	OSCAR42; OSCAR33359; OISST266113	-0.15	1.58	1.92	0.36	0.42	21.3	35.7	16.4	15.8	22.3	76.4
mlr102	-1,0,-1	1,1,8	mlr	8.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116434	-0.19	1.55	1.84	0.36	0.41	27.2	33.1	14.2	15.3	22.4	75.6
mlr100	-1,0,-1	1,1,5	mlr	8.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116441	-0.16	1.57	1.89	0.37	0.42	22.3	35.3	15.5	16.8	22.5	75.0
mlr104	-1,0,0	1,1,3	mlr	8.7e-08	0.87	20	OSCAR42; OSCAR33359; OISST177408	-0.17	1.56	1.88	0.37	0.42	23.6	34.3	15.4	16.6	22.5	79.6
mlr27	-1,0,0	1,1,1	mlr	4.4e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33328	-0.23	1.54	1.77	0.34	0.41	32.9	32.2	12.0	13.2	22.6	69.5
mlr21	-1,0	1,1	mlr	1.7e-08	0.86	20	OSCAR42; OSCAR33342	-0.16	1.57	1.89	0.37	0.42	22.9	35.3	15.6	17.0	22.7	53.0
mlr83	-1,0,-1	1,1,1	mlr	8.3e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR43	-0.14	1.61	1.90	0.37	0.43	19.6	38.7	15.8	16.8	22.7	73.2
mlr76	-1,0,0	1,1,1	mlr	8.1e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33338	-0.15	1.59	1.92	0.37	0.42	21.7	36.8	16.4	16.9	22.9	71.6
mlr14	-1,0	1,1	mlr	1.0e-08	0.87	20	OSCAR42; OSCAR33335	-0.22	1.53	1.82	0.37	0.41	31.7	31.2	13.4	16.2	23.1	60.6
mlr96	-1,0,-1	1,1,9	mlr	8.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR49923	-0.13	1.60	1.97	0.38	0.43	18.7	37.8	18.0	18.8	23.3	103.1
mlr108	-1,0,0	1,1,1	mlr	8.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33342	-0.13	1.62	1.96	0.39	0.43	18.3	39.7	17.8	19.1	23.7	96.8
mlr60	-1,0,-1	1,1,5	mlr	7.3e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116429	-0.20	1.58	1.86	0.36	0.42	27.6	36.4	14.7	16.0	23.7	73.8
mlr77	-1,0,-1	1,1,5	mlr	8.2e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33341	-0.17	1.58	1.93	0.38	0.42	24.0	36.1	16.8	18.0	23.7	80.7

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
nepstar41	0,-1,0,0,-1,-1	4,3,5,4,7,7	mlr	9.6e-10	0.86	30	nepstar	-0.04	1.61	2.14	0.44	0.43	5.5	38.9	23.1	27.4	23.7	119.2
mlr64	-1,0,-1	1,1,1	mlr	7.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116442	-0.18	1.58	1.92	0.38	0.42	25.2	35.7	16.5	17.7	23.8	80.8
mlr105	-1,0,0	1,1,1	mlr	8.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33330	-0.18	1.59	1.94	0.37	0.42	24.8	36.8	17.1	17.2	24.0	75.9
mlr25	-1,0,-1	1,1,3	mlr	4.0e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33350	-0.18	1.60	1.89	0.37	0.43	25.9	37.7	15.7	16.6	24.0	92.8
mlr61	-1,0,0	1,1,1	mlr	7.3e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33347	-0.20	1.59	1.86	0.36	0.43	28.5	37.2	14.6	15.6	24.0	75.4
mlr91	-1,0,0	1,1,1	mlr	8.5e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33333	-0.19	1.58	1.91	0.37	0.42	26.5	36.2	16.2	17.3	24.0	77.8
mlr53	-1,0,-1	1,1,1	mlr	6.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33308	-0.17	1.62	1.90	0.37	0.43	24.5	39.3	15.8	16.9	24.1	80.2
mlr80	-1,0,-1	1,1,8	mlr	8.2e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116438	-0.22	1.57	1.85	0.36	0.42	31.1	35.5	14.3	15.5	24.1	78.0
mlr58	-1,0,0	1,1,5	mlr	7.0e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33326	-0.22	1.58	1.89	0.37	0.42	31.5	35.5	15.5	16.5	24.8	99.1
nepstar33	0,0,-1,-1,0,-1	4,5,5,3,4,7	mlr	3.9e-10	0.87	30	nepstar	-0.22	1.41	2.10	0.44	0.38	31.1	21.0	21.8	26.5	25.1	121.5
mlr26	-1,0,-1	1,1,3	mlr	4.0e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33340	-0.21	1.60	1.92	0.37	0.43	29.8	37.6	16.4	17.5	25.3	85.7
mlr99	-1,0,-1	1,1,12	mlr	8.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR49925	-0.19	1.60	1.99	0.38	0.43	26.4	37.9	18.5	18.4	25.3	71.2
nepstar21	0,0,-1,-1,0,-1	4,5,5,3,4,7	mlr	2.3e-10	0.87	30	nepstar	-0.25	1.41	2.05	0.43	0.38	34.7	21.4	20.3	24.9	25.3	111.0
nepstar3	0,0,-1,-1,-1	4,5,3,7,7	mlr	2.7e-10	0.86	30	nepstar	-0.16	1.52	2.11	0.44	0.41	22.3	31.1	22.2	26.9	25.6	129.5
nepstar20	0,0,-1,-1,-1	4,5,3,7,7	mlr	6.3e-10	0.84	30	nepstar	-0.11	1.55	2.20	0.46	0.41	15.5	33.0	24.9	29.3	25.7	128.3
mlr101	-1,0,-1	1,1,1	mlr	8.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33354	-0.22	1.60	1.93	0.38	0.43	31.0	38.0	16.7	18.0	25.9	85.2
nepstar29	-1,-1,-2,-1	5,5,4,3	mlr	1.4e-08	0.78	30	nepstar	-0.19	1.55	2.05	0.43	0.41	26.4	33.4	20.5	25.3	26.4	109.9
mlr30	-1,0,0	1,1,1	mlr	4.7e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33320	-0.26	1.64	1.83	0.35	0.44	36.7	41.2	13.8	14.4	26.5	67.6
nepstar6	0,-1,0,-1	4,3,5,7	mlr	4.4e-10	0.83	30	nepstar	-0.10	1.56	2.28	0.48	0.42	14.1	34.6	27.5	32.0	27.1	131.5
nepstar34	-1,0,-1,-1,-1,0	5,5,7,5,3,4	mlr	4.0e-09	0.84	30	nepstar	-0.23	1.50	2.06	0.43	0.40	32.9	29.3	20.9	25.7	27.2	90.5
nepstar32	0,-1,0,0,-1	4,3,5,4,7	mlr	1.0e-09	0.84	30	nepstar	-0.01	1.70	2.32	0.48	0.45	0.9	46.6	28.6	33.1	27.3	128.5
nepstar4	0,0,-1,0,-1	4,5,3,4,7	mlr	2.7e-10	0.86	30	nepstar	-0.18	1.52	2.20	0.46	0.41	25.4	30.9	24.9	29.7	27.7	136.6
mlr52	-1,0	1,1	mlr	3.1e-08	0.85	20	OSCAR42; OSCAR33322	-0.46	1.39	1.73	0.36	0.37	65.8	19.7	10.9	14.9	27.8	52.9
mlr79	-1,0,-1	1,1,6	mlr	8.2e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33358	-0.26	1.63	1.96	0.39	0.44	36.2	40.6	17.8	19.0	28.4	76.3
nepstar16	0,0,-1,0,-1	4,5,5,4,7	mlr	2.4e-10	0.86	30	nepstar	-0.23	1.51	2.21	0.45	0.40	32.0	29.5	25.1	28.2	28.7	129.5
nepstar19	0,0,-1,0,-1	4,5,5,4,7	mlr	4.6e-10	0.85	30	nepstar	-0.19	1.51	2.27	0.47	0.40	27.0	29.9	27.2	30.8	28.7	144.0
nepstar22	0,-1,0,-1,-1	4,3,5,7,7	mlr	1.4e-09	0.83	30	nepstar	-0.13	1.62	2.34	0.49	0.43	17.7	39.3	29.3	34.0	30.1	135.5
nepstar17	0,-1,0,-1,-1	4,3,5,7,7	mlr	6.8e-09	0.81	30	nepstar	-0.12	1.60	2.46	0.52	0.43	16.1	37.9	32.9	37.7	31.2	133.7
nepstar37	0,-1,0,-1,-2,0	5,5,5,5,4,4	mlr	1.4e-09	0.85	30	nepstar	-0.34	1.55	2.08	0.43	0.41	47.8	33.1	21.3	24.7	31.7	114.0
mlr116	-1,0	1,1	mlr	8.8e-08	0.83	20	OSCAR42; OSCAR33356	-0.20	1.77	2.11	0.43	0.47	27.5	52.8	22.2	25.8	32.1	75.5
nepstar18	0,0,-1,-1,-1	4,5,7,3,7	mlr	2.0e-09	0.83	30	nepstar	-0.35	1.48	2.26	0.47	0.39	49.1	26.9	26.7	31.4	33.5	122.8
nepstar23	0,0,-1,-1,-1	5,5,7,3,7	mlr	1.1e-09	0.84	30	nepstar	-0.39	1.61	1.97	0.41	0.43	55.2	38.9	18.0	22.1	33.5	95.2
nepstar15	0,0,-1,-1,-1	4,5,7,3,7	mlr	5.8e-10	0.85	30	nepstar	-0.36	1.52	2.19	0.46	0.41	51.2	30.9	24.5	29.3	34.0	136.1
nepstar40	0,-1,0,-1,-2,0	5,5,5,5,4,4	mlr	1.8e-09	0.85	30	nepstar	-0.35	1.62	2.12	0.43	0.43	49.1	39.6	22.5	25.9	34.3	114.9
nepstar26	0,0,0,0,-1	5,4,5,4,7	mlr	5.4e-10	0.85	30	nepstar	-0.29	1.67	2.26	0.47	0.45	41.7	44.1	26.7	31.3	36.0	148.2
nepstar27	0,-1,0,-1,-1,0	5,5,5,7,5,4	mlr	2.0e-09	0.85	30	nepstar	-0.44	1.58	2.06	0.43	0.42	63.0	35.6	20.9	25.3	36.2	93.5
mlr121	-1,0	1,1	mlr	5.2e-07	0.80	20	OSCAR42; OSCAR33333	-0.30	1.78	2.20	0.44	0.47	42.6	53.1	25.0	27.0	36.9	51.1
nepstar10	0,0,0,0,-1	5,4,5,4,7	mlr	4.9e-10	0.85	30	nepstar	-0.31	1.70	2.28	0.48	0.45	44.1	46.6	27.3	32.0	37.5	148.8
nepstar31	0,0,-1,-1,-1	4,5,7,5,7	mlr	2.4e-09	0.83	30	nepstar	-0.29	1.62	2.45	0.51	0.43	41.1	39.6	32.5	36.8	37.5	147.3
mlr119	-1,0	1,1	mlr	3.1e-07	0.81	20	OSCAR42; OSCAR33330	-0.27	1.83	2.27	0.48	0.49	38.0	57.5	27.1	31.9	38.6	113.3
mlr120	-1,0	1,1	mlr	3.8e-07	0.80	20	OSCAR42; OSCAR33337	-0.22	1.92	2.28	0.47	0.51	30.4	65.4	27.4	31.6	38.7	98.4
mlr118	-1,0	1,1	mlr	2.8e-07	0.81	20	OSCAR42; OSCAR33320	-0.45	1.69	2.11	0.43	0.45	64.2	45.2	22.4	24.9	39.2	67.8

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr117	-1,0	1,1	mlr	2.7e-07	0.81	20	OSCAR42; OSCAR33360	-0.42	1.72	2.14	0.44	0.46	59.9	48.5	23.3	26.7	39.6	34.5
nepstar36	0,0,-1,-1,0,-1	4,5,7,5,4,7	mlr	1.9e-09	0.85	30	nepstar	-0.46	1.60	2.37	0.49	0.43	64.9	37.9	30.0	33.2	41.5	135.7
nepstar7	0,0,-1,-1	5,5,7,7	mlr	1.2e-09	0.82	30	nepstar	-0.32	1.89	2.29	0.48	0.51	44.8	63.6	27.7	32.3	42.1	130.5
mlr122	-1,0	1,1	mlr	5.2e-07	0.80	20	OSCAR42; OSCAR33338	-0.41	1.82	2.20	0.46	0.48	58.2	56.7	25.1	29.4	42.3	106.3
nepstar28	0,0,-1,-1,0	4,5,7,5,4	mlr	1.2e-09	0.84	30	nepstar	-0.51	1.63	2.34	0.48	0.43	72.5	40.4	29.3	32.0	43.5	106.2
nepstar11	0,0,-1,-1	5,5,7,7	mlr	1.1e-09	0.82	30	nepstar	-0.35	1.91	2.33	0.49	0.51	49.5	64.7	28.9	33.5	44.1	128.7
mlr127	-1,-1	1,2	mlr	1.3e-05	0.70	20	OSCAR42; OSCAR45	-0.14	2.07	2.67	0.56	0.55	19.5	78.6	39.1	43.4	45.1	62.7
mlr123	-1,0	1,1	mlr	9.9e-07	0.78	20	OSCAR42; OSCAR33347	-0.39	1.93	2.33	0.48	0.51	55.6	66.3	28.8	32.3	45.8	87.3
mlr141	-1,-1	1,2	mlr	4.1e-05	0.66	20	OSCAR42; OSCAR33296	-0.16	1.99	2.84	0.60	0.53	21.8	71.8	44.2	48.7	46.6	26.4
mlr125	-1,0	1,1	mlr	8.0e-06	0.72	20	OSCAR42; OSCAR33328	-0.57	1.65	2.37	0.50	0.44	81.7	42.2	30.2	34.9	47.3	87.6
mlr124	-1,0	1,1	mlr	4.0e-06	0.74	20	OSCAR42; OSCAR33327	-0.54	1.76	2.31	0.48	0.47	76.9	51.7	28.4	33.0	47.5	94.6
OISST177413	0	6	scam_mpi	8.1e-06	0.54	32	truetemp	0.28	2.31	2.77	0.55	0.61	39.8	99.6	42.3	42.2	56.0	190.9
OISST177412	0	6	scam_mpi	9.7e-06	0.55	32	truetemp	0.18	2.42	2.88	0.57	0.65	26.0	109.6	45.4	45.5	56.6	194.4
OISST177417	0	6	scam_mpi	1.1e-05	0.53	32	truetemp	0.25	2.37	2.82	0.56	0.63	35.6	105.2	43.6	43.9	57.1	189.6
OISST177414	0	6	scam_mpi	3.2e-06	0.54	32	truetemp	0.20	2.43	2.87	0.57	0.65	28.4	110.2	45.1	45.2	57.2	189.4
mlr179	-1,-1	1,2	mlr	1.5e-04	0.60	20	OSCAR42; OSCAR33344	-0.18	2.28	3.23	0.68	0.61	26.0	97.4	55.9	60.3	59.9	58.4
OISST177415	0	6	scam_mpi	1.2e-05	0.54	32	truetemp	0.30	2.45	2.88	0.57	0.65	42.4	111.9	45.5	45.8	61.4	192.7
OISST177433	0	6	scam_mpi	1.5e-05	0.51	32	truetemp	0.36	2.39	2.83	0.56	0.64	51.5	107.3	43.9	44.2	61.7	189.2
OISST177422	0	6	scam_mpi	1.8e-05	0.53	32	truetemp	0.44	2.32	2.81	0.56	0.62	62.5	100.6	43.3	43.4	62.4	188.6
mlr126	-1,0	1,4	mlr	9.2e-06	0.71	20	OSCAR42; OSCAR66549	-0.32	2.35	2.99	0.62	0.63	44.9	103.7	48.6	52.9	62.6	127.8
mlr148	-1,-1	1,3	mlr	5.6e-05	0.65	20	OSCAR42; OSCAR33346	-0.46	2.26	2.82	0.59	0.60	65.8	95.7	43.6	47.3	63.1	103.2
mlr188	-1,-1	1,2	mlr	2.0e-04	0.59	20	OSCAR42; OSCAR33332	-0.21	2.32	3.34	0.70	0.62	29.3	101.1	59.3	63.7	63.4	2.4
mlr134	-1,-1	1,5	mlr	3.1e-05	0.67	20	OSCAR42; OSCAR99803	-0.42	2.28	2.95	0.62	0.61	60.3	97.7	47.7	52.2	64.5	128.2
OISST266111	0	6	scam_mpi	7.2e-06	0.51	32	winterdiff	-0.03	2.76	3.26	0.66	0.74	3.6	139.9	56.9	57.6	64.5	221.3
OSCAR44	-1	2	lm	2.0e-04	0.52	20	v	-0.17	2.54	3.27	0.69	0.68	24.5	119.8	57.3	61.6	65.8	184.5
mlr143	-1,0	1,5	mlr	4.1e-05	0.66	20	OSCAR42; lighthouse311951	-0.40	2.35	3.02	0.63	0.63	56.2	103.8	49.8	53.9	65.9	137.1
mlr147	-1,-1	1,1	mlr	5.2e-05	0.65	20	OSCAR42; OSCAR33324	-0.20	2.46	3.34	0.70	0.66	28.7	113.1	59.3	63.5	66.2	91.2
mlr187	-1,-1	1,3	mlr	2.0e-04	0.59	20	OSCAR42; OSCAR33302	-0.17	2.45	3.50	0.73	0.65	24.3	112.1	64.2	68.3	67.2	111.6
mlr161	-1,-1	1,5	mlr	8.4e-05	0.63	20	OSCAR42; OSCAR33348	-0.04	2.79	3.38	0.69	0.74	5.1	142.2	60.4	61.8	67.4	136.3
mlr139	-1,-1	1,1	mlr	3.8e-05	0.66	20	OSCAR42; OSCAR33308	-0.19	2.60	3.27	0.69	0.69	26.7	125.4	57.2	61.6	67.7	129.7
mlr155	-1,0	1,2	mlr	6.8e-05	0.64	20	OSCAR42; OISST177434	-0.46	2.34	3.01	0.63	0.62	65.7	102.2	49.2	53.6	67.7	86.7
mlr138	-1,0	1,5	mlr	3.8e-05	0.66	20	OSCAR42; OSCAR33326	-0.33	2.37	3.31	0.69	0.63	47.2	105.5	58.4	62.8	68.5	266.1
mlr136	-1,0	1,6	mlr	3.6e-05	0.66	20	OSCAR42; OISST177414	-0.37	2.50	3.07	0.64	0.67	52.0	116.4	51.3	55.6	68.8	170.3
mlr198	-1,0	1,5	mlr	2.5e-04	0.58	20	OSCAR42; OSCAR116451	-0.13	2.65	3.44	0.71	0.71	17.9	130.1	62.4	64.8	68.8	112.4
mlr135	-1,0	1,6	mlr	3.4e-05	0.67	20	OSCAR42; OISST177412	-0.39	2.48	3.05	0.64	0.66	54.8	115.2	50.7	55.0	68.9	154.3
mlr129	-1,0	1,3	mlr	2.2e-05	0.68	20	OSCAR42; OISST177418	-0.53	2.38	2.89	0.61	0.64	75.5	106.5	45.7	50.2	69.5	149.5
mlr133	-1,0	1,3	mlr	2.9e-05	0.67	20	OSCAR42; OISST177408	-0.48	2.40	2.99	0.63	0.64	68.4	107.7	48.6	53.1	69.5	156.3
mlr151	-1,-1	1,5	mlr	6.2e-05	0.64	20	OSCAR42; OSCAR33312	-0.04	2.88	3.38	0.69	0.77	4.8	150.1	60.5	62.3	69.5	92.4
mlr152	-1,0	1,2	mlr	6.4e-05	0.64	20	OSCAR42; OISST177428	-0.48	2.38	3.01	0.63	0.63	68.6	106.0	49.5	53.9	69.5	88.2
mlr131	-1,0	1,4	mlr	2.6e-05	0.68	20	OSCAR42; OSCAR116437	-0.45	2.44	3.01	0.63	0.65	64.1	111.5	49.4	53.7	69.7	135.9
mlr157	-1,0	1,2	mlr	7.3e-05	0.64	20	OSCAR42; OISST177426	-0.45	2.40	3.07	0.64	0.64	64.0	108.2	51.3	55.6	69.8	101.3
mlr168	-1,-1	1,7	mlr	1.2e-04	0.61	20	OSCAR42; OISST177416	-0.35	2.41	3.32	0.70	0.64	49.6	108.5	58.7	62.9	69.9	56.3

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr191	-1,-1	1,3	mlr	2.2e-04	0.58	20	OSCAR42; OSCAR33300	-0.21	2.51	3.50	0.73	0.67	30.0	117.9	64.2	68.3	70.1	133.9
OSCAR45	-1	2	lm	2.2e-04	0.51	20	v	-0.08	2.76	3.46	0.72	0.74	11.5	139.7	62.9	66.5	70.1	210.0
mlr171	-1,-1	1,7	mlr	1.3e-04	0.61	20	OSCAR42; OISST177421	-0.33	2.45	3.33	0.70	0.65	46.3	112.6	59.0	63.2	70.3	61.4
OSCAR43	-1	1	lm	1.4e-04	0.54	20	v	-0.30	2.45	3.41	0.72	0.65	42.1	112.7	61.4	65.7	70.5	99.9
mlr137	-1,0	1,6	mlr	3.8e-05	0.66	20	OSCAR42; OISST177413	-0.41	2.51	3.08	0.65	0.67	57.5	117.8	51.5	55.8	70.7	137.0
OSCAR33325	-1	1	scam_mpi	1.1e-04	0.54	20	v	-0.26	2.50	3.47	0.73	0.67	36.1	116.3	63.3	67.7	70.9	99.9
mlr144	-1,0	1,6	mlr	4.8e-05	0.65	20	OSCAR42; OISST177415	-0.36	2.56	3.13	0.66	0.68	51.6	122.2	53.1	57.3	71.0	162.4
mlr206	-1,0	1,5	mlr	3.5e-04	0.56	20	OSCAR42; OSCAR116445	-0.12	2.71	3.52	0.72	0.72	17.2	134.8	64.8	67.0	71.0	103.2
mlr128	-1,0	1,3	mlr	2.2e-05	0.68	20	OSCAR42; OISST177427	-0.53	2.44	2.92	0.61	0.65	75.5	111.6	46.7	51.1	71.2	150.1
mlr132	-1,0	1,3	mlr	2.8e-05	0.67	20	OSCAR42; OISST177411	-0.48	2.45	3.02	0.63	0.65	68.7	112.1	49.7	54.1	71.2	158.4
mlr175	-1,-1	1,10	mlr	1.4e-04	0.61	20	OSCAR42; OSCAR116439	-0.43	2.40	3.24	0.68	0.64	61.1	108.1	56.3	60.2	71.5	102.1
mlr149	-1,0	1,6	mlr	5.7e-05	0.65	20	OSCAR42; OISST177433	-0.34	2.59	3.17	0.66	0.69	48.9	124.9	54.3	58.5	71.6	176.9
mlr154	-1,0	1,2	mlr	6.5e-05	0.64	20	OSCAR42; OISST177425	-0.47	2.45	3.08	0.64	0.65	66.8	112.4	51.4	55.7	71.6	103.4
mlr163	-1,0	1,2	mlr	1.0e-04	0.62	20	OSCAR42; OSCAR99806	-0.19	2.65	3.47	0.72	0.71	27.0	129.9	63.2	66.9	71.7	176.9
OSCAR116444	0	4	scam_mpd	1.1e-04	0.52	21	u	0.15	2.78	3.39	0.71	0.74	20.5	141.3	60.8	64.7	71.8	140.9
OSCAR66549	0	4	lm	1.4e-04	0.52	21	u	0.15	2.78	3.39	0.71	0.74	20.5	141.3	60.8	64.7	71.8	140.9
mlr145	-1,0	1,6	mlr	4.9e-05	0.65	20	OSCAR42; OISST177417	-0.38	2.57	3.13	0.66	0.69	54.2	122.9	53.1	57.3	71.9	145.7
mlr159	-1,0	1,2	mlr	8.1e-05	0.63	20	OSCAR42; OISST177431	-0.43	2.49	3.16	0.66	0.66	61.6	115.9	54.0	58.3	72.4	121.9
mlr142	-1,0	1,3	mlr	4.1e-05	0.66	20	OSCAR42; OISST177430	-0.43	2.50	3.16	0.66	0.67	60.9	116.7	53.9	58.3	72.5	175.7
mlr185	-1,-1	1,8	mlr	1.7e-04	0.60	20	OSCAR42; OISST177437	-0.29	2.56	3.44	0.71	0.68	41.7	121.9	62.2	65.6	72.9	55.9
mlr130	-1,0	1,4	mlr	2.5e-05	0.68	20	OSCAR42; OSCAR116447	-0.46	2.48	3.16	0.66	0.66	64.7	114.9	54.0	58.4	73.0	142.4
mlr153	-1,0	1,2	mlr	6.4e-05	0.64	20	OSCAR42; OISST177435	-0.48	2.50	3.10	0.65	0.67	68.0	117.1	52.2	56.5	73.5	104.6
mlr156	-1,0	1,2	mlr	7.0e-05	0.64	20	OSCAR42; OISST177432	-0.45	2.52	3.17	0.66	0.67	63.7	118.2	54.1	58.4	73.6	123.2
mlr140	-1,0	1,3	mlr	4.0e-05	0.66	20	OSCAR42; OISST177436	-0.43	2.53	3.19	0.67	0.68	60.9	119.7	54.8	59.2	73.7	180.4
OSCAR42	-1	1	lm	1.0e-04	0.55	20	v	-0.23	2.64	3.52	0.74	0.70	32.5	128.9	64.7	68.7	73.7	102.2
OSCAR66548	0	4	lm	7.1e-05	0.55	21	u	-0.28	2.75	3.24	0.68	0.73	38.9	138.6	56.5	60.7	73.7	80.0
mlr146	-1,0	1,6	mlr	5.1e-05	0.65	20	OSCAR42; OISST177423	-0.42	2.59	3.15	0.66	0.69	59.2	124.5	53.7	58.0	73.8	126.4
mlr150	-1,0	1,6	mlr	5.9e-05	0.64	20	OSCAR42; OISST177422	-0.39	2.62	3.18	0.67	0.70	55.8	127.2	54.4	58.7	74.0	133.9
mlr173	-1,-1	1,9	mlr	1.3e-04	0.61	20	OSCAR42; OSCAR49923	-0.14	2.83	3.49	0.72	0.76	19.1	146.0	63.8	67.1	74.0	188.2
mlr165	-1,-1	1,6	mlr	1.1e-04	0.62	20	OSCAR42; OSCAR49924	-0.26	2.71	3.40	0.71	0.72	36.8	135.1	61.1	65.4	74.6	109.5
mlr177	-1,-1	1,5	mlr	1.4e-04	0.61	20	OSCAR42; OSCAR33319	-0.09	2.95	3.49	0.72	0.79	12.7	155.7	63.9	66.2	74.6	111.3
mlr158	-1,0	1,5	mlr	7.4e-05	0.64	20	OSCAR42; lighthouse310799	-0.35	2.66	3.25	0.68	0.71	50.0	131.0	56.8	61.2	74.7	134.8
OSCAR116430	-1	5	scam_mpd	9.9e-04	0.60	20	u	-0.34	2.86	3.13	0.60	0.76	48.1	148.6	53.1	49.9	74.9	135.7
OISST177431	0	2	scam_mpi	1.3e-05	0.51	32	truetemp	-0.35	2.67	3.30	0.69	0.71	49.4	131.9	58.0	62.4	75.4	215.1
mlr193	-1,-1	1,5	mlr	2.3e-04	0.58	20	OSCAR42; OSCAR116432	-0.30	2.71	3.41	0.70	0.72	42.1	134.9	61.3	64.2	75.6	114.1
shore311951	0	5	scam_mpi	3.2e-05	0.59	26	temperature.c.	-0.25	2.75	3.46	0.71	0.73	35.6	138.5	62.9	65.2	75.6	185.4
mlr164	-1,0	1,4	mlr	1.0e-04	0.62	20	OSCAR42; OISST177424	-0.49	2.54	3.19	0.67	0.68	69.3	120.2	54.9	59.0	75.9	202.1
mlr170	-1,-1	1,5	mlr	1.2e-04	0.61	20	OSCAR42; OSCAR33311	-0.12	2.94	3.55	0.72	0.78	16.5	155.3	65.5	66.2	75.9	78.3
OSCAR116447	0	4	scam_mpd	1.3e-04	0.51	21	u	-0.17	2.87	3.47	0.73	0.77	23.9	149.2	63.2	67.5	75.9	78.3
OSCAR66550	0	4	lm	1.6e-04	0.51	21	u	-0.17	2.87	3.47	0.73	0.77	23.8	149.2	63.2	67.5	75.9	78.3
mlr183	-1,-1	1,5	mlr	1.6e-04	0.60	20	OSCAR42; OSCAR33334	-0.21	2.80	3.50	0.73	0.75	29.2	143.3	64.3	68.1	76.2	189.8
mlr186	-1,-1	1,5	mlr	1.7e-04	0.60	20	OSCAR42; OSCAR116429	-0.35	2.68	3.34	0.70	0.71	50.0	132.3	59.3	63.0	76.2	79.6

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr181	-1,0	1,6	mlr	1.6e-04	0.60	20	OSCAR42; OISST266113	-0.34	2.61	3.47	0.72	0.70	48.8	126.4	63.1	66.8	76.3	110.1
mlr209	-1,-1	1,3	mlr	3.9e-04	0.56	20	OSCAR42; OSCAR33350	-0.24	2.69	3.61	0.76	0.72	34.2	133.7	67.4	71.5	76.7	131.4
mlr221	-1,-1	1,1	mlr	6.4e-04	0.53	20	OSCAR42; OSCAR43	-0.19	2.77	3.66	0.77	0.74	26.3	140.1	69.0	73.0	77.1	103.0
OSCAR33296	-1	2	scam_mpi	5.4e-04	0.64	20	v	-0.36	2.66	3.41	0.71	0.71	51.0	130.4	61.5	65.4	77.1	184.1
mlr189	-1,-1	1,1	mlr	2.0e-04	0.59	20	OSCAR42; OSCAR33351	-0.19	2.84	3.56	0.74	0.76	26.3	146.6	66.1	69.9	77.2	173.9
mlr182	-1,0	1,6	mlr	1.6e-04	0.60	20	OSCAR42; OISST266112	-0.30	2.67	3.55	0.74	0.71	42.2	131.7	65.6	69.7	77.3	103.0
mlr180	-1,0	1,6	mlr	1.6e-04	0.60	20	OSCAR42; OISST266111	-0.38	2.63	3.43	0.71	0.70	53.6	128.5	62.1	65.5	77.4	119.9
mlr190	-1,-1	1,9	mlr	2.1e-04	0.59	20	OSCAR42; OSCAR33331	-0.37	2.72	3.32	0.70	0.73	52.0	136.4	58.9	63.1	77.6	81.5
OSCAR33300	-1	3	scam_mpi	9.9e-05	0.60	20	v	-0.23	2.72	3.66	0.77	0.72	32.5	135.7	69.1	73.1	77.6	163.9
mlr176	-1,-1	1,5	mlr	1.4e-04	0.61	20	OSCAR42; OSCAR33314	-0.18	2.90	3.53	0.74	0.77	25.0	151.7	65.2	68.8	77.7	196.8
mlr197	-1,-1	1,6	mlr	2.5e-04	0.58	20	OSCAR42; OSCAR116448	-0.23	2.76	3.62	0.76	0.74	32.2	139.4	67.7	71.7	77.7	163.6
OSCAR33302	-1	3	scam_mpi	1.4e-04	0.59	20	v	-0.17	2.75	3.77	0.79	0.73	24.1	138.6	72.3	75.8	77.7	158.9
mlr167	-1,0	1,2	mlr	1.1e-04	0.62	20	OSCAR42; OISST177419	-0.21	2.79	3.63	0.76	0.74	29.4	141.7	68.1	72.4	77.9	260.5
mlr169	-1,-1	1,8	mlr	1.2e-04	0.61	20	OSCAR42; OSCAR116431	-0.31	2.72	3.49	0.73	0.73	43.7	136.3	63.8	68.2	78.0	221.9
mlr160	-1,0	1,2	mlr	8.3e-05	0.63	20	OSCAR42; OISST177429	-0.29	2.74	3.51	0.74	0.73	41.3	137.9	64.5	68.8	78.1	225.7
mlr220	-1,-1	1,5	mlr	6.4e-04	0.53	20	OSCAR42; OSCAR33341	-0.26	2.75	3.60	0.75	0.73	36.2	138.9	67.1	71.0	78.3	108.8
mlr172	-1,-1	1,5	mlr	1.3e-04	0.61	20	OSCAR42; OSCAR33310	-0.21	2.93	3.53	0.70	0.78	29.6	154.8	65.1	64.3	78.4	84.5
mlr178	-1,-1	1,8	mlr	1.4e-04	0.60	20	OSCAR42; OSCAR116436	-0.46	2.60	3.35	0.70	0.69	65.4	125.4	59.5	63.9	78.6	198.1
mlr166	-1,0	1,4	mlr	1.1e-04	0.62	20	OSCAR42; OISST177409	-0.49	2.59	3.30	0.69	0.69	70.2	124.5	58.1	62.3	78.8	224.6
mlr199	-1,-1	1,5	mlr	2.8e-04	0.57	20	OSCAR42; OSCAR33305	-0.24	2.86	3.54	0.73	0.76	34.3	148.2	65.3	68.5	79.1	118.5
mlr203	-1,-1	1,5	mlr	3.1e-04	0.57	20	OSCAR42; OSCAR116430	-0.31	2.77	3.52	0.72	0.74	44.2	140.6	64.8	67.1	79.2	122.1
OSCAR116437	0	4	scam_mpd	5.1e-05	0.55	21	u	-0.34	2.82	3.35	0.70	0.75	48.8	144.6	59.7	63.9	79.2	80.0
mlr214	-1,-1	1,1	mlr	4.6e-04	0.55	20	OSCAR42; OSCAR33345	-0.33	2.65	3.64	0.76	0.71	46.9	129.4	68.4	72.5	79.3	140.3
OISST177423	0	6	scam_mpi	2.1e-05	0.52	32	truetemp	0.61	2.64	3.06	0.61	0.70	86.5	129.3	50.9	51.3	79.5	189.7
mlr216	-1,-1	1,1	mlr	4.6e-04	0.55	20	OSCAR42; OSCAR33352	-0.32	2.67	3.64	0.76	0.71	45.3	131.8	68.5	72.7	79.6	140.2
mlr195	-1,-1	1,8	mlr	2.4e-04	0.58	20	OSCAR42; OSCAR116433	-0.39	2.68	3.49	0.73	0.71	54.9	132.2	63.7	67.9	79.7	186.9
mlr204	-1,-1	1,5	mlr	3.2e-04	0.57	20	OSCAR42; OSCAR33329	-0.27	2.85	3.53	0.73	0.76	38.7	147.7	65.1	68.3	80.0	123.6
mlr213	-1,-1	1,11	mlr	4.5e-04	0.55	20	OSCAR42; OSCAR33304	-0.21	2.86	3.67	0.77	0.76	29.8	148.2	69.2	73.2	80.1	152.1
mlr196	-1,-1	1,5	mlr	2.4e-04	0.58	20	OSCAR42; OSCAR33306	-0.21	2.94	3.62	0.75	0.78	29.0	154.9	67.7	71.0	80.7	166.6
OSCAR33350	-1	3	scam_mpi	2.1e-04	0.51	20	v	0.03	3.12	3.77	0.79	0.83	4.2	171.2	72.2	75.8	80.9	180.6
mlr174	-1,0	1,4	mlr	1.3e-04	0.61	20	OSCAR42; OISST177410	-0.48	2.65	3.40	0.71	0.71	67.9	130.0	61.2	65.4	81.1	232.2
mlr192	-1,-1	1,8	mlr	2.3e-04	0.58	20	OSCAR42; OSCAR116434	-0.38	2.72	3.54	0.74	0.73	53.9	136.2	65.2	69.4	81.2	196.1
mlr205	-1,-1	1,1	mlr	3.3e-04	0.56	20	OSCAR42; OSCAR33355	-0.33	2.82	3.53	0.74	0.75	46.3	144.4	65.0	69.0	81.2	177.3
mlr184	-1,0	1,4	mlr	1.7e-04	0.60	20	OSCAR42; OISST177420	-0.44	2.70	3.45	0.72	0.72	62.4	134.5	62.8	66.9	81.6	223.7
mlr208	-1,-1	1,6	mlr	3.9e-04	0.56	20	OSCAR42; OSCAR116440	-0.23	2.86	3.76	0.79	0.76	33.0	147.9	72.1	75.8	82.2	161.1
mlr210	-1,-1	1,1	mlr	4.2e-04	0.55	20	OSCAR42; OSCAR33323	-0.20	2.90	3.79	0.79	0.77	27.6	151.8	72.8	76.4	82.2	123.6
mlr201	-1,-1	1,1	mlr	2.8e-04	0.57	20	OSCAR42; OSCAR116435	-0.41	2.72	3.55	0.74	0.72	57.9	135.8	65.6	69.9	82.3	71.5
OISST177432	0	2	scam_mpi	1.1e-05	0.51	32	truetemp	-0.45	2.78	3.36	0.70	0.74	64.0	141.1	59.9	64.2	82.3	220.8
mlr217	-1,-1	1,1	mlr	5.0e-04	0.54	20	OSCAR42; OSCAR33354	-0.33	2.85	3.56	0.74	0.76	47.0	147.1	65.9	69.8	82.4	124.9
mlr218	-1,-1	1,5	mlr	5.6e-04	0.54	20	OSCAR42; OSCAR116443	-0.33	2.80	3.66	0.76	0.75	46.2	142.8	69.1	71.7	82.5	110.5
OSCAR33333	0	1	scam_mpi	3.8e-04	0.52	21	v	-0.22	2.90	3.75	0.79	0.77	30.4	152.1	71.8	75.7	82.5	199.3
mlr215	-1,-1	1,3	mlr	4.6e-04	0.55	20	OSCAR42; OSCAR33340	-0.34	2.74	3.71	0.78	0.73	48.2	137.5	70.4	74.4	82.6	140.7

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
OSCAR33334	-1	5	scam_mpi	1.0e-03	0.52	20	v	-0.22	3.15	3.52	0.71	0.84	31.4	173.7	64.7	64.9	83.7	217.5
OISST177426	0	2	scam_mpi	4.2e-05	0.51	32	truetemp	-0.44	2.79	3.47	0.73	0.74	61.9	142.4	63.2	67.5	83.8	201.2
OSCAR33326	0	5	scam_mpi	3.8e-04	0.54	21	v	-0.14	2.96	3.98	0.82	0.79	20.3	156.8	78.5	80.3	84.0	227.2
OSCAR33360	0	1	scam_mpi	6.4e-04	0.50	21	v	-0.31	2.87	3.68	0.77	0.76	44.1	149.0	69.5	73.5	84.0	220.8
shore310799	0	5	scam_mpi	2.7e-04	0.52	26	temperature.c.	-0.46	2.87	3.34	0.69	0.77	65.9	149.5	59.3	62.8	84.4	191.3
mlr219	-1,-1	1,4	mlr	5.8e-04	0.53	20	OSCAR42; OSCAR33309	-0.30	2.86	3.74	0.78	0.76	42.9	148.5	71.4	75.3	84.5	127.9
mlr194	-1,-1	1,5	mlr	2.3e-04	0.58	20	OSCAR42; OSCAR116441	-0.34	2.88	3.65	0.76	0.77	48.8	150.0	68.7	72.7	85.1	107.8
OSCAR33342	0	1	scam_mpi	2.2e-03	0.52	21	v	-0.20	3.02	3.84	0.80	0.81	28.3	162.2	74.5	78.0	85.8	257.1
OSCAR33344	-1	2	scam_mpi	7.3e-04	0.51	20	v	-0.07	3.08	4.08	0.85	0.82	9.0	167.7	81.6	85.1	85.8	265.8
mlr162	-1,-1	1,6	mlr	9.7e-05	0.62	20	OSCAR42; OSCAR33358	-0.61	2.54	3.59	0.75	0.68	87.1	120.6	66.9	71.2	86.5	159.4
OISST177409	0	4	scam_mpi	1.3e-06	0.58	32	truetemp	-0.72	2.56	3.31	0.70	0.68	102.8	121.8	58.5	62.9	86.5	233.7
mlr200	-1,-1	1,8	mlr	2.8e-04	0.57	20	OSCAR42; OSCAR116438	-0.40	2.83	3.70	0.77	0.75	56.5	145.5	70.2	74.1	86.6	204.5
OISST266113	0	6	scam_mpi	2.2e-06	0.50	32	winterdiff	0.32	3.06	3.60	0.73	0.82	45.1	166.1	67.1	68.1	86.6	220.9
OSCAR33304	-1	11	scam_mpi	2.4e-05	0.58	21	v	-0.56	2.90	3.29	0.66	0.77	80.0	151.5	57.7	57.6	86.7	201.5
mlr207	-1,-1	1,4	mlr	3.6e-04	0.56	20	OSCAR42; OSCAR33353	-0.41	2.85	3.67	0.77	0.76	58.3	147.1	69.2	73.2	86.9	118.9
mlr212	-1,-1	1,1	mlr	4.4e-04	0.55	20	OSCAR42; OSCAR33321	-0.40	2.92	3.60	0.75	0.78	56.7	153.1	67.2	71.1	87.0	146.7
OISST177425	0	2	scam_mpi	5.0e-05	0.52	32	truetemp	-0.56	2.79	3.43	0.72	0.74	79.5	141.9	62.2	66.5	87.5	202.7
mlr202	-1,-1	1,1	mlr	2.9e-04	0.57	20	OSCAR42; OSCAR116442	-0.43	2.84	3.67	0.77	0.76	60.9	146.7	69.3	73.5	87.6	79.8
OISST177434	0	2	scam_mpi	3.1e-05	0.51	32	truetemp	-0.47	2.90	3.51	0.74	0.77	66.6	151.9	64.4	68.6	87.9	193.2
mlr211	-1,-1	1,12	mlr	4.3e-04	0.55	20	OSCAR42; OSCAR49925	-0.37	2.93	3.79	0.79	0.78	52.9	154.5	73.0	76.4	89.2	150.1
OISST177428	0	2	scam_mpi	2.5e-05	0.51	32	truetemp	-0.64	2.81	3.46	0.73	0.75	90.6	144.2	63.0	67.2	91.3	193.8
OSCAR33301	-1	2	scam_mpi	2.0e-04	0.60	20	v	-0.43	3.06	3.69	0.76	0.82	60.5	165.7	69.8	72.6	92.1	231.1
OSCAR33330	0	1	scam_mpi	4.1e-04	0.53	21	v	0.28	3.17	3.89	0.81	0.85	40.3	175.4	76.0	79.4	92.8	282.0
OISST177435	0	2	scam_mpi	7.7e-05	0.50	32	truetemp	-0.65	2.88	3.46	0.73	0.77	91.8	150.1	63.0	67.3	93.0	205.3
OSCAR33338	0	1	scam_mpi	4.1e-04	0.52	21	v	0.10	3.22	4.27	0.90	0.86	13.7	179.6	87.5	91.5	93.1	258.0
OSCAR33315	0	1	scam_mpi	9.6e-04	0.56	21	v	-0.45	2.98	3.85	0.81	0.80	63.2	158.9	74.8	78.9	94.0	262.7
OSCAR33353	-1	4	scam_mpi	3.0e-03	0.51	20	v	-0.38	3.21	3.76	0.77	0.86	54.2	179.4	72.0	72.9	94.6	162.2
OSCAR33308	-1	1	scam_mpi	8.3e-04	0.57	20	v	-0.45	3.01	3.84	0.80	0.80	64.5	161.9	74.3	78.1	94.7	103.0
OSCAR33323	-1	1	scam_mpi	1.8e-03	0.54	20	v	-0.41	3.03	3.93	0.82	0.81	58.8	162.9	77.1	81.2	95.0	159.3
OSCAR33340	-1	3	scam_mpi	2.0e-03	0.52	20	v	-0.46	3.04	3.83	0.80	0.81	65.4	164.0	74.1	78.2	95.4	313.7
OSCAR33322	0	1	scam_mpi	1.4e-03	0.54	21	v	-0.55	2.91	3.81	0.80	0.78	78.4	152.3	73.5	77.7	95.5	218.4
OISST177420	0	4	scam_mpi	1.2e-05	0.53	32	truetemp	-0.53	2.94	3.87	0.80	0.79	75.1	155.6	75.4	77.3	95.8	292.8
OSCAR33356	0	1	scam_mpi	2.4e-03	0.50	21	v	-0.26	3.23	4.08	0.85	0.86	36.1	180.8	81.5	85.4	95.9	255.2
OSCAR33337	0	1	scam_mpi	2.0e-03	0.52	21	v	-0.10	3.40	4.23	0.89	0.91	13.6	195.9	86.2	90.3	96.5	256.0
OSCAR99806	0	2	scam_mpi	2.3e-03	0.51	21	u	-0.27	3.40	3.98	0.82	0.91	37.9	195.2	78.6	80.2	98.0	244.5
OSCAR33335	0	1	scam_mpi	1.7e-03	0.52	21	v	-0.38	3.17	4.05	0.85	0.85	54.4	175.4	80.8	84.7	98.8	239.1
OISST177410	0	4	scam_mpi	2.8e-06	0.57	32	truetemp	-0.65	2.93	3.86	0.81	0.78	92.3	154.7	74.9	79.1	100.3	327.3
OISST266112	0	6	scam_mpi	8.2e-06	0.51	32	winterdiff	-0.34	3.22	4.22	0.87	0.86	48.3	180.0	85.9	87.2	100.3	227.5
OISST177424	0	4	scam_mpi	9.2e-05	0.52	32	truetemp	-0.84	2.87	3.51	0.74	0.76	119.8	148.8	64.6	68.8	100.5	236.2
OSCAR116451	0	5	scam_mpd	5.9e-04	0.50	21	u	-0.10	3.58	4.47	0.87	0.96	13.3	211.7	93.3	87.2	101.4	198.4
OSCAR33359	0	1	scam_mpi	3.2e-03	0.50	21	v	-0.32	3.33	4.20	0.87	0.89	45.0	189.5	85.3	87.8	101.9	287.1
OSCAR116445	0	5	scam_mpd	1.2e-04	0.52	21	u	-0.30	3.33	4.27	0.87	0.89	42.8	189.8	87.5	87.9	102.0	271.8

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
OSCAR33332	-1	2	scam_mpi	2.8e-03	0.53	20	v	-0.28	3.31	4.38	0.91	0.88	39.0	188.2	90.7	92.9	102.7	137.6
OSCAR116434	-1	8	scam_mpd	2.2e-04	0.59	20	u	-0.71	3.12	3.84	0.78	0.83	101.5	170.8	74.4	75.6	105.6	146.2
OSCAR116439	-1	10	scam_mpd	1.4e-03	0.53	21	u	-0.63	3.07	4.08	0.85	0.82	89.8	166.3	81.7	84.6	105.6	234.6
OISST177437	-1	8	scam_mpi	4.3e-05	0.50	31	truetemp	-0.67	3.12	3.95	0.80	0.83	95.7	171.5	77.6	78.0	105.7	151.9
OSCAR33328	0	1	scam_mpi	2.0e-03	0.53	21	v	-0.81	2.92	3.91	0.82	0.78	114.7	153.2	76.6	80.1	106.1	197.7
OSCAR33351	-1	1	scam_mpi	8.1e-04	0.51	20	v	-0.41	3.40	4.19	0.88	0.91	57.5	195.9	85.0	89.0	106.9	249.4
OISST177416	-1	7	scam_mpi	7.7e-05	0.53	31	truetemp	-0.59	3.29	4.09	0.85	0.88	84.1	185.8	81.8	84.3	109.0	159.7
OISST177421	-1	7	scam_mpi	6.1e-05	0.53	31	truetemp	-0.59	3.34	4.16	0.86	0.89	83.5	190.8	83.9	86.6	111.2	169.9
OSCAR33327	0	1	scam_mpi	1.4e-03	0.53	21	v	-0.66	3.19	4.20	0.88	0.85	93.2	177.2	85.3	89.2	111.2	203.7
OSCAR116433	-1	8	scam_mpd	1.7e-04	0.59	20	u	-0.79	3.25	3.86	0.80	0.87	112.9	182.5	75.0	77.1	111.9	166.5
OSCAR116441	-1	5	scam_mpd	5.8e-02	0.53	20	u	-0.44	3.49	4.35	0.90	0.93	62.3	203.9	89.9	92.2	112.1	229.4
OSCAR116448	-1	6	scam_mpd	2.4e-03	0.51	20	u	-0.04	3.90	4.75	0.98	1.04	5.3	239.5	101.9	102.6	112.3	189.9
OSCAR116432	-1	5	scam_mpd	8.0e-04	0.59	20	u	-0.68	3.44	3.94	0.79	0.92	96.6	199.6	77.4	76.4	112.5	134.9
OSCAR116436	-1	8	scam_mpd	2.6e-03	0.56	20	u	-0.93	3.12	3.73	0.78	0.83	132.6	171.4	71.1	74.8	112.5	181.4
OSCAR33355	-1	1	scam_mpi	1.8e-03	0.50	20	v	-0.78	3.19	4.05	0.84	0.85	110.7	177.1	80.6	83.3	112.9	280.9
OSCAR33329	-1	5	scam_mpi	1.3e-04	0.53	20	v	-0.08	3.64	5.06	1.04	0.97	11.8	217.0	111.3	112.0	113.0	176.0
OSCAR99803	-1	5	scam_mpi	4.8e-04	0.58	20	u	-1.03	2.94	3.93	0.82	0.79	146.1	155.7	77.2	80.7	114.9	141.5
OSCAR33320	0	1	scam_mpi	1.2e-03	0.55	21	v	-0.73	3.11	4.40	0.92	0.83	103.7	170.5	91.4	95.0	115.2	195.8
OSCAR116440	-1	6	scam_mpd	2.5e-04	0.53	20	u	-0.24	3.79	4.64	0.95	1.01	33.3	229.6	98.7	99.6	115.3	283.7
OSCAR49924	-1	6	scam_mpd	4.8e-04	0.53	20	v	-0.57	3.48	4.32	0.88	0.93	81.6	202.3	88.9	89.5	115.6	170.6
OSCAR116438	-1	8	scam_mpd	2.6e-03	0.54	20	u	-0.79	3.36	3.99	0.82	0.90	112.1	192.3	79.0	80.2	115.9	140.0
OSCAR33309	-1	4	scam_mpi	1.3e-03	0.57	20	v	-0.78	3.19	4.31	0.88	0.85	110.3	176.8	88.5	88.9	116.1	190.9
OSCAR33324	-1	1	scam_mpi	1.6e-03	0.54	20	v	-0.68	3.38	4.22	0.88	0.90	96.2	193.6	85.9	88.6	116.1	136.2
OSCAR33354	-1	1	scam_mpi	2.2e-03	0.51	20	v	-0.64	3.48	4.21	0.85	0.93	90.9	202.7	85.6	85.3	116.1	313.1
OSCAR49923	-1	9	scam_mpd	7.6e-04	0.56	20	v	-0.68	3.38	4.25	0.86	0.90	97.0	194.1	86.8	86.8	116.2	238.9
OISST177418	0	3	scam_mpi	1.1e-05	0.53	32	truetemp	-1.06	3.01	3.84	0.80	0.80	151.4	161.4	74.3	78.4	116.4	177.3
OISST177429	0	2	scam_mpi	1.3e-04	0.51	32	truetemp	-1.02	3.10	3.82	0.80	0.83	144.9	169.4	73.9	77.6	116.4	238.2
OSCAR116431	-1	8	scam_mpd	1.0e-04	0.60	20	u	-0.46	3.64	4.45	0.93	0.97	65.9	216.9	92.8	96.1	117.9	166.7
OISST177430	0	3	scam_mpi	6.3e-05	0.51	32	truetemp	-1.08	3.19	3.71	0.77	0.85	153.3	176.8	70.5	74.2	118.7	226.2
OSCAR33305	-1	5	scam_mpi	4.2e-05	0.58	20	v	-0.69	3.35	4.44	0.91	0.89	98.7	191.1	92.5	93.3	118.9	191.5
OSCAR33319	-1	5	scam_mpi	1.2e-03	0.55	20	v	-0.78	3.33	4.30	0.87	0.89	111.6	189.5	88.1	88.3	119.4	197.4
OISST177427	0	3	scam_mpi	2.0e-05	0.51	32	truetemp	-1.11	3.08	3.87	0.81	0.82	157.7	167.9	75.4	79.5	120.1	183.3
OSCAR33310	-1	5	scam_mpi	2.5e-04	0.56	20	v	-0.84	3.22	4.37	0.89	0.86	119.3	179.5	90.4	91.2	120.1	192.6
OSCAR33358	-1	6	scam_mpi	2.9e-03	0.50	20	v	-0.74	3.21	4.57	0.96	0.86	105.7	178.9	96.5	100.1	120.3	194.8
OSCAR33347	0	1	scam_mpi	2.2e-03	0.51	21	v	-0.65	3.38	4.58	0.96	0.90	92.0	193.5	96.8	100.6	120.7	249.1
OSCAR33346	-1	3	scam_mpi	3.2e-03	0.51	20	v	-0.90	3.44	4.08	0.83	0.92	128.3	199.2	81.8	81.4	122.7	162.9
OISST177436	0	3	scam_mpi	7.5e-05	0.50	32	truetemp	-1.10	3.26	3.81	0.80	0.87	156.8	183.4	73.6	77.4	122.8	232.5
OSCAR49925	-1	12	scam_mpd	8.2e-04	0.50	21	v	-0.66	3.51	4.58	0.94	0.94	94.5	205.0	96.6	97.6	123.5	227.5
OSCAR33352	-1	1	scam_mpi	3.2e-03	0.51	20	v	-0.84	3.52	4.16	0.87	0.94	120.0	206.5	84.2	87.9	124.7	170.5
OSCAR116443	-1	5	scam_mpd	5.1e-03	0.52	20	u	-0.88	3.66	4.04	0.80	0.98	125.8	218.7	80.3	78.0	125.7	167.9
OSCAR33341	-1	5	scam_mpi	1.7e-04	0.52	20	v	-0.52	3.74	4.85	0.99	1.00	74.3	225.2	104.8	105.1	127.3	232.7
OSCAR33345	-1	1	scam_mpi	2.2e-03	0.51	20	v	-1.01	3.43	4.20	0.88	0.91	143.4	197.8	85.4	89.4	129.0	158.4

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
OSCAR33321	-1	1	scam_mpi	2.2e-03	0.54	20	v	-0.91	3.47	4.45	0.93	0.92	129.4	201.4	92.7	95.6	129.8	240.2
OSCAR33312	-1	5	scam_mpi	2.7e-04	0.56	20	v	-0.95	3.48	4.41	0.90	0.93	135.3	202.6	91.5	91.9	130.3	184.4
median8	0	0	median8	NA			median8	0.24	4.18	5.14	1.03	1.11	33.2	263.8	113.7	110.7	130.4	309.6
OSCAR116429	-1	5	scam_mpd	4.3e-04	0.62	20	u	-1.02	3.43	4.35	0.90	0.91	145.3	198.0	89.9	91.8	131.2	143.7
OSCAR116435	-1	1	scam_mpd	2.5e-04	0.56	20	u	-1.01	3.54	4.49	0.94	0.94	143.9	207.5	94.0	97.4	135.7	171.5
OSCAR33314	-1	5	scam_mpi	3.0e-04	0.56	20	v	-0.98	3.57	4.56	0.94	0.95	139.4	210.7	96.2	97.1	135.8	245.5
OSCAR33311	-1	5	scam_mpi	6.3e-05	0.56	20	v	-0.97	3.63	4.67	0.96	0.97	137.8	215.6	99.3	100.0	138.2	194.0
OSCAR116442	-1	1	scam_mpd	6.8e-04	0.53	20	u	-1.11	3.56	4.61	0.96	0.95	157.5	210.1	97.7	100.9	141.5	187.3
OSCAR33331	-1	9	scam_mpi	1.4e-04	0.53	20	v	-1.27	3.55	4.60	0.94	0.95	181.0	209.1	97.3	98.0	146.4	184.2
median4	0	0	median4	NA			median4	-0.53	4.53	5.29	1.06	1.21	75.2	294.7	118.1	114.8	150.7	281.6
OSCAR33306	-1	5	scam_mpi	4.2e-05	0.58	20	v	-1.29	3.86	4.83	0.99	1.03	184.2	235.9	104.3	105.3	157.4	228.8
OISST177419	0	2	scam_mpi	1.1e-05	0.53	32	truetemp	-1.58	3.77	4.92	1.03	1.00	224.9	227.9	107.1	110.6	167.6	264.2
median.all	0	0	median.all	NA			median.all	-1.91	3.85	5.01	1.01	1.03	272.5	235.4	109.7	106.9	181.1	159.9
OISST177408	0	3	scam_mpi	2.7e-07	0.59	32	truetemp	-1.98	3.96	5.77	1.21	1.06	281.8	244.6	132.5	135.5	198.6	185.8
OISST177411	0	3	scam_mpi	9.2e-06	0.55	32	truetemp	-2.02	4.06	5.70	1.19	1.08	287.9	253.2	130.5	133.6	201.3	195.2
OSCAR33348	-1	5	scam_mpi	2.0e-04	0.51	20	v	0.99	4.94	8.20	1.71	1.32	140.8	330.5	205.8	206.5	220.9	181.9
OSCAR33316	-1	1	scam_mpi	7.5e-05	0.55	20	v	2.72	5.59	14.24	2.99	1.49	388.0	388.0	388.0	388.0	388.0	102.2

Table 14. Performance results for all qualifying models used to forecast Early Stuart timing based on jackknife.short analysis. Each row represents a single model tested, some columns include: year adjust (year of environmental data same as return year [0] or prior year [-1]), month, summary statistics (P value, adjusted R squared, sample size), data name, data variables (which are sorted by their relative influence in the model). As the NEPSTAR regression models comprise more than one variable, only year-month of the latest variable is presented. Latitude and longtitude of NEPSTAR variables are excluded due to space limitations. The PMs include mean raw error, mean absolute error, root mean squared error, Thiel's U-statistic, and MASE. The initial three PMs are in day units, the latter two are unit-less. All PMs are described in the methods section. All PMs, except MASE, are given a rank. The best rank has a value of zero. The last rank equals total number of models (n). The average of the PM ranks by model (row) is included, as is the average rank for the alternate performance test method. The rows are sorted by average rank of performance method listed in caption. The first row is the best model, the last row is the worst.

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr188	-1,-1	1,2	mlr	2.0e-04	0.59	20	OSCAR42; OSCAR33332	-0.04	0.83	1.10	0.42	0.41	5.6	0.0	2.1	2.1	2.4	63.4
mlr1	-1,0,-1	1,1,8	mlr	4.6e-10	0.93	20	OSCAR42; OSCAR33359; OISST177437	0.08	0.98	1.08	0.42	0.49	12.9	21.8	0.0	0.0	8.7	5.4
mlr3	-1,0,-1	1,1,7	mlr	2.1e-09	0.92	20	OSCAR42; OSCAR33359; OISST177416	-0.19	1.05	1.23	0.48	0.53	28.6	32.3	17.5	17.5	24.0	7.2
mlr2	-1,0,-1	1,1,7	mlr	1.5e-09	0.92	20	OSCAR42; OSCAR33359; OISST177421	-0.11	1.12	1.25	0.49	0.56	17.5	42.2	19.6	19.6	24.7	5.6
mlr141	-1,-1	1,2	mlr	4.1e-05	0.66	20	OSCAR42; OSCAR33296	0.38	0.91	1.23	0.48	0.46	58.4	12.2	17.5	17.5	26.4	46.6
mlr4	-1,0,-1	1,1,5	mlr	6.7e-09	0.90	20	OSCAR42; OSCAR33359; OSCAR33312	0.09	1.14	1.32	0.51	0.57	14.5	44.4	27.3	27.3	28.4	6.2
mlr117	-1,0	1,1	mlr	2.7e-07	0.81	20	OSCAR42; OSCAR33360	-0.03	1.27	1.39	0.54	0.64	4.9	63.7	34.7	34.7	34.5	39.6
mlr6	-1,0,-1	1,1,5	mlr	1.1e-08	0.90	20	OSCAR42; OSCAR33359; OSCAR33319	0.02	1.27	1.45	0.56	0.64	2.5	64.2	41.4	41.4	37.4	7.0
mlr7	-1,0,-1	1,1,5	mlr	1.2e-08	0.89	20	OSCAR42; OSCAR33359; OSCAR33310	0.14	1.19	1.47	0.57	0.60	20.8	52.3	43.9	43.9	40.3	3.8
mlr8	-1,0,-1	1,1,5	mlr	1.4e-08	0.89	20	OSCAR42; OSCAR33359; OSCAR33311	0.21	1.13	1.47	0.57	0.57	32.9	43.6	43.6	43.6	40.9	6.3
mlr17	-1,0,-1	1,1,2	mlr	2.6e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR45	0.37	1.16	1.46	0.57	0.58	56.6	47.4	42.6	42.6	47.3	9.5
mlr9	-1,0,0	1,1,1	mlr	1.5e-08	0.89	20	OSCAR42; OSCAR33359; OSCAR33322	0.18	1.32	1.49	0.58	0.66	27.1	71.5	45.7	45.7	47.5	19.5
mlr121	-1,0	1,1	mlr	5.2e-07	0.80	20	OSCAR42; OSCAR33333	0.37	1.23	1.48	0.57	0.62	56.8	58.3	44.6	44.6	51.1	36.9
mlr24	-1,0,0	1,1,5	mlr	3.9e-08	0.88	20	OSCAR42; OSCAR33359; lighthouse311951	-0.11	1.34	1.61	0.62	0.67	16.2	73.6	59.0	59.0	52.0	19.5
mlr52	-1,0	1,1	mlr	3.1e-08	0.85	20	OSCAR42; OSCAR33322	0.21	1.29	1.58	0.61	0.65	32.0	67.1	56.3	56.3	52.9	27.8
mlr21	-1,0	1,1	mlr	1.7e-08	0.86	20	OSCAR42; OSCAR33342	0.28	1.35	1.50	0.58	0.67	43.3	74.7	46.9	46.9	53.0	22.7
mlr16	-1,0	1,1	mlr	1.1e-08	0.87	20	OSCAR42; OSCAR33315	0.56	1.22	1.42	0.55	0.61	86.5	56.4	38.5	38.5	55.0	22.1
mlr29	-1,0,-1	1,1,11	mlr	4.5e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33304	0.39	1.27	1.52	0.59	0.63	59.9	63.5	49.4	49.4	55.6	20.3
mlr185	-1,-1	1,8	mlr	1.7e-04	0.60	20	OSCAR42; OISST177437	0.02	1.38	1.71	0.66	0.69	2.4	79.0	71.0	71.0	55.9	72.9
mlr5	-1,0,-1	1,1,5	mlr	8.6e-09	0.90	20	OSCAR42; OSCAR33359; OSCAR33348	0.03	1.47	1.65	0.64	0.73	3.8	92.0	63.8	63.8	55.9	7.5
mlr168	-1,-1	1,7	mlr	1.2e-04	0.61	20	OSCAR42; OISST177416	-0.39	1.24	1.55	0.60	0.62	60.3	58.8	53.0	53.0	56.3	69.9
mlr43	-1,0,0	1,1,1	mlr	5.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33360	0.19	1.37	1.63	0.63	0.68	29.6	77.8	61.3	61.3	57.5	21.2
mlr179	-1,-1	1,2	mlr	1.5e-04	0.60	20	OSCAR42; OSCAR33344	0.48	1.29	1.50	0.58	0.64	73.7	65.9	46.9	46.9	58.4	59.9
mlr12	-1,0,0	1,1,1	mlr	2.2e-08	0.89	20	OSCAR42; OSCAR33359; OSCAR33315	0.36	1.41	1.50	0.58	0.71	55.1	84.5	47.5	47.5	58.6	21.2
mlr34	-1,0,-1	1,1,5	mlr	5.2e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116430	-0.02	1.51	1.70	0.66	0.75	3.4	97.7	68.8	68.8	59.7	20.6
mlr38	-1,0,-1	1,1,5	mlr	5.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116443	-0.03	1.49	1.70	0.66	0.75	4.2	96.0	69.9	69.9	60.0	20.0
mlr22	-1,0,0	1,1,1	mlr	3.7e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33335	0.01	1.47	1.73	0.67	0.74	2.1	93.1	72.5	72.5	60.1	17.6
mlr14	-1,0	1,1	mlr	1.0e-08	0.87	20	OSCAR42; OSCAR33335	-0.31	1.26	1.67	0.65	0.63	46.8	62.6	66.4	66.4	60.6	23.1
mlr171	-1,-1	1,7	mlr	1.3e-04	0.61	20	OSCAR42; OISST177421	-0.26	1.39	1.64	0.63	0.69	40.4	80.3	62.4	62.4	61.4	70.3
mlr87	-1,0,0	1,1,4	mlr	8.4e-08	0.87	20	OSCAR42; OSCAR33359; OISST177424	0.19	1.39	1.71	0.66	0.69	29.5	80.8	70.1	70.1	62.6	17.3
mlr127	-1,-1	1,2	mlr	1.3e-05	0.70	20	OSCAR42; OSCAR45	0.40	1.31	1.62	0.63	0.66	60.9	69.7	60.2	60.2	62.7	45.1

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr28	-1,0,-1	1,1,5	mlr	4.5e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33329	0.27	1.32	1.70	0.66	0.66	41.9	71.4	69.8	69.8	63.2	14.4
mlr15	-1,0,-1	1,1,4	mlr	2.3e-08	0.89	20	OSCAR42; OSCAR33359; OSCAR33353	0.12	1.52	1.69	0.65	0.76	18.1	99.0	68.3	68.3	63.4	18.5
mlr51	-1,0,-1	1,1,2	mlr	6.4e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33296	0.33	1.30	1.69	0.65	0.65	50.4	68.2	67.8	67.8	63.5	14.7
mlr48	-1,0,0	1,1,6	mlr	6.1e-08	0.87	20	OSCAR42; OSCAR33359; OISST177423	-0.03	1.45	1.80	0.70	0.73	4.5	89.7	80.5	80.5	63.8	21.7
mlr19	-1,0,-1	1,1,1	mlr	3.2e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33351	0.06	1.45	1.79	0.69	0.72	9.6	89.1	79.4	79.4	64.4	12.4
mlr32	-1,0,0	1,1,4	mlr	4.9e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116437	0.00	1.58	1.75	0.68	0.79	0.0	107.9	74.9	74.9	64.4	21.6
mlr57	-1,0,-1	1,1,5	mlr	6.9e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116432	0.12	1.50	1.72	0.67	0.75	18.3	97.3	71.3	71.3	64.6	21.2
mlr45	-1,0,0	1,1,6	mlr	5.9e-08	0.87	20	OSCAR42; OSCAR33359; OISST177422	-0.07	1.45	1.82	0.71	0.73	10.2	89.6	82.9	82.9	66.4	20.9
mlr92	-1,0,0	1,1,4	mlr	8.5e-08	0.87	20	OSCAR42; OSCAR33359; OISST177409	0.24	1.43	1.72	0.67	0.71	36.5	86.4	72.1	72.1	66.8	17.3
mlr31	-1,0,0	1,1,4	mlr	4.8e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116447	0.02	1.58	1.78	0.69	0.79	3.0	108.8	77.9	77.9	66.9	21.8
mlr47	-1,0,0	1,1,6	mlr	5.9e-08	0.87	20	OSCAR42; OSCAR33359; OISST177413	-0.06	1.46	1.83	0.71	0.73	8.9	91.3	84.0	84.0	67.0	21.4
mlr30	-1,0,0	1,1,1	mlr	4.7e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33320	0.19	1.53	1.71	0.66	0.77	29.3	101.3	69.9	69.9	67.6	26.5
mlr59	-1,0,-1	1,1,9	mlr	7.2e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33331	0.24	1.44	1.73	0.67	0.72	36.6	88.4	72.6	72.6	67.6	20.7
mlr118	-1,0	1,1	mlr	2.8e-07	0.81	20	OSCAR42; OSCAR33320	0.30	1.40	1.72	0.67	0.70	45.7	82.9	71.3	71.3	67.8	39.2
mlr41	-1,0,-1	1,1,5	mlr	5.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33305	0.26	1.42	1.74	0.67	0.71	40.6	85.3	74.0	74.0	68.5	15.2
mlr68	-1,0,0	1,1,1	mlr	7.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33337	0.28	1.44	1.73	0.67	0.72	43.7	88.0	72.4	72.4	69.1	22.1
mlr27	-1,0,0	1,1,1	mlr	4.4e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33328	0.33	1.42	1.72	0.66	0.71	50.6	84.9	71.2	71.2	69.5	22.6
mlr94	-1,0,0	1,1,4	mlr	8.5e-08	0.87	20	OSCAR42; OSCAR33359; OISST177410	0.27	1.46	1.74	0.67	0.73	41.4	90.9	73.7	73.7	69.9	17.2
mlr63	-1,0,-1	1,1,8	mlr	7.4e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116431	0.44	1.33	1.70	0.66	0.67	68.1	73.0	69.5	69.5	70.0	16.1
mlr93	-1,0,0	1,1,4	mlr	8.5e-08	0.87	20	OSCAR42; OSCAR33359; OISST177420	0.27	1.46	1.74	0.67	0.73	41.4	91.5	73.7	73.7	70.1	17.2
mlr39	-1,0,0	1,1,6	mlr	5.6e-08	0.87	20	OSCAR42; OSCAR33359; OISST177417	-0.10	1.47	1.85	0.72	0.73	15.9	91.9	86.6	86.6	70.3	20.7
mlr10	-1,0	1,1	mlr	9.3e-09	0.87	20	OSCAR42; OSCAR33359	0.29	1.46	1.75	0.68	0.73	44.2	91.5	74.4	74.4	71.1	17.3
mlr70	-1,0,-1	1,1,6	mlr	7.9e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116448	0.34	1.42	1.74	0.67	0.71	51.8	85.7	73.5	73.5	71.2	19.6
mlr99	-1,0,-1	1,1,12	mlr	8.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR49925	0.28	1.46	1.76	0.68	0.73	42.6	90.7	75.7	75.7	71.2	25.3
mlr201	-1,-1	1,1	mlr	2.8e-04	0.57	20	OSCAR42; OSCAR116435	0.01	1.60	1.86	0.72	0.80	2.1	110.4	86.9	86.9	71.5	82.3
mlr42	-1,0,-1	1,1,1	mlr	5.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33323	0.18	1.55	1.77	0.69	0.77	28.0	103.7	77.3	77.3	71.6	15.7
mlr76	-1,0,0	1,1,1	mlr	8.1e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33338	0.30	1.45	1.75	0.68	0.73	46.0	89.7	75.4	75.4	71.6	22.9
mlr11	-1,0,-1	1,1,5	mlr	2.1e-08	0.89	20	OSCAR42; OSCAR33359; OSCAR99803	0.23	1.57	1.73	0.67	0.79	34.9	107.4	72.3	72.3	71.8	20.2
mlr74	-1,0,0	1,1,2	mlr	8.0e-08	0.87	20	OSCAR42; OSCAR33359; OISST177428	0.30	1.46	1.75	0.68	0.73	45.5	91.4	75.5	75.5	71.9	18.9
mlr82	-1,0,0	1,1,2	mlr	8.3e-08	0.87	20	OSCAR42; OSCAR33359; OISST177434	0.30	1.46	1.75	0.68	0.73	46.1	91.3	75.1	75.1	71.9	19.0
mlr44	-1,0,0	1,1,6	mlr	5.7e-08	0.87	20	OSCAR42; OSCAR33359; OISST177412	-0.10	1.48	1.88	0.73	0.74	15.7	94.4	89.6	89.6	72.3	21.2
mlr83	-1,0,-1	1,1,1	mlr	8.3e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR43	0.24	1.52	1.78	0.69	0.76	36.8	99.1	78.5	78.5	73.2	22.7
mlr46	-1,0,-1	1,1,6	mlr	5.9e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR49924	0.37	1.44	1.75	0.68	0.72	56.0	88.5	75.0	75.0	73.6	16.9
mlr75	-1,0,0	1,1,2	mlr	8.1e-08	0.87	20	OSCAR42; OSCAR33359; OISST177431	0.28	1.49	1.78	0.69	0.74	43.3	95.2	78.0	78.0	73.7	19.7
mlr60	-1,0,-1	1,1,5	mlr	7.3e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116429	0.25	1.48	1.81	0.70	0.74	38.2	94.4	81.3	81.3	73.8	23.7
mlr65	-1,0,-1	1,1,10	mlr	7.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116439	0.38	1.40	1.79	0.69	0.70	57.6	82.9	78.9	78.9	74.6	20.5
mlr56	-1,0,0	1,1,2	mlr	6.8e-08	0.87	20	OSCAR42; OSCAR33359; OISST177419	0.39	1.45	1.75	0.68	0.73	60.3	89.5	74.5	74.5	74.7	17.5
mlr115	-1,0,0	1,1,2	mlr	8.8e-08	0.87	20	OSCAR42; OSCAR33359; OISST177426	0.31	1.49	1.78	0.69	0.75	46.9	95.9	78.1	78.1	74.8	19.8
mlr100	-1,0,-1	1,1,5	mlr	8.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116441	0.28	1.49	1.81	0.70	0.74	43.2	94.6	81.1	81.1	75.0	22.5
mlr111	-1,0,-1	1,1,3	mlr	8.8e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33346	0.22	1.53	1.82	0.70	0.76	34.1	101.0	82.6	82.6	75.1	20.2
mlr62	-1,0,-1	1,1,1	mlr	7.3e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33355	0.30	1.47	1.80	0.70	0.74	46.7	93.1	80.5	80.5	75.2	17.2
mlr61	-1,0,0	1,1,1	mlr	7.3e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33347	0.20	1.55	1.82	0.71	0.78	30.9	104.4	83.2	83.2	75.4	24.0

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr116	-1,0	1,1	mlr	8.8e-08	0.83	20	OSCAR42; OSCAR33356	-0.02	1.62	1.91	0.74	0.81	2.5	113.3	93.1	93.1	75.5	32.1
mlr102	-1,0,-1	1,1,8	mlr	8.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116434	0.16	1.58	1.83	0.71	0.79	25.0	108.8	84.3	84.3	75.6	22.4
mlr109	-1,0,0	1,1,2	mlr	8.7e-08	0.87	20	OSCAR42; OSCAR33359; OISST177425	0.32	1.50	1.78	0.69	0.75	48.4	96.6	78.7	78.7	75.6	19.8
mlr110	-1,0,-1	1,1,8	mlr	8.8e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116433	0.26	1.53	1.81	0.70	0.76	39.4	100.7	81.4	81.4	75.7	21.2
mlr20	-1,0,-1	1,1,5	mlr	3.6e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33334	-0.02	1.63	1.91	0.74	0.81	2.5	114.9	92.8	92.8	75.8	18.1
mlr35	-1,0,0	1,1,6	mlr	5.5e-08	0.87	20	OSCAR42; OSCAR33359; OISST177415	-0.15	1.49	1.91	0.74	0.75	23.4	95.5	92.2	92.2	75.8	20.6
mlr105	-1,0,0	1,1,1	mlr	8.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33330	0.24	1.53	1.82	0.71	0.76	36.4	100.7	83.3	83.3	75.9	24.0
mlr86	-1,0,0	1,1,2	mlr	8.4e-08	0.87	20	OSCAR42; OSCAR33359; OISST177432	0.31	1.50	1.79	0.69	0.75	47.5	97.1	79.5	79.5	75.9	20.1
mlr49	-1,0,-1	1,1,1	mlr	6.2e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33324	0.29	1.53	1.79	0.69	0.77	44.0	101.6	79.2	79.2	76.0	21.5
mlr81	-1,0,0	1,1,3	mlr	8.3e-08	0.87	20	OSCAR42; OSCAR33359; OISST177418	0.27	1.54	1.80	0.70	0.77	41.4	102.6	80.1	80.1	76.0	22.1
mlr23	-1,0,0	1,1,4	mlr	3.9e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR66549	0.14	1.60	1.85	0.72	0.80	20.9	110.6	86.5	86.5	76.1	18.2
mlr79	-1,0,-1	1,1,6	mlr	8.2e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33358	0.27	1.54	1.80	0.70	0.77	41.9	102.1	80.6	80.6	76.3	28.4
mlr73	-1,0,0	1,1,6	mlr	8.0e-08	0.87	20	OSCAR42; OSCAR33359; OISST266113	0.29	1.53	1.80	0.70	0.76	44.3	100.5	80.4	80.4	76.4	22.3
mlr72	-1,0,0	1,1,3	mlr	7.9e-08	0.87	20	OSCAR42; OSCAR33359; OISST177436	0.40	1.47	1.76	0.68	0.73	61.1	91.7	76.6	76.6	76.5	20.8
mlr106	-1,0,0	1,1,2	mlr	8.7e-08	0.87	20	OSCAR42; OSCAR33359; OISST177435	0.32	1.51	1.79	0.69	0.75	49.5	97.7	79.7	79.7	76.6	19.9
mlr85	-1,0,-1	1,1,1	mlr	8.3e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33321	0.33	1.50	1.80	0.70	0.75	51.3	96.1	80.0	80.0	76.9	20.7
mlr40	-1,0,0	1,1,6	mlr	5.7e-08	0.87	20	OSCAR42; OSCAR33359; OISST177414	-0.14	1.51	1.93	0.75	0.75	20.7	98.0	94.8	94.8	77.1	21.4
mlr55	-1,0,0	1,1,1	mlr	6.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33327	0.36	1.50	1.78	0.69	0.75	55.0	96.4	78.7	78.7	77.2	21.6
mlr37	-1,0,-1	1,1,4	mlr	5.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33309	0.26	1.56	1.82	0.70	0.78	39.5	104.7	82.7	82.7	77.4	21.6
mlr95	-1,0,0	1,1,3	mlr	8.5e-08	0.87	20	OSCAR42; OSCAR33359; OISST177427	0.30	1.54	1.80	0.70	0.77	45.6	102.7	80.7	80.7	77.4	22.0
mlr91	-1,0,0	1,1,1	mlr	8.5e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33333	0.24	1.54	1.85	0.72	0.77	36.5	102.4	86.2	86.2	77.8	24.0
mlr80	-1,0,-1	1,1,8	mlr	8.2e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116438	0.08	1.65	1.89	0.73	0.83	12.7	118.4	90.4	90.4	78.0	24.1
mlr170	-1,-1	1,5	mlr	1.2e-04	0.61	20	OSCAR42; OSCAR33311	0.12	1.66	1.87	0.72	0.83	17.8	119.1	88.1	88.1	78.3	75.9
mlr84	-1,0,0	1,1,6	mlr	8.3e-08	0.87	20	OSCAR42; OSCAR33359; OISST266111	0.31	1.53	1.81	0.70	0.76	48.2	100.8	82.2	82.2	78.3	22.1
OSCAR116447	0	4	scam_mpd	1.3e-04	0.51	21	u	-0.02	1.67	1.93	0.75	0.83	2.8	120.6	94.9	94.9	78.3	75.9
OSCAR66550	0	4	lm	1.6e-04	0.51	21	u	-0.02	1.67	1.93	0.75	0.83	2.8	120.6	94.9	94.9	78.3	75.9
mlr69	-1,0,0	1,1,5	mlr	7.7e-08	0.87	20	OSCAR42; OSCAR33359; lighthouse310799	0.38	1.50	1.79	0.69	0.75	57.5	97.0	79.9	79.9	78.6	18.5
mlr88	-1,0,0	1,1,3	mlr	8.4e-08	0.87	20	OSCAR42; OSCAR33359; OISST177430	0.39	1.49	1.80	0.70	0.75	60.0	95.3	80.0	80.0	78.8	21.3
nepstar13	0,-1,0,-1,-1	5,5,5,3,7	mlr	1.8e-10	0.86	30	nepstar	0.32	1.55	1.81	0.70	0.77	48.6	103.6	82.1	82.1	79.1	16.8
mlr54	-1,0,0	1,1,6	mlr	6.6e-08	0.87	20	OSCAR42; OSCAR33359; OISST266112	0.27	1.56	1.84	0.71	0.78	40.8	105.7	85.3	85.3	79.3	21.9
mlr18	-1,0,-1	1,1,3	mlr	2.9e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33300	-0.25	1.52	1.88	0.73	0.76	37.8	99.9	89.9	89.9	79.4	21.1
mlr104	-1,0,0	1,1,3	mlr	8.7e-08	0.87	20	OSCAR42; OSCAR33359; OISST177408	0.32	1.55	1.82	0.70	0.78	49.2	104.1	82.6	82.6	79.6	22.5
mlr186	-1,-1	1,5	mlr	1.7e-04	0.60	20	OSCAR42; OSCAR116429	-0.05	1.66	1.94	0.75	0.83	6.9	119.2	96.3	96.3	79.6	76.2
mlr113	-1,0,0	1,1,3	mlr	8.8e-08	0.87	20	OSCAR42; OSCAR33359; OISST177411	0.35	1.54	1.81	0.70	0.77	53.3	102.0	82.0	82.0	79.8	22.2
mlr202	-1,-1	1,1	mlr	2.9e-04	0.57	20	OSCAR42; OSCAR116442	0.05	1.67	1.93	0.75	0.83	8.0	120.9	95.1	95.1	79.8	87.6
OSCAR116437	0	4	scam_mpd	5.1e-05	0.55	21	u	-0.36	1.61	1.76	0.68	0.81	54.6	112.6	76.4	76.4	80.0	79.2
OSCAR66548	0	4	lm	7.1e-05	0.55	21	u	-0.36	1.61	1.76	0.68	0.81	54.6	112.6	76.4	76.4	80.0	73.7
mlr53	-1,0,-1	1,1,1	mlr	6.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33308	0.21	1.60	1.87	0.73	0.80	32.0	111.4	88.7	88.7	80.2	24.1
mlr13	-1,0,-1	1,1,3	mlr	2.3e-08	0.89	20	OSCAR42; OSCAR33359; OSCAR33302	-0.28	1.50	1.89	0.73	0.75	43.0	96.4	90.9	90.9	80.3	19.5
mlr114	-1,0,-1	1,1,8	mlr	8.8e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116436	0.23	1.58	1.88	0.73	0.79	35.4	108.7	89.1	89.1	80.6	22.1
mlr36	-1,0,0	1,1,6	mlr	5.5e-08	0.87	20	OSCAR42; OSCAR33359; OISST177433	-0.18	1.52	1.95	0.76	0.76	27.7	100.3	97.4	97.4	80.7	20.9
mlr77	-1,0,-1	1,1,5	mlr	8.2e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33341	0.35	1.54	1.82	0.71	0.77	54.1	102.6	83.1	83.1	80.7	23.7

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr64	-1,0,-1	1,1,1	mlr	7.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116442	0.36	1.51	1.84	0.71	0.75	55.8	98.0	84.6	84.6	80.8	23.8
mlr67	-1,0,-1	1,1,6	mlr	7.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116440	0.38	1.51	1.83	0.71	0.75	58.2	97.7	83.5	83.5	80.8	20.5
mlr190	-1,-1	1,9	mlr	2.1e-04	0.59	20	OSCAR42; OSCAR33331	-0.06	1.76	1.90	0.73	0.88	9.0	134.7	91.2	91.2	81.5	77.6
nepstar8	0,-1,0,-1,0,-1	5,5,5,5,4,7	mlr	1.1e-10	0.88	30	nepstar	0.47	1.60	1.72	0.67	0.80	71.7	111.3	72.1	72.1	81.8	15.8
mlr97	-1,0,0	1,1,1	mlr	8.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33356	0.31	1.59	1.86	0.72	0.79	46.8	109.3	87.4	87.4	82.8	22.0
mlr107	-1,0,-1	1,1,1	mlr	8.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33345	0.35	1.57	1.85	0.72	0.78	53.7	106.4	86.3	86.3	83.2	19.3
mlr50	-1,0,-1	1,1,5	mlr	6.3e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33306	0.19	1.66	1.91	0.74	0.83	29.4	119.5	92.5	92.5	83.5	18.3
mlr172	-1,-1	1,5	mlr	1.3e-04	0.61	20	OSCAR42; OSCAR33310	-0.03	1.77	1.97	0.76	0.89	4.3	135.5	99.1	99.1	84.5	78.4
mlr103	-1,0,0	1,1,5	mlr	8.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116445	0.40	1.58	1.85	0.72	0.79	60.6	107.9	86.0	86.0	85.1	20.9
mlr101	-1,0,-1	1,1,1	mlr	8.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33354	0.33	1.57	1.90	0.73	0.79	51.1	107.3	91.2	91.2	85.2	25.9
mlr89	-1,0,-1	1,1,1	mlr	8.4e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33352	0.38	1.57	1.87	0.72	0.79	58.0	107.0	88.5	88.5	85.5	19.9
mlr26	-1,0,-1	1,1,3	mlr	4.0e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33340	-0.17	1.66	1.96	0.76	0.83	26.5	119.3	98.4	98.4	85.7	25.3
nepstar12	0,-1,0,-1,0,-1	5,5,5,5,4,7	mlr	1.1e-10	0.88	30	nepstar	0.56	1.59	1.74	0.67	0.80	85.8	110.3	73.4	73.4	85.7	18.4
mlr155	-1,0	1,2	mlr	6.8e-05	0.64	20	OSCAR42; OISST177434	0.25	1.64	1.94	0.75	0.82	38.5	116.1	96.1	96.1	86.7	67.7
mlr33	-1,0,-1	1,1,5	mlr	5.1e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33314	0.15	1.69	1.97	0.76	0.85	22.8	124.5	99.8	99.8	86.7	17.3
mlr71	-1,0,-1	1,1,1	mlr	7.9e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116435	0.40	1.55	1.89	0.73	0.78	61.7	104.6	90.9	90.9	87.0	22.1
mlr123	-1,0	1,1	mlr	9.9e-07	0.78	20	OSCAR42; OSCAR33347	0.41	1.56	1.89	0.73	0.78	62.7	105.7	90.4	90.4	87.3	45.8
mlr98	-1,0,0	1,1,5	mlr	8.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR116451	0.41	1.59	1.87	0.73	0.80	63.1	109.8	88.6	88.6	87.5	20.4
mlr125	-1,0	1,1	mlr	8.0e-06	0.72	20	OSCAR42; OSCAR33328	0.38	1.34	2.06	0.80	0.67	58.3	73.9	109.1	109.1	87.6	47.3
mlr152	-1,0	1,2	mlr	6.4e-05	0.64	20	OSCAR42; OISST177428	0.17	1.71	1.97	0.76	0.86	26.4	127.4	99.5	99.5	88.2	69.5
nepstar2	0,-1,0,0,-1	5,5,5,4,7	mlr	5.6e-11	0.87	30	nepstar	0.51	1.62	1.81	0.70	0.81	77.6	113.4	81.9	81.9	88.7	16.6
mlr78	-1,0,0	1,1,2	mlr	8.2e-08	0.87	20	OSCAR42; OSCAR33359; OISST177429	0.46	1.56	1.89	0.73	0.78	69.9	105.0	90.6	90.6	89.0	19.7
nepstar39	0,-1,0,-1,-1	5,3,5,7,7	mlr	2.7e-09	0.82	30	nepstar	0.82	1.49	1.70	0.66	0.74	125.7	94.6	69.0	69.0	89.6	18.0
nepstar34	-1,0,-1,-1,-1,0	5,5,7,5,3,4	mlr	4.0e-09	0.84	30	nepstar	0.95	1.37	1.70	0.66	0.68	145.3	77.7	69.4	69.4	90.5	27.2
mlr66	-1,0,0	1,1,2	mlr	7.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR99806	0.35	1.68	1.92	0.74	0.84	54.0	122.4	93.8	93.8	91.0	21.0
mlr147	-1,-1	1,1	mlr	5.2e-05	0.65	20	OSCAR42; OSCAR33324	0.17	1.66	2.06	0.80	0.83	26.7	119.3	109.4	109.4	91.2	66.2
mlr90	-1,0,-1	1,1,2	mlr	8.4e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33344	0.45	1.57	1.93	0.75	0.79	69.1	106.9	94.6	94.6	91.3	21.3
mlr151	-1,-1	1,5	mlr	6.2e-05	0.64	20	OSCAR42; OSCAR33312	-0.05	1.93	1.99	0.77	0.96	7.3	158.4	101.9	101.9	92.4	69.5
mlr25	-1,0,-1	1,1,3	mlr	4.0e-08	0.88	20	OSCAR42; OSCAR33359; OSCAR33350	-0.18	1.73	2.04	0.79	0.86	27.0	129.3	107.4	107.4	92.8	24.0
nepstar1	0,-1,0,0,-1	5,5,5,4,7	mlr	5.6e-11	0.87	30	nepstar	0.62	1.61	1.82	0.71	0.80	95.3	112.5	82.8	82.8	93.3	19.7
nepstar27	0,-1,0,-1,-1,0	5,5,5,7,5,4	mlr	2.0e-09	0.85	30	nepstar	0.61	1.63	1.82	0.71	0.81	92.9	115.0	83.1	83.1	93.5	36.2
mlr124	-1,0	1,1	mlr	4.0e-06	0.74	20	OSCAR42; OSCAR33327	0.39	1.61	2.00	0.77	0.81	60.1	112.8	102.7	102.7	94.6	47.5
nepstar23	0,0,-1,-1,-1	5,5,7,3,7	mlr	1.1e-09	0.84	30	nepstar	0.57	1.62	1.88	0.73	0.81	87.1	114.1	89.8	89.8	95.2	33.5
mlr108	-1,0,0	1,1,1	mlr	8.7e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33342	0.45	1.65	1.97	0.76	0.83	68.9	118.4	99.8	99.8	96.8	23.7
mlr112	-1,0,-1	1,1,2	mlr	8.8e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33332	0.46	1.64	1.99	0.77	0.82	69.9	116.5	101.2	101.2	97.2	19.5
nepstar9	0,-1,-2,-1,0	5,5,4,3,4	mlr	1.3e-09	0.83	30	nepstar	0.76	1.54	1.86	0.72	0.77	116.0	102.8	87.0	87.0	98.2	19.6
nepstar25	0,0,-1,-1,-1	5,5,3,7,7	mlr	5.2e-10	0.85	30	nepstar	0.79	1.54	1.84	0.71	0.77	120.8	101.9	85.3	85.3	98.3	19.8
mlr120	-1,0	1,1	mlr	3.8e-07	0.80	20	OSCAR42; OSCAR33337	0.32	1.80	2.00	0.77	0.90	49.2	139.3	102.5	102.5	98.4	38.7
mlr58	-1,0,0	1,1,5	mlr	7.0e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR33326	-0.07	1.93	2.10	0.81	0.96	10.6	157.8	114.0	114.0	99.1	24.8
OSCAR33325	-1	1	scam_mpi	1.1e-04	0.54	20	v	0.59	1.49	2.04	0.79	0.74	90.2	94.8	107.3	107.3	99.9	70.9
OSCAR43	-1	1	lm	1.4e-04	0.54	20	v	0.59	1.49	2.04	0.79	0.74	90.2	94.8	107.3	107.3	99.9	70.5
mlr157	-1,0	1,2	mlr	7.3e-05	0.64	20	OSCAR42; OISST177426	0.39	1.69	2.07	0.80	0.84	60.1	123.9	110.5	110.5	101.3	69.8

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr175	-1,-1	1,10	mlr	1.4e-04	0.61	20	OSCAR42; OSCAR116439	0.34	1.44	2.28	0.88	0.72	51.7	87.8	134.4	134.4	102.1	71.5
OSCAR33316	-1	1	scam_mpi	7.5e-05	0.55	20	v	0.22	1.70	2.19	0.85	0.85	34.2	125.9	124.3	124.3	102.2	388.0
OSCAR42	-1	1	lm	1.0e-04	0.55	20	v	0.22	1.70	2.19	0.85	0.85	34.2	125.9	124.3	124.3	102.2	73.7
nepstar38	0,0,-1,-1,-1	5,5,3,7,7	mlr	1.1e-09	0.84	30	nepstar	0.77	1.61	1.89	0.73	0.81	117.7	112.9	90.0	90.0	102.6	18.5
mlr182	-1,0	1,6	mlr	1.6e-04	0.60	20	OSCAR42; OISST266112	0.53	1.58	2.08	0.80	0.79	81.3	108.1	111.3	111.3	103.0	77.3
mlr221	-1,-1	1,1	mlr	6.4e-04	0.53	20	OSCAR42; OSCAR43	0.27	1.68	2.19	0.85	0.84	41.4	123.2	123.7	123.7	103.0	77.1
OSCAR33308	-1	1	scam_mpi	8.3e-04	0.57	20	v	0.20	1.87	2.11	0.82	0.94	31.3	150.5	115.0	115.0	103.0	94.7
mlr96	-1,0,-1	1,1,9	mlr	8.6e-08	0.87	20	OSCAR42; OSCAR33359; OSCAR49923	0.12	1.79	2.22	0.86	0.90	18.9	138.7	127.5	127.5	103.1	23.3
nepstar24	0,0,-1,-1,0,-1	5,5,5,3,4,7	mlr	3.5e-10	0.87	30	nepstar	0.94	1.51	1.84	0.71	0.75	145.1	97.8	84.7	84.7	103.1	20.5
mlr148	-1,-1	1,3	mlr	5.6e-05	0.65	20	OSCAR42; OSCAR33346	0.13	1.84	2.19	0.85	0.92	20.2	145.3	123.6	123.6	103.2	63.1
mlr206	-1,0	1,5	mlr	3.5e-04	0.56	20	OSCAR42; OSCAR116445	-0.10	1.87	2.19	0.85	0.93	15.5	149.5	123.9	123.9	103.2	71.0
mlr154	-1,0	1,2	mlr	6.5e-05	0.64	20	OSCAR42; OISST177425	0.32	1.77	2.10	0.81	0.89	49.6	136.0	113.9	113.9	103.4	71.6
mlr153	-1,0	1,2	mlr	6.4e-05	0.64	20	OSCAR42; OISST177435	0.26	1.83	2.12	0.82	0.92	40.6	144.2	116.7	116.7	104.6	73.5
nepstar28	0,0,-1,-1,0	4,5,7,5,4	mlr	1.2e-09	0.84	30	nepstar	0.12	1.73	2.32	0.90	0.87	18.4	130.4	138.0	138.0	106.2	43.5
mlr122	-1,0	1,1	mlr	5.2e-07	0.80	20	OSCAR42; OSCAR33338	0.31	1.85	2.11	0.82	0.92	47.5	146.5	115.6	115.6	106.3	42.3
mlr194	-1,-1	1,5	mlr	2.3e-04	0.58	20	OSCAR42; OSCAR116441	0.12	1.83	2.29	0.89	0.91	17.6	144.0	134.7	134.7	107.8	85.1
mlr220	-1,-1	1,5	mlr	6.4e-04	0.53	20	OSCAR42; OSCAR33341	0.26	1.73	2.27	0.88	0.87	39.4	130.2	132.8	132.8	108.8	78.3
mlr165	-1,-1	1,6	mlr	1.1e-04	0.62	20	OSCAR42; OSCAR49924	0.05	2.10	2.19	0.85	1.05	7.4	182.3	124.2	124.2	109.5	74.6
nepstar29	-1,-1,-2,-1	5,5,4,3	mlr	1.4e-08	0.78	30	nepstar	-0.31	1.83	2.19	0.85	0.91	47.4	143.6	124.3	124.3	109.9	26.4
mlr181	-1,0	1,6	mlr	1.6e-04	0.60	20	OSCAR42; OISST266113	0.58	1.65	2.12	0.82	0.82	89.7	117.8	116.5	116.5	110.1	76.3
mlr218	-1,-1	1,5	mlr	5.6e-04	0.54	20	OSCAR42; OSCAR116443	-0.19	1.75	2.33	0.90	0.88	29.6	132.9	139.7	139.7	110.5	82.5
nepstar35	-1,0,-1,-2,-1,0	5,5,5,4,3,4	mlr	1.8e-09	0.85	30	nepstar	0.75	1.68	1.99	0.77	0.84	115.4	122.7	102.0	102.0	110.5	18.3
nepstar21	0,0,-1,-1,0,-1	4,5,5,3,4,7	mlr	2.3e-10	0.87	30	nepstar	0.28	1.74	2.29	0.89	0.87	43.6	130.9	134.7	134.7	111.0	25.3
mlr177	-1,-1	1,5	mlr	1.4e-04	0.61	20	OSCAR42; OSCAR33319	-0.20	2.03	2.17	0.84	1.01	30.2	172.3	121.4	121.4	111.3	74.6
mlr187	-1,-1	1,3	mlr	2.0e-04	0.59	20	OSCAR42; OSCAR33302	-0.71	1.65	2.06	0.80	0.83	108.9	118.4	109.5	109.5	111.6	67.2
mlr198	-1,0	1,5	mlr	2.5e-04	0.58	20	OSCAR42; OSCAR116451	-0.18	1.97	2.23	0.86	0.98	27.9	164.1	128.8	128.8	112.4	68.8
mlr119	-1,0	1,1	mlr	3.1e-07	0.81	20	OSCAR42; OSCAR33330	0.78	1.80	1.95	0.75	0.90	119.8	139.8	96.8	96.8	113.3	38.6
nepstar37	0,-1,0,-1,-2,0	5,5,5,5,4,4	mlr	1.4e-09	0.85	30	nepstar	0.39	1.82	2.22	0.86	0.91	59.5	142.5	127.0	127.0	114.0	31.7
mlr193	-1,-1	1,5	mlr	2.3e-04	0.58	20	OSCAR42; OSCAR116432	-0.37	1.77	2.27	0.88	0.88	56.6	134.8	132.5	132.5	114.1	75.6
nepstar40	0,-1,0,-1,-2,0	5,5,5,5,4,4	mlr	1.8e-09	0.85	30	nepstar	0.52	1.83	2.14	0.83	0.91	79.6	143.7	118.1	118.1	114.9	34.3
mlr199	-1,-1	1,5	mlr	2.8e-04	0.57	20	OSCAR42; OSCAR33305	0.14	1.93	2.40	0.93	0.96	20.9	157.9	147.7	147.7	118.5	79.1
mlr207	-1,-1	1,4	mlr	3.6e-04	0.56	20	OSCAR42; OSCAR33353	0.01	1.95	2.48	0.96	0.97	1.8	160.7	156.7	156.7	118.9	86.9
nepstar41	0,-1,0,0,-1,-1	4,3,5,4,7,7	mlr	9.6e-10	0.86	30	nepstar	0.16	1.78	2.49	0.96	0.89	25.1	137.2	157.2	157.2	119.2	23.7
nepstar5	0,-1,0,-1,0,-1	5,5,5,3,4,7	mlr	2.5e-10	0.87	30	nepstar	0.93	1.57	2.10	0.81	0.79	143.1	107.1	113.6	113.6	119.4	14.2
nepstar14	0,-1,0,-1,0,-1	5,5,5,3,4,7	mlr	2.9e-10	0.87	30	nepstar	0.86	1.63	2.11	0.82	0.82	132.8	115.6	114.9	114.9	119.5	12.3
mlr180	-1,0	1,6	mlr	1.6e-04	0.60	20	OSCAR42; OISST266111	0.58	1.75	2.24	0.87	0.87	88.7	132.6	129.1	129.1	119.9	77.4
nepstar33	0,0,-1,-1,0,-1	4,5,5,3,4,7	mlr	3.9e-10	0.87	30	nepstar	0.35	1.85	2.36	0.91	0.93	53.5	147.2	142.6	142.6	121.5	25.1
mlr159	-1,0	1,2	mlr	8.1e-05	0.63	20	OSCAR42; OISST177431	0.58	1.81	2.24	0.87	0.90	88.3	141.1	129.0	129.0	121.9	72.4
mlr203	-1,-1	1,5	mlr	3.1e-04	0.57	20	OSCAR42; OSCAR116430	-0.44	1.76	2.36	0.91	0.88	67.9	134.4	143.1	143.1	122.1	79.2
nepstar18	0,0,-1,-1,-1	4,5,7,3,7	mlr	2.0e-09	0.83	30	nepstar	-0.04	1.80	2.63	1.02	0.90	6.6	139.7	172.5	172.5	122.8	33.5
mlr156	-1,0	1,2	mlr	7.0e-05	0.64	20	OSCAR42; OISST177432	0.53	1.83	2.28	0.88	0.92	80.7	144.2	134.0	134.0	123.2	73.6
mlr204	-1,-1	1,5	mlr	3.2e-04	0.57	20	OSCAR42; OSCAR33329	0.20	1.98	2.41	0.93	0.99	30.7	165.8	149.0	149.0	123.6	80.0

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr210	-1,-1	1,1	mlr	4.2e-04	0.55	20	OSCAR42; OSCAR33323	-0.01	1.95	2.56	0.99	0.98	0.9	162.0	165.8	165.8	123.6	82.2
mlr217	-1,-1	1,1	mlr	5.0e-04	0.54	20	OSCAR42; OSCAR33354	0.66	1.94	2.15	0.83	0.97	100.6	160.0	119.5	119.5	124.9	82.4
mlr146	-1,0	1,6	mlr	5.1e-05	0.65	20	OSCAR42; OISST177423	-1.03	1.85	1.98	0.77	0.92	158.2	146.4	100.4	100.4	126.4	73.8
mlr126	-1,0	1,4	mlr	9.2e-06	0.71	20	OSCAR42; OSCAR66549	-0.22	1.86	2.55	0.99	0.93	34.3	148.1	164.5	164.5	127.8	62.6
mlr219	-1,-1	1,4	mlr	5.8e-04	0.53	20	OSCAR42; OSCAR33309	0.21	1.92	2.53	0.98	0.96	32.0	156.8	161.4	161.4	127.9	84.5
mlr134	-1,-1	1,5	mlr	3.1e-05	0.67	20	OSCAR42; OSCAR99803	0.17	2.04	2.48	0.96	1.02	25.9	174.9	156.1	156.1	128.2	64.5
nepstar20	0,0,-1,-1,-1	4,5,3,7,7	mlr	6.3e-10	0.84	30	nepstar	0.04	1.94	2.64	1.02	0.97	5.7	159.7	174.0	174.0	128.3	25.7
nepstar32	0,-1,0,0,-1	4,3,5,4,7	mlr	1.0e-09	0.84	30	nepstar	0.35	1.81	2.50	0.97	0.91	54.4	141.6	159.1	159.1	128.5	27.3
nepstar11	0,0,-1,-1	5,5,7,7	mlr	1.1e-09	0.82	30	nepstar	0.75	1.90	2.18	0.84	0.95	115.0	154.7	122.6	122.6	128.7	44.1
nepstar16	0,0,-1,0,-1	4,5,5,4,7	mlr	2.4e-10	0.86	30	nepstar	0.41	1.91	2.42	0.94	0.95	63.2	155.5	149.7	149.7	129.5	28.7
nepstar3	0,0,-1,-1,-1	4,5,3,7,7	mlr	2.7e-10	0.86	30	nepstar	-0.05	1.99	2.62	1.02	0.99	6.9	166.8	172.2	172.2	129.5	25.6
mlr139	-1,-1	1,1	mlr	3.8e-05	0.66	20	OSCAR42; OSCAR33308	-0.32	2.06	2.39	0.93	1.03	48.3	177.7	146.4	146.4	129.7	67.7
nepstar7	0,0,-1,-1	5,5,7,7	mlr	1.2e-09	0.82	30	nepstar	0.65	1.95	2.25	0.87	0.98	99.8	161.5	130.3	130.3	130.5	42.1
mlr209	-1,-1	1,3	mlr	3.9e-04	0.56	20	OSCAR42; OSCAR33350	-0.40	2.06	2.37	0.92	1.03	60.9	176.6	144.0	144.0	131.4	76.7
nepstar6	0,-1,0,-1	4,3,5,7	mlr	4.4e-10	0.83	30	nepstar	-0.42	1.66	2.61	1.01	0.83	64.4	120.3	170.6	170.6	131.5	27.1
nepstar17	0,-1,0,-1,-1	4,3,5,7,7	mlr	6.8e-09	0.81	30	nepstar	0.00	1.96	2.75	1.06	0.98	0.5	162.2	186.0	186.0	133.7	31.2
mlr150	-1,0	1,6	mlr	5.9e-05	0.64	20	OSCAR42; OISST177422	-1.10	1.90	2.03	0.79	0.95	168.7	153.5	106.6	106.6	133.9	74.0
mlr191	-1,-1	1,3	mlr	2.2e-04	0.58	20	OSCAR42; OSCAR33300	-0.72	1.89	2.30	0.89	0.95	109.9	152.9	136.4	136.4	133.9	70.1
mlr158	-1,0	1,5	mlr	7.4e-05	0.64	20	OSCAR42; lighthouse310799	0.02	2.24	2.57	1.00	1.12	3.1	202.4	166.9	166.9	134.8	74.7
OSCAR116432	-1	5	scam_mpd	8.0e-04	0.59	20	u	0.15	2.32	2.44	0.94	1.16	22.5	214.2	151.4	151.4	134.9	112.5
nepstar22	0,-1,0,-1,-1	4,3,5,7,7	mlr	1.4e-09	0.83	30	nepstar	-0.21	1.79	2.74	1.06	0.90	31.6	138.8	185.7	185.7	135.5	30.1
nepstar36	0,0,-1,-1,0,-1	4,5,7,5,4,7	mlr	1.9e-09	0.85	30	nepstar	0.08	2.00	2.70	1.05	1.00	12.5	169.0	180.7	180.7	135.7	41.5
OSCAR116430	-1	5	scam_mpd	9.9e-04	0.60	20	u	0.06	2.37	2.48	0.96	1.19	8.5	221.8	156.1	156.1	135.7	74.9
mlr131	-1,0	1,4	mlr	2.6e-05	0.68	20	OSCAR42; OSCAR116437	-0.72	2.05	2.23	0.87	1.02	110.2	175.6	129.0	129.0	135.9	69.7
nepstar15	0,0,-1,-1,-1	4,5,7,3,7	mlr	5.8e-10	0.85	30	nepstar	-0.20	1.90	2.69	1.04	0.95	31.3	154.0	179.7	179.7	136.1	34.0
OSCAR33324	-1	1	scam_mpi	1.6e-03	0.54	20	v	1.09	1.91	2.07	0.80	0.95	167.9	154.9	111.0	111.0	136.2	116.1
mlr161	-1,-1	1,5	mlr	8.4e-05	0.63	20	OSCAR42; OSCAR33348	-0.21	2.26	2.45	0.95	1.13	32.7	206.3	153.1	153.1	136.3	67.4
nepstar4	0,0,-1,0,-1	4,5,3,4,7	mlr	2.7e-10	0.86	30	nepstar	0.30	1.98	2.58	1.00	0.99	45.9	166.1	167.3	167.3	136.6	27.7
mlr137	-1,0	1,6	mlr	3.8e-05	0.66	20	OSCAR42; OISST177413	-1.15	1.90	2.06	0.80	0.95	176.3	153.5	109.1	109.1	137.0	70.7
mlr143	-1,0	1,5	mlr	4.1e-05	0.66	20	OSCAR42; lighthouse311951	-1.03	1.91	2.12	0.82	0.96	158.8	156.3	116.7	116.7	137.1	65.9
OSCAR33332	-1	2	scam_mpi	2.8e-03	0.53	20	v	0.33	2.14	2.48	0.96	1.07	50.6	188.0	155.9	155.9	137.6	102.7
OSCAR116438	-1	8	scam_mpd	2.6e-03	0.54	20	u	0.23	2.19	2.56	0.99	1.09	34.5	195.6	164.9	164.9	140.0	115.9
mlr216	-1,-1	1,1	mlr	4.6e-04	0.55	20	OSCAR42; OSCAR33352	-0.27	1.92	2.71	1.05	0.96	40.6	156.7	181.7	181.7	140.2	79.6
mlr214	-1,-1	1,1	mlr	4.6e-04	0.55	20	OSCAR42; OSCAR33345	-0.27	1.89	2.73	1.06	0.94	41.8	152.0	183.8	183.8	140.3	79.3
mlr215	-1,-1	1,3	mlr	4.6e-04	0.55	20	OSCAR42; OSCAR33340	-0.37	2.00	2.59	1.00	1.00	57.2	168.6	168.6	168.6	140.7	82.6
OSCAR116444	0	4	scam_mpd	1.1e-04	0.52	21	u	0.82	1.80	2.41	0.93	0.90	125.5	140.3	148.9	148.9	140.9	71.8
OSCAR66549	0	4	lm	1.4e-04	0.52	21	u	0.82	1.80	2.41	0.93	0.90	125.5	140.3	148.9	148.9	140.9	71.8
OSCAR99803	-1	5	scam_mpi	4.8e-04	0.58	20	u	1.45	1.55	2.15	0.83	0.77	222.8	103.3	119.9	119.9	141.5	114.9
mlr130	-1,0	1,4	mlr	2.5e-05	0.68	20	OSCAR42; OSCAR116447	-0.63	2.04	2.42	0.94	1.02	97.1	174.1	149.3	149.3	142.4	73.0
OSCAR116429	-1	5	scam_mpd	4.3e-04	0.62	20	u	0.46	2.11	2.51	0.97	1.05	71.1	183.9	160.0	160.0	143.7	131.2
nepstar19	0,0,-1,0,-1	4,5,5,4,7	mlr	4.6e-10	0.85	30	nepstar	0.48	2.07	2.53	0.98	1.03	73.5	178.0	162.3	162.3	144.0	28.7
nepstar30	0,-1,0,-1,0,-1	4,5,5,3,4,7	mlr	5.1e-10	0.86	30	nepstar	0.44	1.99	2.61	1.01	1.00	67.2	167.4	171.3	171.3	144.3	21.0

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr145	-1,0	1,6	mlr	4.9e-05	0.65	20	OSCAR42; OISST177417	-1.22	1.96	2.12	0.82	0.98	186.6	162.9	116.6	116.6	145.7	71.9
OSCAR116434	-1	8	scam_mpd	2.2e-04	0.59	20	u	0.08	2.39	2.64	1.02	1.19	11.6	224.4	174.4	174.4	146.2	105.6
mlr212	-1,-1	1,1	mlr	4.4e-04	0.55	20	OSCAR42; OSCAR33321	0.48	2.21	2.49	0.97	1.10	73.2	198.0	157.8	157.8	146.7	87.0
nepstar31	0,0,-1,-1,-1	4,5,7,5,7	mlr	2.4e-09	0.83	30	nepstar	-0.00	2.10	2.90	1.12	1.05	0.5	183.5	202.6	202.6	147.3	37.5
nepstar26	0,0,0,0,-1	5,4,5,4,7	mlr	5.4e-10	0.85	30	nepstar	0.42	2.18	2.58	1.00	1.09	63.7	194.5	167.3	167.3	148.2	36.0
nepstar10	0,0,0,0,-1	5,4,5,4,7	mlr	4.9e-10	0.85	30	nepstar	0.49	2.16	2.56	0.99	1.08	74.5	191.4	164.8	164.8	148.8	37.5
mlr129	-1,0	1,3	mlr	2.2e-05	0.68	20	OSCAR42; OISST177418	-0.29	2.38	2.56	0.99	1.19	44.8	223.3	164.9	164.9	149.5	69.5
mlr128	-1,0	1,3	mlr	2.2e-05	0.68	20	OSCAR42; OISST177427	-0.23	2.41	2.59	1.00	1.21	35.8	227.6	168.5	168.5	150.1	71.2
mlr211	-1,-1	1,12	mlr	4.3e-04	0.55	20	OSCAR42; OSCAR49925	0.36	2.29	2.58	1.00	1.14	54.8	210.1	167.8	167.8	150.1	89.2
OISST177437	-1	8	scam_mpi	4.3e-05	0.50	31	truetemp	0.75	2.11	2.46	0.95	1.06	114.4	184.8	154.2	154.2	151.9	105.7
mlr213	-1,-1	1,11	mlr	4.5e-04	0.55	20	OSCAR42; OSCAR33304	0.04	2.33	2.81	1.09	1.16	6.5	215.5	193.2	193.2	152.1	80.1
mlr135	-1,0	1,6	mlr	3.4e-05	0.67	20	OSCAR42; OISST177412	-1.28	2.01	2.21	0.85	1.00	195.9	169.6	125.9	125.9	154.3	68.9
mlr133	-1,0	1,3	mlr	2.9e-05	0.67	20	OSCAR42; OISST177408	-0.14	2.49	2.71	1.05	1.25	21.9	239.0	182.1	182.1	156.3	69.5
mlr132	-1,0	1,3	mlr	2.8e-05	0.67	20	OSCAR42; OISST177411	-0.08	2.53	2.76	1.07	1.27	12.8	245.0	187.8	187.8	158.4	71.2
OSCAR33345	-1	1	scam_mpi	2.2e-03	0.51	20	v	-0.07	2.56	2.75	1.07	1.28	11.4	248.8	186.7	186.7	158.4	129.0
OSCAR33302	-1	3	scam_mpi	1.4e-04	0.59	20	v	-1.13	2.04	2.37	0.92	1.02	173.6	174.8	143.6	143.6	158.9	77.7
OSCAR33323	-1	1	scam_mpi	1.8e-03	0.54	20	v	0.70	2.26	2.53	0.98	1.13	107.3	206.6	161.6	161.6	159.3	95.0
mlr162	-1,-1	1,6	mlr	9.7e-05	0.62	20	OSCAR42; OSCAR33358	-0.10	2.28	2.94	1.14	1.14	14.9	208.1	207.2	207.2	159.4	86.5
OISST177416	-1	7	scam_mpi	7.7e-05	0.53	31	truetemp	0.85	2.21	2.47	0.96	1.10	129.8	198.1	155.3	155.3	159.7	109.0
median.all	0	0	median.all	NA			0	0.67	2.33	2.52	0.97	1.17	102.3	216.4	160.4	160.4	159.9	181.1
mlr208	-1,-1	1,6	mlr	3.9e-04	0.56	20	OSCAR42; OSCAR116440	-0.01	2.29	3.02	1.17	1.14	1.5	209.9	216.6	216.6	161.1	82.2
OSCAR33353	-1	4	scam_mpi	3.0e-03	0.51	20	v	0.77	2.25	2.54	0.98	1.13	118.5	204.6	162.8	162.8	162.2	94.6
mlr144	-1,0	1,6	mlr	4.8e-05	0.65	20	OSCAR42; OISST177415	-1.33	2.08	2.27	0.88	1.04	204.5	179.9	132.7	132.7	162.4	71.0
OSCAR33346	-1	3	scam_mpi	3.2e-03	0.51	20	v	0.79	2.27	2.52	0.98	1.14	121.5	207.5	161.3	161.3	162.9	122.7
mlr197	-1,-1	1,6	mlr	2.5e-04	0.58	20	OSCAR42; OSCAR116448	-0.35	2.31	2.82	1.09	1.16	53.2	213.4	193.9	193.9	163.6	77.7
OSCAR33300	-1	3	scam_mpi	9.9e-05	0.60	20	v	-1.14	2.19	2.35	0.91	1.10	175.1	196.3	142.2	142.2	163.9	77.6
OSCAR116433	-1	8	scam_mpd	1.7e-04	0.59	20	u	0.06	2.55	2.92	1.13	1.27	9.0	247.2	204.9	204.9	166.5	111.9
mlr196	-1,-1	1,5	mlr	2.4e-04	0.58	20	OSCAR42; OSCAR33306	-0.18	2.47	2.88	1.12	1.23	28.2	235.4	201.4	201.4	166.6	80.7
OSCAR116431	-1	8	scam_mpd	1.0e-04	0.60	20	u	0.56	2.46	2.63	1.02	1.23	85.2	235.2	173.2	173.2	166.7	117.9
OSCAR116443	-1	5	scam_mpd	5.1e-03	0.52	20	u	0.12	2.69	2.81	1.09	1.35	18.4	267.8	192.7	192.7	167.9	125.7
OISST177421	-1	7	scam_mpi	6.1e-05	0.53	31	truetemp	1.01	2.19	2.55	0.99	1.09	155.2	195.4	164.4	164.4	169.9	111.2
mlr136	-1,0	1,6	mlr	3.6e-05	0.66	20	OSCAR42; OISST177414	-1.37	2.13	2.35	0.91	1.06	210.4	186.7	142.2	142.2	170.3	68.8
OSCAR33352	-1	1	scam_mpi	3.2e-03	0.51	20	v	0.14	2.71	2.83	1.09	1.36	21.5	270.6	195.0	195.0	170.5	124.7
OSCAR49924	-1	6	scam_mpd	4.8e-04	0.53	20	v	0.94	2.36	2.51	0.97	1.18	143.7	220.3	159.1	159.1	170.6	115.6
OSCAR116435	-1	1	scam_mpd	2.5e-04	0.56	20	u	0.60	2.50	2.67	1.03	1.25	91.8	240.2	177.0	177.0	171.5	135.7
mlr189	-1,-1	1,1	mlr	2.0e-04	0.59	20	OSCAR42; OSCAR33351	-0.25	2.36	3.04	1.18	1.18	38.0	219.5	219.1	219.1	173.9	77.2
mlr142	-1,0	1,3	mlr	4.1e-05	0.66	20	OSCAR42; OISST177430	0.15	2.63	2.96	1.15	1.32	23.2	259.1	210.3	210.3	175.7	72.5
OSCAR33329	-1	5	scam_mpi	1.3e-04	0.53	20	v	1.15	2.16	2.58	1.00	1.08	176.3	191.8	168.0	168.0	176.0	113.0
mlr149	-1,0	1,6	mlr	5.7e-05	0.65	20	OSCAR42; OISST177433	-1.40	2.20	2.40	0.93	1.10	215.0	197.5	147.6	147.6	176.9	71.6
mlr163	-1,0	1,2	mlr	1.0e-04	0.62	20	OSCAR42; OSCAR99806	0.38	2.35	3.01	1.16	1.18	58.6	219.3	214.9	214.9	176.9	71.7
mlr205	-1,-1	1,1	mlr	3.3e-04	0.56	20	OSCAR42; OSCAR33355	0.88	2.35	2.67	1.04	1.17	134.9	218.4	177.9	177.9	177.3	81.2
OISST177418	0	3	scam_mpi	1.1e-05	0.53	32	truetemp	0.36	2.64	2.84	1.10	1.32	55.8	260.7	196.3	196.3	177.3	116.4

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr140	-1,0	1,3	mlr	4.0e-05	0.66	20	OSCAR42; OISST177436	0.21	2.65	3.00	1.16	1.32	31.7	261.3	214.3	214.3	180.4	73.7
OSCAR33350	-1	3	scam_mpi	2.1e-04	0.51	20	v	-0.53	2.62	2.80	1.09	1.31	81.0	257.1	192.2	192.2	180.6	80.9
OSCAR116436	-1	8	scam_mpd	2.6e-03	0.56	20	u	-0.29	2.65	2.96	1.15	1.32	44.7	261.7	209.6	209.6	181.4	112.5
OSCAR33348	-1	5	scam_mpi	2.0e-04	0.51	20	v	0.92	2.42	2.68	1.04	1.21	141.6	228.9	178.6	178.6	181.9	220.9
OISST177427	0	3	scam_mpi	2.0e-05	0.51	32	truetemp	0.40	2.68	2.90	1.12	1.34	61.9	265.7	202.8	202.8	183.3	120.1
OSCAR33296	-1	2	scam_mpi	5.4e-04	0.64	20	v	0.94	2.47	2.68	1.04	1.23	144.0	235.4	178.5	178.5	184.1	77.1
OSCAR33331	-1	9	scam_mpi	1.4e-04	0.53	20	v	0.91	2.45	2.71	1.05	1.23	139.1	233.8	181.9	181.9	184.2	146.4
OSCAR33312	-1	5	scam_mpi	2.7e-04	0.56	20	v	1.26	2.26	2.60	1.01	1.13	192.8	205.6	169.6	169.6	184.4	130.3
OSCAR44	-1	2	lm	2.0e-04	0.52	20	v	1.13	2.36	2.62	1.02	1.18	173.9	220.0	172.0	172.0	184.5	65.8
shore311951	0	5	scam_mpi	3.2e-05	0.59	26	temperature.c.	-0.42	2.63	2.95	1.14	1.32	64.1	259.5	209.0	209.0	185.4	75.6
OISST177408	0	3	scam_mpi	2.7e-07	0.59	32	truetemp	0.35	2.73	2.95	1.14	1.37	53.2	273.5	208.3	208.3	185.8	198.6
mlr195	-1,-1	1,8	mlr	2.4e-04	0.58	20	OSCAR42; OSCAR116433	-0.64	2.38	2.99	1.16	1.19	98.3	223.0	213.2	213.2	186.9	79.7
OSCAR116442	-1	1	scam_mpd	6.8e-04	0.53	20	u	0.87	2.51	2.75	1.07	1.26	134.1	241.9	186.5	186.5	187.3	141.5
mlr173	-1,-1	1,9	mlr	1.3e-04	0.61	20	OSCAR42; OSCAR49923	-0.18	2.69	3.13	1.21	1.34	28.3	267.1	228.7	228.7	188.2	74.0
OISST177422	0	6	scam_mpi	1.8e-05	0.53	32	truetemp	0.76	2.59	2.80	1.08	1.30	117.0	253.5	192.0	192.0	188.6	62.4
OISST177433	0	6	scam_mpi	1.5e-05	0.51	32	truetemp	0.79	2.58	2.80	1.08	1.29	121.5	251.2	192.1	192.1	189.2	61.7
OISST177414	0	6	scam_mpi	3.2e-06	0.54	32	truetemp	0.89	2.52	2.77	1.07	1.26	136.5	243.4	188.8	188.8	189.4	57.2
OISST177417	0	6	scam_mpi	1.1e-05	0.53	32	truetemp	0.73	2.62	2.82	1.09	1.31	111.4	258.1	194.4	194.4	189.6	57.1
OISST177423	0	6	scam_mpi	2.1e-05	0.52	32	truetemp	0.82	2.57	2.79	1.08	1.29	125.4	250.8	191.3	191.3	189.7	79.5
mlr183	-1,-1	1,5	mlr	1.6e-04	0.60	20	OSCAR42; OSCAR33334	-0.51	2.57	3.01	1.16	1.29	78.5	250.6	215.1	215.1	189.8	76.2
OSCAR116448	-1	6	scam_mpd	2.4e-03	0.51	20	u	0.74	2.60	2.83	1.10	1.30	114.3	254.9	195.1	195.1	189.9	112.3
OISST177413	0	6	scam_mpi	8.1e-06	0.54	32	truetemp	0.79	2.60	2.81	1.09	1.30	122.0	254.7	193.4	193.4	190.9	56.0
OSCAR33309	-1	4	scam_mpi	1.3e-03	0.57	20	v	0.88	2.54	2.79	1.08	1.27	135.2	246.6	190.8	190.8	190.9	116.1
shore310799	0	5	scam_mpi	2.7e-04	0.52	26	temperature.c.	0.84	2.44	2.89	1.12	1.22	128.9	232.1	202.1	202.1	191.3	84.4
OSCAR33305	-1	5	scam_mpi	4.2e-05	0.58	20	v	1.00	2.48	2.76	1.07	1.24	152.8	237.3	187.9	187.9	191.5	118.9
OSCAR33310	-1	5	scam_mpi	2.5e-04	0.56	20	v	1.01	2.48	2.77	1.07	1.24	155.7	237.4	188.7	188.7	192.6	120.1
OISST177415	0	6	scam_mpi	1.2e-05	0.54	32	truetemp	0.77	2.63	2.84	1.10	1.31	118.6	258.5	196.8	196.8	192.7	61.4
OISST177434	0	2	scam_mpi	3.1e-05	0.51	32	truetemp	1.01	2.49	2.78	1.08	1.24	155.3	238.3	189.5	189.5	193.2	87.9
OISST177428	0	2	scam_mpi	2.5e-05	0.51	32	truetemp	0.90	2.56	2.82	1.09	1.28	138.6	248.4	194.0	194.0	193.8	91.3
OSCAR33311	-1	5	scam_mpi	6.3e-05	0.56	20	v	1.04	2.48	2.78	1.08	1.24	159.6	237.2	189.6	189.6	194.0	138.2
OISST177412	0	6	scam_mpi	9.7e-06	0.55	32	truetemp	0.85	2.60	2.84	1.10	1.30	130.3	254.7	196.2	196.2	194.4	56.6
OSCAR33358	-1	6	scam_mpi	2.9e-03	0.50	20	v	0.88	2.57	2.84	1.10	1.29	135.6	250.8	196.4	196.4	194.8	120.3
OISST177411	0	3	scam_mpi	9.2e-06	0.55	32	truetemp	0.48	2.75	3.01	1.17	1.37	74.2	276.2	215.2	215.2	195.2	201.3
OSCAR33320	0	1	scam_mpi	1.2e-03	0.55	21	v	1.54	2.27	2.60	1.01	1.13	236.7	207.0	169.8	169.8	195.8	115.2
mlr192	-1,-1	1,8	mlr	2.3e-04	0.58	20	OSCAR42; OSCAR116434	-0.68	2.40	3.12	1.21	1.20	103.9	226.1	227.2	227.2	196.1	81.2
mlr176	-1,-1	1,5	mlr	1.4e-04	0.61	20	OSCAR42; OSCAR33314	-0.26	2.82	3.14	1.22	1.41	40.3	286.9	230.1	230.1	196.8	77.7
OSCAR33319	-1	5	scam_mpi	1.2e-03	0.55	20	v	0.88	2.60	2.87	1.11	1.30	135.0	255.3	199.6	199.6	197.4	119.4
OSCAR33328	0	1	scam_mpi	2.0e-03	0.53	21	v	1.44	2.27	2.71	1.05	1.13	220.5	207.2	181.6	181.6	197.7	106.1
mlr178	-1,-1	1,8	mlr	1.4e-04	0.60	20	OSCAR42; OSCAR116436	-0.81	2.43	3.04	1.18	1.21	123.8	230.2	219.3	219.3	198.1	78.6
OSCAR116451	0	5	scam_mpd	5.9e-04	0.50	21	u	-0.20	2.74	3.27	1.27	1.37	31.3	274.4	244.0	244.0	198.4	101.4
OSCAR33333	0	1	scam_mpi	3.8e-04	0.52	21	v	1.15	2.44	2.82	1.09	1.22	177.3	231.5	194.3	194.3	199.3	82.5
OISST177426	0	2	scam_mpi	4.2e-05	0.51	32	truetemp	1.15	2.47	2.84	1.10	1.24	176.3	236.1	196.2	196.2	201.2	83.8

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
OSCAR33304	-1	11	scam_mpi	2.4e-05	0.58	21	v	0.86	2.67	2.92	1.13	1.33	131.5	264.1	205.1	205.1	201.5	86.7
mlr164	-1,0	1,4	mlr	1.0e-04	0.62	20	OSCAR42; OISST177424	-1.17	2.34	2.92	1.13	1.17	180.4	218.0	205.0	205.0	202.1	75.9
OISST177425	0	2	scam_mpi	5.0e-05	0.52	32	truetemp	1.06	2.54	2.88	1.12	1.27	162.6	245.6	201.2	201.2	202.7	87.5
OSCAR33327	0	1	scam_mpi	1.4e-03	0.53	21	v	1.61	2.35	2.64	1.02	1.18	247.8	219.4	173.8	173.8	203.7	111.2
mlr200	-1,-1	1,8	mlr	2.8e-04	0.57	20	OSCAR42; OSCAR116438	-0.63	2.40	3.30	1.28	1.20	96.9	225.4	247.9	247.9	204.5	86.6
OISST177435	0	2	scam_mpi	7.7e-05	0.50	32	truetemp	1.00	2.59	2.94	1.14	1.30	153.4	253.3	207.3	207.3	205.3	93.0
OSCAR45	-1	2	lm	2.2e-04	0.51	20	v	1.47	2.40	2.82	1.09	1.20	226.3	225.8	193.9	193.9	210.0	70.1
OISST177431	0	2	scam_mpi	1.3e-05	0.51	32	truetemp	1.31	2.49	2.96	1.15	1.25	200.7	239.3	210.1	210.1	215.1	75.4
OSCAR33334	-1	5	scam_mpi	1.0e-03	0.52	20	v	0.78	2.82	3.16	1.22	1.41	119.1	286.9	232.1	232.1	217.5	83.7
OSCAR33322	0	1	scam_mpi	1.4e-03	0.54	21	v	1.59	2.54	2.80	1.08	1.27	244.4	245.8	191.7	191.7	218.4	95.5
OISST177432	0	2	scam_mpi	1.1e-05	0.51	32	truetemp	1.28	2.56	3.04	1.18	1.28	196.1	248.8	219.1	219.1	220.8	82.3
OSCAR33360	0	1	scam_mpi	6.4e-04	0.50	21	v	1.19	2.67	3.03	1.17	1.34	182.4	265.5	217.7	217.7	220.8	84.0
OISST266113	0	6	scam_mpi	2.2e-06	0.50	32	winterdiff	1.33	2.55	3.01	1.17	1.28	204.3	247.7	215.8	215.8	220.9	86.6
OISST266111	0	6	scam_mpi	7.2e-06	0.51	32	winterdiff	1.35	2.56	3.00	1.16	1.28	207.2	248.8	214.6	214.6	221.3	64.5
mlr169	-1,-1	1,8	mlr	1.2e-04	0.61	20	OSCAR42; OSCAR116431	-0.80	2.74	3.27	1.27	1.37	123.5	275.5	244.2	244.2	221.9	78.0
mlr184	-1,0	1,4	mlr	1.7e-04	0.60	20	OSCAR42; OISST177420	-1.21	2.49	3.19	1.24	1.24	185.5	238.3	235.5	235.5	223.7	81.6
mlr166	-1,0	1,4	mlr	1.1e-04	0.62	20	OSCAR42; OISST177409	-1.25	2.48	3.18	1.23	1.24	191.5	238.2	234.4	234.4	224.6	78.8
mlr160	-1,0	1,2	mlr	8.3e-05	0.63	20	OSCAR42; OISST177429	0.77	2.65	3.42	1.33	1.32	117.8	261.9	261.6	261.6	225.7	78.1
OISST177430	0	3	scam_mpi	6.3e-05	0.51	32	truetemp	0.61	2.98	3.33	1.29	1.49	93.2	308.7	251.4	251.4	226.2	118.7
OSCAR33326	0	5	scam_mpi	3.8e-04	0.54	21	v	0.98	2.84	3.18	1.23	1.42	150.6	288.9	234.7	234.7	227.2	84.0
OISST266112	0	6	scam_mpi	8.2e-06	0.51	32	winterdiff	1.38	2.58	3.08	1.19	1.29	211.8	252.5	222.9	222.9	227.5	100.3
OSCAR49925	-1	12	scam_mpd	8.2e-04	0.50	21	v	1.84	2.28	2.96	1.14	1.14	282.0	209.4	209.4	209.4	227.5	123.5
OSCAR33306	-1	5	scam_mpi	4.2e-05	0.58	20	v	0.60	3.01	3.36	1.30	1.50	92.7	313.5	254.5	254.5	228.8	157.4
OSCAR116441	-1	5	scam_mpd	5.8e-02	0.53	20	u	1.43	2.62	3.06	1.18	1.31	219.2	257.4	220.5	220.5	229.4	112.1
OSCAR33301	-1	2	scam_mpi	2.0e-04	0.60	20	v	1.22	2.78	3.13	1.21	1.39	187.2	280.2	228.4	228.4	231.1	92.1
mlr174	-1,0	1,4	mlr	1.3e-04	0.61	20	OSCAR42; OISST177410	-1.26	2.53	3.28	1.27	1.27	193.8	245.1	245.0	245.0	232.2	81.1
OISST177436	0	3	scam_mpi	7.5e-05	0.50	32	truetemp	0.68	3.00	3.38	1.31	1.50	104.6	312.7	256.2	256.2	232.5	122.8
OSCAR33341	-1	5	scam_mpi	1.7e-04	0.52	20	v	1.08	2.78	3.25	1.26	1.39	165.9	280.3	242.3	242.3	232.7	127.3
OISST177409	0	4	scam_mpi	1.3e-06	0.58	32	truetemp	-0.76	2.84	3.45	1.34	1.42	116.6	288.6	264.8	264.8	233.7	86.5
OSCAR116439	-1	10	scam_mpd	1.4e-03	0.53	21	u	1.77	2.15	3.21	1.25	1.08	272.0	190.2	238.2	238.2	234.6	105.6
OISST177424	0	4	scam_mpi	9.2e-05	0.52	32	truetemp	-0.63	2.96	3.51	1.36	1.48	96.5	306.4	270.9	270.9	236.2	100.5
OISST177429	0	2	scam_mpi	1.3e-04	0.51	32	truetemp	0.81	2.80	3.52	1.36	1.40	124.6	283.2	272.4	272.4	238.2	116.4
OSCAR49923	-1	9	scam_mpd	7.6e-04	0.56	20	v	1.51	2.83	3.03	1.17	1.41	232.3	287.6	217.8	217.8	238.9	116.2
OSCAR33335	0	1	scam_mpi	1.7e-03	0.52	21	v	1.29	2.79	3.21	1.25	1.39	198.0	281.9	238.2	238.2	239.1	98.8
OSCAR33321	-1	1	scam_mpi	2.2e-03	0.54	20	v	1.55	2.42	3.30	1.28	1.21	238.1	228.2	247.4	247.4	240.2	129.8
OSCAR99806	0	2	scam_mpi	2.3e-03	0.51	21	u	1.43	2.71	3.27	1.27	1.35	219.5	270.0	244.3	244.3	244.5	98.0
OSCAR33314	-1	5	scam_mpi	3.0e-04	0.56	20	v	1.27	2.82	3.33	1.29	1.41	194.4	286.3	250.7	250.7	245.5	135.8
OSCAR33347	0	1	scam_mpi	2.2e-03	0.51	21	v	1.84	2.75	3.04	1.18	1.37	283.2	276.1	218.5	218.5	249.1	120.7
OSCAR33351	-1	1	scam_mpi	8.1e-04	0.51	20	v	0.56	3.28	3.58	1.39	1.64	85.6	353.0	279.5	279.5	249.4	106.9
OSCAR33356	0	1	scam_mpi	2.4e-03	0.50	21	v	1.47	2.83	3.35	1.30	1.42	225.3	288.2	253.7	253.7	255.2	95.9
OSCAR33337	0	1	scam_mpi	2.0e-03	0.52	21	v	1.58	2.87	3.27	1.27	1.43	242.9	292.8	244.1	244.1	256.0	96.5
OSCAR33342	0	1	scam_mpi	2.2e-03	0.52	21	v	1.63	2.79	3.30	1.28	1.40	249.6	282.5	248.1	248.1	257.1	85.8

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
OSCAR33338	0	1	scam_mpi	4.1e-04	0.52	21	v	1.35	2.84	3.48	1.35	1.42	207.5	289.0	267.8	267.8	258.0	93.1
mlr167	-1,0	1,2	mlr	1.1e-04	0.62	20	OSCAR42; OISST177419	0.99	2.88	3.75	1.45	1.44	151.8	294.8	297.7	297.7	260.5	77.9
OSCAR33315	0	1	scam_mpi	9.6e-04	0.56	21	v	1.97	2.82	3.15	1.22	1.41	302.4	286.9	230.7	230.7	262.7	94.0
OISST177419	0	2	scam_mpi	1.1e-05	0.53	32	truetemp	0.82	3.11	3.78	1.47	1.56	125.1	328.5	301.6	301.6	264.2	167.6
OSCAR33344	-1	2	scam_mpi	7.3e-04	0.51	20	v	1.07	3.08	3.65	1.42	1.54	164.6	323.9	287.3	287.3	265.8	85.8
mlr138	-1,0	1,5	mlr	3.8e-05	0.66	20	OSCAR42; OSCAR33326	-0.68	3.06	3.95	1.53	1.53	103.8	320.2	320.2	320.2	266.1	68.5
OSCAR116445	0	5	scam_mpd	1.2e-04	0.52	21	u	-0.02	3.29	4.35	1.69	1.65	2.5	353.9	365.3	365.3	271.8	102.0
OSCAR33355	-1	1	scam_mpi	1.8e-03	0.50	20	v	1.89	2.72	3.60	1.39	1.36	290.2	271.9	280.7	280.7	280.9	112.9
median4	0	0	median4	NA			0	1.00	3.50	3.72	1.44	1.75	153.5	384.0	294.5	294.5	281.6	150.7
OSCAR33330	0	1	scam_mpi	4.1e-04	0.53	21	v	2.03	3.02	3.33	1.29	1.51	311.2	315.1	250.9	250.9	282.0	92.8
OSCAR116440	-1	6	scam_mpd	2.5e-04	0.53	20	u	1.38	3.17	3.71	1.44	1.58	211.6	335.9	293.6	293.6	283.7	115.3
OSCAR33359	0	1	scam_mpi	3.2e-03	0.50	21	v	1.72	3.13	3.56	1.38	1.56	264.8	330.3	276.7	276.7	287.1	101.9
OISST177420	0	4	scam_mpi	1.2e-05	0.53	32	truetemp	-0.99	3.01	4.24	1.64	1.50	152.5	313.6	352.6	352.6	292.8	95.8
median8	0	0	median8	NA			0	2.50	2.83	3.62	1.40	1.42	384.0	288.2	283.1	283.1	309.6	130.4
OSCAR33354	-1	1	scam_mpi	2.2e-03	0.51	20	v	2.35	2.98	3.69	1.43	1.49	360.3	309.5	291.2	291.2	313.1	116.1
OSCAR33340	-1	3	scam_mpi	2.0e-03	0.52	20	v	-1.90	3.38	3.75	1.45	1.69	292.0	366.9	298.1	298.1	313.7	95.4
OISST177410	0	4	scam_mpi	2.8e-06	0.57	32	truetemp	-1.28	3.23	4.52	1.75	1.61	196.7	344.6	384.0	384.0	327.3	100.3

APPENDIX B: CHILKO TIMING MODEL PERFORMANCE RESULTS

Table 15. Performance results for all qualifying models used to forecast Chilko timing based on retrospective analysis. Each row represents a single model tested, some columns include: year adjust (year of environmental data same as return year [0] or prior year [-1]), month, summary statistics (P value, adjusted R squared, sample size), data name, data variables (which are sorted by their relative influence in the model). As the NEPSTAR regression models comprise more than one variable, only year-month of the latest variable is presented. Latitude and longtitude of NEPSTAR variables are excluded due to space limitations. The PMs include mean raw error, mean absolute error, root mean squared error, Thiel's U-statistic, and MASE. The initial three PMs are in day units, the latter two are unit-less. All PMs are described in the methods section. All PMs, except MASE, are given a rank. The best rank has a value of zero. The last rank equals total number of models (n). The average of the PM ranks by model (row) is included, as is the average rank for the alternate performance test method. The rows are sorted by average rank of performance method listed in caption. The first row is the best model, the last row is the worst.

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
nepstar3	-1,0,0,-1	7,2,3,5	mlr	2.5e-08	0.83	25	nepstar	-0.42	1.53	1.88	0.31	0.26	6.4	0.0	0.0	0.0	1.6	5.5
nepstar14	-1,0,0,-1,0	7,3,3,5,3	mlr	9.5e-08	0.83	25	nepstar	-0.15	1.66	2.06	0.35	0.29	2.3	1.9	1.3	4.5	2.5	12.2
nepstar2	-1,0,-1	6,3,5	mlr	4.2e-09	0.84	25	nepstar	-0.29	1.62	2.27	0.39	0.28	4.4	1.4	2.7	8.0	4.1	9.3
nepstar1	-1,0,-1	7,3,5	mlr	3.1e-08	0.80	25	nepstar	-0.51	1.86	2.12	0.34	0.32	7.9	4.9	1.7	3.2	4.4	14.4
nepstar9	0,-1,0,-1	3,5,3,5	mlr	2.6e-08	0.83	25	nepstar	-0.43	1.96	2.15	0.36	0.34	6.6	6.5	1.9	4.9	5.0	7.2
nepstar4	-1,0,0,-1	7,4,3,5	mlr	2.4e-08	0.83	25	nepstar	-0.87	1.98	2.27	0.31	0.34	13.4	6.8	2.8	0.6	5.9	7.7
nepstar11	0,-1,0,-1	2,5,3,5	mlr	7.3e-08	0.81	25	nepstar	-1.09	1.82	2.06	0.33	0.31	16.9	4.4	1.3	2.1	6.2	5.7
nepstar5	-2,-1,0,0	7,5,3,3	mlr	1.1e-08	0.85	25	nepstar	0.04	2.37	2.51	0.39	0.41	0.5	12.7	4.5	8.6	6.6	11.9
nepstar6	0,-1,0,0	3,5,3,3	mlr	4.3e-09	0.86	25	nepstar	0.63	1.85	2.64	0.45	0.32	9.7	4.7	5.4	14.0	8.4	16.3
nepstar7	-1,0,0,-1	6,3,3,5	mlr	7.0e-09	0.85	25	nepstar	-0.24	2.19	2.78	0.46	0.38	3.7	9.9	6.4	15.5	8.9	11.1
nepstar12	0,-1,0,-1	3,4,3,5	mlr	7.1e-08	0.82	25	nepstar	-1.30	2.42	2.64	0.42	0.42	20.2	13.4	5.4	10.8	12.4	16.8
nepstar8	-1,-1,0	4,5,3	mlr	2.0e-06	0.71	25	nepstar	-0.22	2.55	3.20	0.54	0.44	3.3	15.4	9.4	23.1	12.8	44.3
nepstar10	-1,-1,-1,0	7,4,5,3	mlr	2.1e-06	0.74	25	nepstar	1.01	2.32	2.88	0.49	0.40	15.7	11.9	7.1	18.2	13.2	38.2
mlr25	0,0	5,4	mlr	1.8e-05	0.74	18	OSCAR62986; OSCAR27008	-1.00	2.10	3.26	0.56	0.36	15.5	8.6	9.8	24.6	14.6	16.8
nepstar13	-1,-1,0,-1,-1,0,0	6,5,3,4,5,3,3	mlr	3.0e-08	0.89	25	nepstar	-1.59	2.20	2.83	0.48	0.38	24.6	10.1	6.8	17.4	14.7	2.5
mlr27	0,0	5,4	mlr	1.9e-05	0.73	18	OSCAR62986; OSCAR27004	-0.46	2.54	3.37	0.58	0.44	7.1	15.3	10.6	26.5	14.9	29.1
OSCAR18038	0	5	scam_mpi	1.6e-03	0.51	18	v	0.06	2.79	3.61	0.61	0.48	0.9	19.0	12.3	30.2	15.6	57.0
mlr1	0,-1,0	5,12,4	mlr	2.8e-06	0.83	18	OSCAR62986; OSCAR63007; OSCAR27019	-0.26	3.13	3.55	0.57	0.54	4.0	24.2	11.9	25.7	16.5	12.1
mlr10	0,0	5,6	mlr	9.0e-06	0.76	18	OSCAR62986; OSCAR36001	-0.27	2.97	3.51	0.60	0.51	4.1	21.8	11.6	28.8	16.6	17.9
mlr2	0,-1,0	5,12,4	mlr	3.2e-06	0.83	18	OSCAR62986; OSCAR63007; OSCAR27026	-0.60	2.91	3.54	0.56	0.50	9.2	20.9	11.8	25.1	16.7	11.4
mlr12	0,-1,-1	5,12,12	mlr	1.3e-05	0.79	18	OSCAR62986; OSCAR63007; OSCAR27027	-0.69	2.86	3.52	0.56	0.49	10.7	20.0	11.6	24.9	16.8	10.8
mlr8	0,-1,-1	5,12,11	mlr	1.2e-05	0.79	18	OSCAR62986; OSCAR63007; OSCAR18030	-0.04	3.35	3.64	0.58	0.58	0.6	27.5	12.5	27.0	16.9	2.6
mlr72	0,0	5,4	mlr	4.3e-05	0.70	18	OSCAR62986; OSCAR27011	-1.04	2.32	3.51	0.60	0.40	16.0	12.0	11.6	28.9	17.1	19.0
OSCAR27008	0	4	scam_mpd	1.9e-03	0.59	18	v	0.16	3.07	3.77	0.63	0.53	2.4	23.4	13.4	31.9	17.8	59.7
mlr3	0,-1,0	5,12,4	mlr	4.0e-06	0.82	18	OSCAR62986; OSCAR63007; OSCAR27004	-0.56	3.24	3.65	0.56	0.56	8.7	25.8	12.6	24.4	17.9	19.2
mlr35	0,0	5,4	mlr	2.7e-05	0.72	18	OSCAR62986; OSCAR27019	-0.39	2.86	3.74	0.64	0.49	6.0	20.2	13.2	32.7	18.0	17.7
mlr90	0,0	5,4	mlr	5.6e-05	0.69	18	OSCAR62986; OSCAR27015	-0.46	2.86	3.72	0.63	0.49	7.1	20.2	13.0	32.0	18.1	29.6

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
OSCAR27002	0	4	scam_mpd	9.8e-05	0.64	18	v	1.11	2.67	3.47	0.58	0.46	17.2	17.2	11.3	26.7	18.1	59.5
mlr20	0,0	5,6	mlr	1.4e-05	0.75	18	OSCAR62986; OSCAR63008	-0.38	3.12	3.65	0.62	0.54	5.8	24.1	12.5	30.8	18.3	20.3
mlr11	0,-1,0	5,12,6	mlr	1.3e-05	0.79	18	OSCAR62986; OSCAR63007; OSCAR36001	-0.37	3.33	3.65	0.59	0.57	5.7	27.3	12.6	28.0	18.4	13.4
mlr51	0,0	5,4	mlr	3.6e-05	0.71	18	OSCAR62986; OSCAR27005	-0.74	2.70	3.70	0.63	0.46	11.4	17.6	12.9	31.9	18.4	32.6
mlr105	0,0	5,4	mlr	1.0e-04	0.67	18	OSCAR62986; OSCAR18007	-0.41	2.88	3.79	0.65	0.50	6.3	20.5	13.6	33.6	18.5	26.7
mlr17	0,-1,0	5,12,5	mlr	1.6e-05	0.78	18	OSCAR62986; OSCAR63007; OSCAR18038	-0.70	3.18	3.59	0.58	0.55	10.8	25.0	12.1	27.1	18.8	10.1
mlr19	0,-1,0	5,12,1	mlr	1.7e-05	0.78	18	OSCAR62986; OSCAR63007; OSCAR18019	-0.37	3.32	3.78	0.61	0.57	5.7	27.1	13.5	29.5	18.9	15.7
mlr16	0,-1,0	5,12,4	mlr	1.5e-05	0.79	18	OSCAR62986; OSCAR63007; OSCAR27011	-0.76	3.17	3.69	0.58	0.55	11.7	24.8	12.8	26.8	19.0	16.1
mlr101	0,0	5,4	mlr	9.5e-05	0.67	18	OSCAR62986; OSCAR18010	-0.53	2.88	3.81	0.65	0.50	8.2	20.4	13.7	33.9	19.1	21.5
mlr89	0,0	5,5	mlr	5.3e-05	0.70	18	OSCAR62986; OSCAR53996	0.37	3.05	3.84	0.66	0.53	5.7	22.9	13.9	34.3	19.2	21.8
mlr15	0,-1,0	5,12,4	mlr	1.5e-05	0.79	18	OSCAR62986; OSCAR63007; OSCAR27008	-0.82	3.17	3.74	0.58	0.55	12.7	24.8	13.2	26.7	19.3	15.2
mlr23	0,-1,0	5,12,6	mlr	2.1e-05	0.78	18	OSCAR62986; OSCAR63007; OSCAR63008	-0.46	3.38	3.73	0.60	0.58	7.0	28.0	13.1	29.2	19.3	12.9
mlr95	0,0	5,4	mlr	7.5e-05	0.68	18	OSCAR62986; OSCAR27010	-0.69	2.89	3.77	0.65	0.50	10.6	20.5	13.4	33.2	19.5	27.2
mlr91	0,0	5,5	mlr	5.9e-05	0.69	18	OSCAR62986; OSCAR18038	-0.83	2.86	3.73	0.64	0.49	12.9	20.1	13.1	32.5	19.6	27.0
mlr78	0,-1,0	5,12,2	mlr	5.3e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18049	-0.52	3.34	3.80	0.61	0.58	8.0	27.4	13.6	29.7	19.7	19.3
mlr102	0,0	5,5	mlr	9.7e-05	0.67	18	OSCAR62986; OSCAR18022	-0.65	2.90	3.85	0.66	0.50	10.0	20.8	14.0	34.6	19.8	31.2
mlr13	0,-1,0	5,12,4	mlr	1.5e-05	0.79	18	OSCAR62986; OSCAR63007; OSCAR27015	-0.65	3.32	3.80	0.60	0.57	10.1	27.1	13.6	28.5	19.8	17.1
mlr108	0,0	5,3	mlr	1.1e-04	0.66	18	OSCAR62986; OSCAR18044	-0.84	2.77	3.84	0.66	0.48	12.9	18.8	13.9	34.3	20.0	23.6
mlr21	0,-1,0	5,12,4	mlr	1.9e-05	0.78	18	OSCAR62986; OSCAR63007; OSCAR27010	-0.51	3.42	3.82	0.61	0.59	7.8	28.5	13.8	29.9	20.0	20.9
mlr28	0,-1,0	5,12,4	mlr	2.7e-05	0.77	18	OSCAR62986; OSCAR63007; OSCAR18007	-0.48	3.44	3.89	0.61	0.59	7.4	28.8	14.3	29.7	20.1	13.0
mlr113	0,0	5,3	mlr	1.3e-04	0.66	18	OSCAR62986; OSCAR18013	-0.62	2.96	3.92	0.67	0.51	9.6	21.7	14.5	35.2	20.2	22.8
mlr34	0,-1,0	5,12,6	mlr	3.3e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR62989	-0.54	3.44	3.84	0.62	0.59	8.4	28.9	13.9	30.7	20.5	13.9
mlr36	0,-1,0	5,12,5	mlr	3.4e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR18022	-0.52	3.42	3.87	0.63	0.59	8.0	28.5	14.1	31.3	20.5	19.4
mlr7	0,-1,0	5,12,4	mlr	1.0e-05	0.80	18	OSCAR62986; OSCAR63007; OSCAR27005	-0.74	3.33	3.87	0.60	0.57	11.4	27.3	14.1	29.2	20.5	20.3
mlr71	0,-1,-1	5,12,12	mlr	5.2e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR63004	-0.61	3.39	3.86	0.62	0.58	9.3	28.1	14.1	30.6	20.5	13.0
mlr31	0,-1,-1	5,12,12	mlr	3.0e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR18028	-0.63	3.41	3.85	0.62	0.59	9.8	28.5	14.0	30.3	20.6	15.9
mlr98	0,0	5,4	mlr	8.6e-05	0.67	18	OSCAR62986; OSCAR27012	-0.81	2.92	3.86	0.66	0.50	12.5	21.0	14.0	34.7	20.6	31.6
OSCAR63008	0	6	scam_mpd	1.8e-03	0.51	18	u	0.76	3.21	3.72	0.64	0.55	11.7	25.3	13.0	32.3	20.6	79.8
mlr111	0,0	5,5	mlr	1.1e-04	0.66	18	OSCAR62986; OSCAR18031	-0.48	3.11	3.98	0.68	0.54	7.3	23.9	14.9	36.7	20.7	38.0
mlr48	0,-1,0	5,12,4	mlr	4.1e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18035	-0.41	3.48	3.91	0.64	0.60	6.2	29.4	14.4	32.6	20.7	15.5
mlr9	0,-1	5,12	mlr	8.7e-06	0.76	18	OSCAR62986; OSCAR63007	-0.56	3.44	3.86	0.62	0.59	8.7	28.9	14.1	31.0	20.7	13.2
mlr22	0,-1,0	5,12,4	mlr	1.9e-05	0.78	18	OSCAR62986; OSCAR63007; OSCAR27012	-0.71	3.41	3.88	0.61	0.59	11.0	28.5	14.2	30.0	20.9	21.4
mlr41	0,-1,0	5,12,3	mlr	3.7e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR18013	0.17	3.42	4.02	0.69	0.59	2.5	28.6	15.2	37.2	20.9	16.5
mlr44	0,-1,0	5,12,6	mlr	3.9e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR62992	-0.53	3.55	3.89	0.62	0.61	8.2	30.6	14.2	30.7	20.9	15.4
mlr42	0,0	5,6	mlr	3.0e-05	0.72	18	OSCAR62986; OSCAR62989	-0.61	3.25	3.88	0.66	0.56	9.3	26.1	14.2	34.3	21.0	25.1
OSCAR27010	0	4	scam_mpd	3.7e-03	0.57	18	v	-0.07	3.27	4.19	0.72	0.56	1.0	26.3	16.4	40.1	21.0	69.3
mlr100	0,-1	5,12	mlr	9.2e-05	0.67	18	OSCAR62986; OSCAR18028	-0.75	3.09	3.88	0.66	0.53	11.6	23.6	14.2	34.9	21.1	35.5
mlr106	0,0	5,6	mlr	1.0e-04	0.67	18	OSCAR62986; OSCAR62992	-0.54	3.33	3.89	0.66	0.57	8.3	27.2	14.3	34.8	21.1	35.1
mlr120	0,0	5,3	mlr	1.6e-04	0.65	18	OSCAR62986; OSCAR18011	-0.81	2.95	3.95	0.68	0.51	12.6	21.5	14.7	36.3	21.2	24.5
mlr39	0,-1,0	5,12,4	mlr	3.6e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR18010	-0.55	3.53	3.96	0.62	0.61	8.5	30.3	14.7	31.1	21.2	16.0
mlr40	0,-1,0	5,12,3	mlr	3.6e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR18044	-0.03	3.62	4.09	0.69	0.62	0.4	31.6	15.6	37.2	21.2	17.1
mlr45	0,-1,0	5,12,5	mlr	3.9e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18031	-0.43	3.53	3.97	0.64	0.61	6.6	30.3	14.9	33.1	21.2	23.6

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
mlr49	0,-1,0	5,12,6	mlr	4.2e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR62990	-0.60	3.55	3.90	0.62	0.61	9.2	30.6	14.3	30.7	21.2	13.7
mlr55	0,-1,-1	5,12,11	mlr	4.6e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR54004	-0.85	3.46	3.79	0.61	0.60	13.1	29.1	13.6	29.7	21.4	13.6
mlr66	0,-1,-1	5,12,11	mlr	5.0e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR54003	-0.53	3.49	3.98	0.64	0.60	8.2	29.6	14.9	33.0	21.4	16.2
mlr82	0,-1,0	5,12,1	mlr	5.4e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18029	-0.63	3.53	3.92	0.62	0.61	9.8	30.3	14.5	30.8	21.4	14.9
OSCAR27004	0	4	scam_mpd	6.2e-04	0.62	18	v	1.54	2.99	3.80	0.57	0.51	23.8	22.0	13.6	25.9	21.4	79.8
mlr112	0,0	5,6	mlr	1.2e-04	0.66	18	OSCAR62986; OSCAR27025	-0.35	3.44	4.03	0.68	0.59	5.3	28.9	15.3	36.6	21.5	31.1
mlr14	0,-1	5,12	mlr	1.1e-05	0.75	18	OSCAR62986; OSCAR62997	-0.47	3.55	3.92	0.65	0.61	7.2	30.6	14.5	33.5	21.5	16.0
mlr37	0,-1,0	5,12,1	mlr	3.4e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR18046	-0.75	3.60	3.95	0.60	0.62	11.6	31.3	14.7	28.5	21.5	12.6
mlr38	0,-1,0	5,12,1	mlr	3.5e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR18024	-0.69	3.58	3.94	0.61	0.62	10.7	31.1	14.6	29.5	21.5	11.5
mlr53	0,-1,0	5,12,6	mlr	4.5e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR27025	-0.48	3.62	4.02	0.63	0.62	7.3	31.6	15.2	31.7	21.5	16.2
mlr126	0,0	5,3	mlr	1.8e-04	0.64	18	OSCAR62986; OSCAR18012	-0.83	2.96	3.99	0.68	0.51	12.8	21.6	15.0	36.9	21.6	27.8
mlr123	0,0	5,3	mlr	1.8e-04	0.64	18	OSCAR62986; OSCAR18020	-0.86	2.98	3.98	0.68	0.51	13.3	21.9	14.9	36.8	21.7	29.5
mlr84	0,-1,0	5,12,1	mlr	5.4e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18021	-0.55	3.59	3.97	0.64	0.62	8.5	31.2	14.8	32.2	21.7	10.5
mlr104	0,0	5,6	mlr	1.0e-04	0.67	18	OSCAR62986; OSCAR62990	-0.69	3.35	3.89	0.66	0.58	10.6	27.5	14.3	34.6	21.8	32.5
mlr116	0,0	5,4	mlr	1.4e-04	0.65	18	OSCAR62986; OSCAR18008	-0.66	3.09	4.05	0.69	0.53	10.3	23.6	15.4	37.8	21.8	27.5
mlr125	0,0	5,1	mlr	1.8e-04	0.64	18	OSCAR62986; OSCAR18021	-0.67	3.13	4.01	0.69	0.54	10.4	24.3	15.1	37.3	21.8	31.9
mlr130	0,0	5,1	mlr	2.0e-04	0.64	18	OSCAR62986; OSCAR18039	-0.67	3.11	4.04	0.69	0.54	10.3	24.0	15.3	37.6	21.8	32.4
mlr67	0,-1,0	5,12,1	mlr	5.1e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR63001	-0.51	3.55	4.02	0.65	0.61	7.8	30.5	15.1	33.7	21.8	22.7
mlr77	0,-1,0	5,12,1	mlr	5.3e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18025	-0.72	3.56	3.91	0.62	0.61	11.2	30.8	14.4	30.7	21.8	12.1
mlr80	0,-1,0	5,12,2	mlr	5.3e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR53998	-0.52	3.59	3.97	0.64	0.62	8.1	31.2	14.8	33.0	21.8	19.1
mlr4	0,-1,0	5,12,5	mlr	6.2e-06	0.81	18	OSCAR62986; OSCAR63007; OSCAR53996	0.81	3.57	3.82	0.62	0.62	12.4	30.9	13.7	30.4	21.9	10.1
mlr50	0,-1,0	5,12,3	mlr	4.4e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18011	-0.41	3.64	4.04	0.66	0.63	6.3	31.9	15.3	34.3	21.9	21.7
mlr54	0,-1,0	5,12,3	mlr	4.6e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18033	0.19	3.55	4.10	0.70	0.61	3.0	30.6	15.8	38.4	21.9	19.5
mlr69	0,-1,0	5,12,1	mlr	5.1e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR63002	-0.51	3.54	4.02	0.65	0.61	7.9	30.4	15.2	34.0	21.9	22.2
OSCAR27012	0	4	scam_mpd	5.5e-03	0.56	18	v	0.12	3.55	4.16	0.71	0.61	1.8	30.5	16.2	39.1	21.9	55.5
mlr29	0,-1,0	5,12,1	mlr	2.7e-05	0.77	18	OSCAR62986; OSCAR63007; OSCAR18042	-0.78	3.65	3.98	0.60	0.63	12.1	32.1	14.9	29.1	22.0	13.8
mlr128	0,0	5,4	mlr	1.9e-04	0.64	18	OSCAR62986; OSCAR18035	-0.42	3.35	4.10	0.70	0.58	6.5	27.6	15.7	38.5	22.1	31.6
mlr134	0,0	5,1	mlr	2.1e-04	0.63	18	OSCAR62986; OSCAR18041	-0.69	3.15	4.04	0.69	0.54	10.7	24.5	15.3	37.7	22.1	29.5
mlr62	0,-1,0	5,12,3	mlr	5.0e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18020	0.01	3.77	4.16	0.70	0.65	0.1	33.9	16.1	38.3	22.1	19.7
mlr68	0,-1,0	5,12,1	mlr	5.1e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR63003	-0.69	3.49	3.97	0.64	0.60	10.7	29.7	14.9	33.2	22.1	25.3
mlr70	0,-1,0	5,12,4	mlr	5.2e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18016	-0.59	3.59	4.01	0.64	0.62	9.0	31.3	15.1	33.2	22.1	20.6
mlr85	0,-1,0	5,12,1	mlr	5.4e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18041	-0.60	3.64	4.01	0.63	0.63	9.3	31.9	15.1	32.2	22.1	11.7
mlr60	0,-1,0	5,12,4	mlr	4.9e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18008	-0.71	3.54	4.00	0.63	0.61	11.0	30.5	15.0	32.1	22.2	17.9
mlr63	0,-1,0	5,12,3	mlr	5.0e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18045	-0.33	3.76	4.07	0.66	0.65	5.0	33.7	15.5	34.5	22.2	17.1
mlr75	0,-1,0	5,12,1	mlr	5.2e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR63010	-0.56	3.54	4.05	0.66	0.61	8.7	30.3	15.4	34.5	22.2	22.7
mlr121	0,0	5,1	mlr	1.6e-04	0.65	18	OSCAR62986; OSCAR18019	-0.53	3.24	4.13	0.71	0.56	8.2	25.9	16.0	39.2	22.3	28.2
mlr147	0,0	5,3	mlr	2.8e-04	0.62	18	OSCAR62986; OSCAR18045	-0.77	3.13	4.05	0.69	0.54	11.9	24.3	15.4	37.8	22.3	27.9
mlr18	0,-1,0	5,12,4	mlr	1.6e-05	0.78	18	OSCAR62986; OSCAR63007; OSCAR27002	-0.66	3.49	4.08	0.65	0.60	10.1	29.6	15.6	34.0	22.3	19.9
mlr73	0,-1,0	5,12,3	mlr	5.2e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18048	-0.26	3.79	4.11	0.67	0.65	3.9	34.3	15.8	35.2	22.3	18.4
mlr79	0,-1,0	5,12,1	mlr	5.3e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR63011	-0.20	3.76	4.14	0.68	0.65	3.0	33.8	16.0	36.3	22.3	20.8
mlr81	0,-1,-1	5,12,12	mlr	5.4e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR62997	-0.63	3.58	3.96	0.65	0.62	9.8	31.1	14.7	33.5	22.3	18.6
OSCAR62992	0	6	scam_mpd	5.8e-04	0.57	18	u	0.98	3.34	3.79	0.65	0.58	15.2	27.4	13.5	33.2	22.3	72.6

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
mlr26	0,-1,-1	5,12,11	mlr	2.4e-05	0.77	18	OSCAR62986; OSCAR63007; OSCAR53997	-0.28	3.69	4.14	0.68	0.64	4.4	32.6	16.1	36.4	22.4	17.2
mlr56	0,-1,0	5,12,3	mlr	4.6e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18043	-0.29	3.73	4.09	0.67	0.64	4.5	33.3	15.6	36.0	22.4	20.3
mlr76	0,-1,0	5,12,1	mlr	5.2e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR62996	-0.64	3.56	4.05	0.65	0.61	10.0	30.7	15.4	33.6	22.4	20.9
mlr87	0,-1,0	5,12,1	mlr	5.4e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR63006	-0.65	3.51	4.04	0.66	0.61	10.1	30.0	15.3	34.2	22.4	24.5
mlr148	0,0	5,3	mlr	2.8e-04	0.62	18	OSCAR62986; OSCAR18048	-0.71	3.18	4.08	0.70	0.55	11.0	25.0	15.6	38.4	22.5	28.9
mlr150	0,0	5,2	mlr	2.9e-04	0.62	18	OSCAR62986; OSCAR18049	-0.74	3.19	4.07	0.70	0.55	11.4	25.1	15.5	38.1	22.5	29.3
mlr65	0,-1,0	5,12,3	mlr	5.0e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18012	0.16	3.70	4.16	0.70	0.64	2.4	32.8	16.1	38.8	22.5	18.6
OSCAR27011	0	4	scam_mpd	4.4e-03	0.56	18	v	-0.40	3.47	4.15	0.70	0.60	6.1	29.3	16.1	38.6	22.5	74.6
OSCAR35998	0	5	lm	4.0e-05	0.64	18	u	-0.71	3.19	4.08	0.70	0.55	10.9	25.1	15.6	38.3	22.5	24.7
OSCAR62986	0	5	scam_mpd	2.2e-05	0.64	18	u	-0.71	3.19	4.08	0.70	0.55	10.9	25.1	15.6	38.3	22.5	31.7
mlr118	0,0	5,3	mlr	1.5e-04	0.65	18	OSCAR62986; OSCAR18043	-0.98	3.07	4.01	0.68	0.53	15.2	23.3	15.1	36.8	22.6	25.5
mlr145	0,0	5,1	mlr	2.6e-04	0.62	18	OSCAR62986; OSCAR18029	-0.69	3.21	4.10	0.70	0.55	10.7	25.4	15.7	38.7	22.6	31.5
mlr33	0,-1,-1	5,12,4	mlr	3.3e-05	0.76	18	OSCAR62986; OSCAR63007; lighthouse72126	-0.67	3.42	4.06	0.67	0.59	10.4	28.6	15.5	35.9	22.6	19.9
mlr46	0,-1,0	5,12,4	mlr	3.9e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR27013	-0.83	3.49	4.01	0.64	0.60	12.8	29.6	15.1	32.9	22.6	18.4
mlr86	0,-1,0	5,12,1	mlr	5.4e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18039	-0.71	3.69	4.03	0.63	0.64	11.0	32.6	15.3	31.7	22.6	13.1
OSCAR36000	0	5	lm	1.7e-04	0.57	18	u	1.04	3.33	3.85	0.64	0.57	16.1	27.2	14.0	33.1	22.6	37.1
mlr146	0,0	5,1	mlr	2.7e-04	0.62	18	OSCAR62986; OSCAR18046	-0.71	3.24	4.08	0.70	0.56	11.0	25.8	15.6	38.4	22.7	28.0
mlr153	0,0	5,1	mlr	2.9e-04	0.62	18	OSCAR62986; OSCAR18024	-0.69	3.21	4.11	0.70	0.55	10.6	25.5	15.8	38.9	22.7	27.1
mlr94	0,-1	5,11	mlr	7.4e-05	0.68	18	OSCAR62986; OSCAR53997	-0.14	3.47	4.30	0.74	0.60	2.1	29.4	17.2	42.1	22.7	30.4
mlr32	0,0	5,5	mlr	2.6e-05	0.72	18	OSCAR62986; OSCAR53991	0.95	3.15	3.99	0.68	0.54	14.7	24.5	15.0	36.9	22.8	29.0
mlr74	0,-1,0	5,12,3	mlr	5.2e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18040	-0.71	3.68	3.97	0.64	0.63	11.0	32.5	14.8	33.0	22.8	17.7
OSCAR27026	0	4	scam_mpd	1.7e-03	0.51	18	v	1.32	3.28	3.98	0.61	0.57	20.4	26.5	14.9	29.4	22.8	77.0
OSCAR36001	0	6	lm	5.0e-04	0.51	18	u	1.58	3.25	3.56	0.60	0.56	24.4	26.0	11.9	29.0	22.8	59.6
mlr142	0,0	5,1	mlr	2.5e-04	0.62	18	OSCAR62986; OSCAR18025	-0.71	3.22	4.12	0.71	0.56	11.0	25.6	15.9	39.1	22.9	29.2
mlr6	0,-1,0	5,12,5	mlr	9.3e-06	0.80	18	OSCAR62986; OSCAR63007; OSCAR18047	-0.81	3.61	3.96	0.65	0.62	12.5	31.4	14.7	33.4	23.0	20.3
mlr141	0,0	5,1	mlr	2.5e-04	0.63	18	OSCAR62986; OSCAR18042	-0.75	3.26	4.11	0.70	0.56	11.6	26.2	15.8	38.9	23.1	29.9
mlr61	0,-1,0	5,12,6	mlr	4.9e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR54001	-0.88	3.42	4.10	0.66	0.59	13.6	28.6	15.8	34.8	23.2	22.3
mlr136	0,0	5,6	mlr	2.2e-04	0.63	18	OSCAR62986; OSCAR54001	-1.00	2.92	4.20	0.72	0.50	15.5	21.0	16.4	40.3	23.3	37.6
mlr43	0,-1,0	5,12,3	mlr	3.7e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR54005	-0.58	3.70	4.10	0.67	0.64	8.9	32.9	15.7	35.7	23.3	27.8
mlr88	0,0	5,5	mlr	4.5e-05	0.70	18	OSCAR62986; OSCAR18047	-0.84	3.32	4.10	0.70	0.57	12.9	27.1	15.7	38.7	23.6	36.7
mlr124	0,0	5,4	mlr	1.8e-04	0.64	18	OSCAR62986; OSCAR27013	-0.97	3.13	4.17	0.71	0.54	15.0	24.1	16.3	39.8	23.8	28.7
mlr24	0,-1,0	5,12,5	mlr	2.2e-05	0.78	18	OSCAR62986; OSCAR63007; OSCAR36000	-0.71	3.43	4.30	0.70	0.59	11.0	28.7	17.1	38.5	23.8	19.4
mlr59	0,-1,0	5,12,6	mlr	4.9e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR62994	-0.70	3.69	4.18	0.67	0.64	10.9	32.6	16.3	35.6	23.8	18.8
OSCAR18020	0	3	scam_mpi	4.4e-03	0.54	18	v	-0.12	3.28	4.66	0.79	0.57	1.8	26.5	19.7	47.3	23.8	66.7
OSCAR62991	0	5	scam_mpd	1.3e-04	0.57	18	u	1.11	3.40	3.97	0.66	0.59	17.2	28.3	14.8	35.1	23.9	42.9
OSCAR63005	0	6	scam_mpd	4.2e-04	0.51	18	u	1.65	3.32	3.65	0.62	0.57	25.6	27.2	12.5	30.4	23.9	74.6
mlr140	0,0	5,4	mlr	2.5e-04	0.63	18	OSCAR62986; OSCAR18016	-0.73	3.39	4.21	0.72	0.58	11.2	28.2	16.6	40.6	24.1	33.3
OSCAR27015	0	4	scam_mpd	5.4e-03	0.54	18	v	0.76	3.39	4.34	0.71	0.58	11.7	28.1	17.4	39.3	24.1	36.8
mlr114	0,0	5,1	mlr	1.3e-04	0.66	18	OSCAR62986; OSCAR62996	-0.99	3.11	4.23	0.72	0.54	15.4	23.8	16.7	40.9	24.2	42.4
mlr127	0,0	5,3	mlr	1.8e-04	0.64	18	OSCAR62986; OSCAR18040	-0.82	3.41	4.18	0.71	0.59	12.7	28.4	16.3	39.5	24.2	29.2
mlr93	0,0	5,1	mlr	7.3e-05	0.68	18	OSCAR62986; OSCAR63003	-1.05	3.09	4.20	0.72	0.53	16.3	23.6	16.5	40.4	24.2	43.6
mlr30	0,-1,0	5,12,5	mlr	2.9e-05	0.77	18	OSCAR62986; OSCAR63007; OSCAR62993	-0.73	3.60	4.27	0.70	0.62	11.3	31.3	16.9	38.1	24.4	24.8

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
mlr5	0,-1,0	5,12,5	mlr	6.8e-06	0.81	18	OSCAR62986; OSCAR63007; OSCAR53991	0.91	3.70	4.05	0.66	0.64	14.1	32.9	15.4	35.0	24.4	15.6
mlr129	0,0	5,1	mlr	1.9e-04	0.64	18	OSCAR62986; OSCAR63001	-0.70	3.33	4.33	0.74	0.57	10.8	27.2	17.4	42.6	24.5	50.3
OSCAR27005	0	4	scam_mpd	8.8e-04	0.61	18	v	2.03	3.05	3.71	0.62	0.53	31.5	22.9	13.0	30.8	24.5	45.9
OSCAR62989	0	6	scam_mpd	9.2e-04	0.60	18	u	-0.12	3.57	4.56	0.78	0.62	1.7	30.8	19.0	46.5	24.5	81.6
mlr110	0,0	5,4	mlr	1.1e-04	0.66	18	OSCAR62986; OSCAR27002	-0.84	3.26	4.31	0.74	0.56	12.9	26.2	17.2	42.2	24.6	30.5
mlr109	0,0	5,1	mlr	1.1e-04	0.66	18	OSCAR62986; OSCAR63006	-0.92	3.18	4.32	0.74	0.55	14.2	24.9	17.3	42.5	24.7	45.4
mlr52	0,-1,0	5,12,5	mlr	4.4e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR63000	-1.02	3.47	4.20	0.68	0.60	15.8	29.4	16.5	37.0	24.7	28.0
mlr99	0,-1	5,4	mlr	9.1e-05	0.67	18	OSCAR62986; lighthouse72126	-0.48	3.46	4.54	0.75	0.60	7.4	29.2	18.9	43.2	24.7	29.6
mlr122	0,0	5,1	mlr	1.7e-04	0.64	18	OSCAR62986; OSCAR63002	-0.79	3.29	4.36	0.75	0.57	12.1	26.6	17.6	43.1	24.8	47.5
mlr58	0,-1,0	5,12,6	mlr	4.8e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR62995	-0.72	3.75	4.29	0.69	0.65	11.1	33.7	17.1	37.7	24.9	19.8
mlr143	0,0	5,3	mlr	2.6e-04	0.62	18	OSCAR62986; OSCAR18033	0.10	3.96	4.49	0.75	0.68	1.4	36.8	18.5	43.1	25.0	31.1
mlr115	0,0	5,1	mlr	1.4e-04	0.65	18	OSCAR62986; OSCAR63010	-0.88	3.24	4.37	0.75	0.56	13.7	25.9	17.6	43.2	25.1	43.9
mlr57	0,-1,0	5,12,5	mlr	4.7e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR35999	-1.00	3.52	4.27	0.70	0.61	15.5	30.0	17.0	38.2	25.2	21.9
OSCAR18028	-1	12	scam_mpi	3.3e-03	0.52	18	v	0.66	3.47	4.41	0.75	0.60	10.2	29.4	17.9	43.7	25.3	71.6
mlr103	0,0	5,1	mlr	1.0e-04	0.67	18	OSCAR62986; OSCAR63011	-1.38	3.17	4.20	0.70	0.55	21.5	24.8	16.4	38.9	25.4	32.6
mlr107	0,0	5,3	mlr	1.0e-04	0.67	18	OSCAR62986; OSCAR54005	-0.48	3.64	4.43	0.76	0.63	7.4	32.0	18.1	44.3	25.4	48.6
mlr135	0,0	5,2	mlr	2.2e-04	0.63	18	OSCAR62986; OSCAR53998	-0.36	3.72	4.46	0.76	0.64	5.6	33.1	18.3	44.7	25.4	42.4
OSCAR62990	0	6	scam_mpd	1.2e-03	0.58	18	u	0.19	3.85	4.50	0.77	0.66	2.9	35.1	18.6	45.3	25.5	75.0
OSCAR18013	0	3	scam_mpi	5.3e-04	0.57	18	v	-0.67	3.62	4.44	0.74	0.62	10.3	31.7	18.1	42.7	25.7	75.6
OSCAR62994	0	6	scam_mpd	3.6e-04	0.55	18	u	-0.61	3.15	4.80	0.82	0.54	9.5	24.4	20.7	50.5	26.3	73.2
OSCAR18039	0	1	scam_mpi	1.6e-03	0.51	18	v	0.39	3.47	4.79	0.81	0.60	6.0	29.3	20.6	49.6	26.4	80.9
mlr138	0,-1	5,11	mlr	2.4e-04	0.63	18	OSCAR62986; OSCAR54003	-0.40	3.66	4.69	0.80	0.63	6.1	32.2	19.9	48.6	26.7	31.0
OSCAR18012	0	3	scam_mpi	9.6e-04	0.59	18	v	-0.64	3.77	4.52	0.76	0.65	9.9	33.9	18.7	44.9	26.9	74.5
OSCAR18025	0	1	scam_mpi	3.3e-04	0.53	18	v	0.42	3.56	4.80	0.81	0.61	6.5	30.8	20.7	49.7	26.9	80.0
OSCAR18033	0	3	scam_mpi	1.4e-03	0.52	18	v	-0.09	4.04	4.75	0.80	0.70	1.3	38.0	20.4	48.0	26.9	84.0
OSCAR18043	0	3	scam_mpi	5.4e-03	0.51	18	v	0.39	3.58	4.80	0.81	0.62	6.0	31.0	20.7	49.8	26.9	68.3
mlr83	0,-1,0	5,12,6	mlr	5.4e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR62998	-0.60	4.00	4.54	0.74	0.69	9.3	37.4	18.8	42.3	27.0	22.6
mlr96	0,0	5,6	mlr	7.6e-05	0.68	18	OSCAR62986; OSCAR62994	-1.42	3.34	4.37	0.72	0.58	22.0	27.3	17.7	41.0	27.0	28.3
mlr119	0,0	5,4	mlr	1.5e-04	0.65	18	OSCAR62986; OSCAR27026	-0.99	3.56	4.46	0.76	0.61	15.3	30.7	18.3	44.1	27.1	30.6
OSCAR62997	-1	12	scam_mpd	1.0e-03	0.54	18	u	0.48	3.82	4.60	0.79	0.66	7.4	34.7	19.3	47.2	27.1	81.6
mlr139	0,0	5,5	mlr	2.4e-04	0.63	18	OSCAR62986; OSCAR62993	-1.47	3.07	4.45	0.76	0.53	22.8	23.3	18.2	44.4	27.2	37.7
mlr133	0,-1	5,11	mlr	2.1e-04	0.63	18	OSCAR62986; OSCAR18030	-0.47	3.83	4.67	0.80	0.66	7.2	34.8	19.7	47.9	27.4	26.2
mlr64	0,-1,-1	5,12,11	mlr	5.0e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR54002	-1.24	3.44	4.49	0.74	0.59	19.2	28.9	18.5	42.9	27.4	24.8
OSCAR18044	0	3	scam_mpi	8.5e-03	0.51	18	v	0.20	3.89	4.80	0.82	0.67	3.0	35.8	20.7	50.3	27.4	70.6
mlr47	0,-1,-1	5,12,12	mlr	4.0e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR63009	-1.77	3.15	4.37	0.72	0.54	27.4	24.5	17.7	40.6	27.5	24.7
OSCAR54001	0	6	scam_mpi	3.4e-04	0.52	18	u	2.21	3.03	4.13	0.69	0.52	34.3	22.7	15.9	37.5	27.6	63.4
OSCAR63001	0	1	scam_mpd	1.3e-03	0.52	18	u	0.19	3.92	4.92	0.83	0.68	2.9	36.2	21.5	51.7	28.1	84.4
mlr92	0,-1	5,12	mlr	6.9e-05	0.68	18	OSCAR62986; OSCAR63004	-0.58	4.26	4.56	0.75	0.74	8.9	41.4	19.0	43.7	28.3	33.3
mlr132	0,-1	5,11	mlr	2.1e-04	0.63	18	OSCAR62986; OSCAR54004	-0.33	4.05	4.81	0.81	0.70	5.1	38.2	20.8	49.5	28.4	35.8
mlr97	0,0	5,6	mlr	8.0e-05	0.68	18	OSCAR62986; OSCAR62995	-1.55	3.35	4.52	0.75	0.58	24.0	27.6	18.7	43.6	28.5	27.8
OSCAR18042	0	1	scam_mpi	4.7e-04	0.51	18	v	0.01	4.10	5.04	0.85	0.71	0.0	38.9	22.4	53.7	28.7	50.8
OSCAR63010	0	1	scam_mpd	5.6e-04	0.51	18	u	0.00	4.09	5.03	0.85	0.71	0.0	38.8	22.4	53.7	28.7	81.3

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
OSCAR63011	0	1	scam_mpd	2.5e-03	0.50	18	u	-0.08	4.02	5.03	0.85	0.69	1.2	37.7	22.3	53.5	28.7	79.8
OSCAR27019	0	4	scam_mpd	3.4e-03	0.52	18	v	2.37	3.31	4.09	0.67	0.57	36.7	27.0	15.7	35.8	28.8	51.0
OSCAR18008	0	4	scam_mpi	1.4e-03	0.62	18	v	0.08	4.09	5.01	0.85	0.71	1.2	38.8	22.2	53.5	28.9	68.2
OSCAR18021	0	1	scam_mpi	3.1e-04	0.53	18	v	0.12	4.08	5.00	0.85	0.70	1.8	38.6	22.1	53.1	28.9	109.9
OSCAR54002	-1	11	scam_mpi	4.5e-03	0.51	18	u	2.45	2.86	4.22	0.72	0.49	38.0	20.1	16.6	40.7	28.9	33.5
OSCAR63002	0	1	scam_mpd	1.4e-03	0.52	18	u	0.04	4.11	5.04	0.85	0.71	0.5	39.0	22.4	53.7	28.9	83.7
OSCAR63003	0	1	scam_mpd	1.4e-03	0.52	18	u	-0.01	4.10	5.06	0.86	0.71	0.1	39.0	22.6	54.1	28.9	80.6
OSCAR18010	0	4	scam_mpi	1.4e-03	0.62	18	v	0.40	4.04	4.85	0.82	0.70	6.2	38.0	21.0	50.7	29.0	69.1
OSCAR18007	0	4	scam_mpi	9.8e-04	0.63	18	v	0.54	3.99	4.82	0.82	0.69	8.4	37.2	20.8	50.0	29.1	62.5
OSCAR18045	0	3	scam_mpi	4.9e-03	0.51	18	v	0.02	4.11	5.08	0.86	0.71	0.3	39.0	22.7	54.3	29.1	79.3
OSCAR62996	0	1	scam_mpd	2.4e-04	0.54	18	u	-0.06	4.09	5.06	0.86	0.70	0.9	38.7	22.5	54.1	29.1	80.8
OSCAR63006	0	1	scam_mpd	2.3e-03	0.51	18	u	0.03	4.12	5.06	0.86	0.71	0.5	39.2	22.5	54.0	29.1	82.7
mlr137	0,-1	5,11	mlr	2.3e-04	0.63	18	OSCAR62986; OSCAR54002	-1.00	3.46	4.87	0.82	0.60	15.5	29.2	21.2	50.7	29.2	33.1
OSCAR18024	0	1	scam_mpi	3.1e-04	0.53	18	v	0.09	4.12	5.04	0.85	0.71	1.4	39.3	22.4	53.6	29.2	221.7
OSCAR18048	0	3	scam_mpi	5.2e-04	0.50	18	v	-0.20	4.02	5.03	0.85	0.69	3.0	37.7	22.3	53.8	29.2	84.7
OSCAR53998	0	2	scam_mpi	2.4e-04	0.54	18	u	0.10	4.15	5.04	0.85	0.72	1.5	39.7	22.4	53.7	29.3	79.5
OSCAR18022	0	5	scam_mpi	5.3e-03	0.53	18	v	0.75	4.05	4.74	0.79	0.70	11.5	38.1	20.3	47.7	29.4	70.7
OSCAR62998	0	6	scam_mpd	1.0e-03	0.54	18	u	-0.23	3.65	5.27	0.90	0.63	3.6	32.1	24.1	58.4	29.5	65.1
OSCAR18041	0	1	scam_mpi	5.8e-04	0.51	18	v	0.17	4.15	5.05	0.85	0.72	2.5	39.7	22.5	53.7	29.6	213.1
OSCAR18019	0	1	scam_mpi	2.0e-03	0.55	18	v	1.32	3.73	4.61	0.77	0.64	20.5	33.2	19.4	45.6	29.7	85.6
OSCAR63004	-1	12	scam_mpd	3.9e-04	0.52	18	u	-0.31	4.05	5.06	0.86	0.70	4.8	38.1	22.5	54.4	29.9	82.2
mlr151	0,-1	5,12	mlr	2.9e-04	0.62	18	OSCAR62986; OSCAR27027	-0.92	3.90	4.77	0.81	0.67	14.2	35.9	20.5	49.2	30.0	34.9
OSCAR18046	0	1	scam_mpi	2.2e-03	0.51	18	v	0.12	4.22	5.11	0.87	0.73	1.7	40.7	22.9	54.8	30.0	85.1
OSCAR27013	0	4	scam_mpd	7.6e-04	0.55	18	v	0.32	4.30	4.93	0.83	0.74	4.8	41.9	21.6	51.5	30.0	70.7
OSCAR18030	-1	11	scam_mpi	3.6e-04	0.52	18	v	-0.24	4.04	5.13	0.87	0.70	3.7	38.0	23.0	55.7	30.1	86.3
OSCAR18029	0	1	scam_mpi	3.6e-04	0.52	18	v	0.26	4.29	5.12	0.85	0.74	4.0	41.7	22.9	53.7	30.6	84.4
OSCAR18049	0	2	scam_mpi	5.3e-04	0.50	18	v	-0.23	4.16	5.19	0.88	0.72	3.5	39.8	23.4	56.3	30.8	89.9
median8	0	0	median8	NA			median8	0.17	4.50	5.30	0.84	0.78	2.5	45.0	24.2	51.9	30.9	81.9
OSCAR62995	0	6	scam_mpd	2.2e-03	0.55	18	u	-0.85	3.68	5.12	0.88	0.63	13.1	32.5	23.0	55.8	31.1	63.6
OSCAR54003	-1	11	scam_mpi	2.0e-03	0.51	18	u	0.06	4.27	5.35	0.91	0.74	0.8	41.5	24.6	59.0	31.5	83.9
OSCAR27025	0	6	scam_mpd	1.6e-03	0.51	18	v	1.05	4.16	4.82	0.82	0.72	16.3	39.8	20.8	50.1	31.8	56.0
mlr144	0,0	5,5	mlr	2.6e-04	0.62	18	OSCAR62986; OSCAR35999	-2.24	3.27	4.65	0.78	0.56	34.8	26.3	19.6	46.8	31.9	29.1
OSCAR63007	-1	12	scam_mpd	7.2e-03	0.51	18	u	1.10	4.06	4.92	0.83	0.70	17.0	38.4	21.6	51.1	32.0	81.5
mlr117	0,0	5,6	mlr	1.4e-04	0.65	18	OSCAR62986; OSCAR62998	-1.44	3.77	4.93	0.82	0.65	22.4	34.0	21.6	50.7	32.2	32.1
mlr152	0,0	5,5	mlr	2.9e-04	0.62	18	OSCAR62986; OSCAR63000	-2.07	3.48	4.67	0.80	0.60	32.1	29.6	19.8	48.0	32.4	34.9
mlr131	0,-1	5,12	mlr	2.0e-04	0.64	18	OSCAR62986; OSCAR63009	-0.86	4.73	4.98	0.79	0.81	13.2	48.4	22.0	47.8	32.9	36.2
OSCAR35999	0	5	lm	7.6e-05	0.61	18	u	-2.29	3.41	4.79	0.81	0.59	35.5	28.4	20.6	49.2	33.4	29.1
OSCAR62988	0	5	scam_mpd	5.0e-05	0.61	18	u	-2.29	3.41	4.79	0.81	0.59	35.5	28.4	20.6	49.2	33.4	29.6
OSCAR18035	0	4	scam_mpi	7.9e-03	0.51	18	v	0.43	4.55	5.34	0.90	0.79	6.6	45.8	24.5	58.1	33.8	175.4
OSCAR18016	0	4	scam_mpi	6.6e-04	0.56	18	v	0.91	4.62	5.08	0.84	0.80	14.0	46.7	22.7	52.7	34.0	72.4
mlr149	0,0	5,5	mlr	2.9e-04	0.62	18	OSCAR62986; OSCAR36000	-2.15	3.62	4.93	0.82	0.62	33.4	31.6	21.6	50.2	34.2	30.1
OSCAR18040	0	3	scam_mpi	2.2e-03	0.51	18	v	1.16	4.05	5.23	0.89	0.70	17.9	38.2	23.7	57.4	34.3	51.0

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
OSCAR27027	-1	12	scam_mpd	2.3e-03	0.51	18	v	0.47	4.67	5.32	0.90	0.81	7.2	47.6	24.4	58.6	34.4	85.7
shore72126	-1	4	scam_mpi	4.8e-03	0.50	20	temperature.c.	1.14	4.62	5.82	0.86	0.80	17.7	46.7	27.9	53.8	36.5	45.9
OSCAR54005	0	3	scam_mpi	1.8e-03	0.50	18	u	0.73	4.62	5.65	0.96	0.80	11.3	46.7	26.7	63.6	37.1	83.6
OSCAR54004	-1	11	scam_mpi	1.7e-03	0.51	18	u	1.07	4.31	5.66	0.97	0.74	16.6	42.1	26.8	64.7	37.5	80.8
OSCAR53997	-1	11	scam_mpi	1.3e-03	0.54	18	u	2.63	4.03	5.11	0.87	0.69	40.9	37.9	22.9	55.5	39.3	53.2
mean8	0	0	mean8	NA			mean8	1.97	5.01	5.69	0.90	0.86	30.5	52.7	27.0	58.0	42.0	89.9
OSCAR62993	0	5	scam_mpd	1.8e-03	0.56	18	u	0.56	5.25	6.23	1.06	0.90	8.7	56.3	30.8	74.1	42.5	84.3
median4	0	0	median4	NA			median4	0.42	5.75	6.56	1.04	0.99	6.4	63.9	33.2	71.4	43.7	108.1
OSCAR63000	0	5	scam_mpd	4.2e-03	0.53	18	u	-2.60	4.50	5.60	0.95	0.78	40.3	45.0	26.4	63.6	43.8	62.4
OSCAR18031	0	5	scam_mpi	7.1e-03	0.52	18	v	1.47	5.08	6.08	1.03	0.88	22.8	53.7	29.8	70.5	44.2	92.0
lly	0	0	lly	NA			lly	0.83	5.83	6.34	1.00	1.01	12.9	65.2	31.6	68.0	44.4	136.3
mean.all	0	0	mean.all	NA			mean.all	-3.56	4.75	5.98	0.94	0.82	55.3	48.8	29.0	62.4	48.9	188.2
mean4	0	0	mean4	NA			mean4	1.50	6.25	7.11	1.12	1.08	23.2	71.5	37.1	79.9	52.9	100.4
median.all	0	0	median.all	NA			median.all	-4.08	5.08	6.31	1.00	0.88	63.4	53.8	31.4	67.6	54.1	193.1
OSCAR63009	-1	12	scam_mpd	4.1e-03	0.51	18	u	1.84	6.00	7.64	1.21	1.04	28.6	67.8	40.8	88.1	56.3	70.2
OSCAR18047	0	5	scam_mpi	2.7e-03	0.50	18	v	4.60	6.45	9.00	1.53	1.11	71.4	74.6	50.4	120.2	79.2	111.5
OSCAR53991	0	5	scam_mpi	1.3e-03	0.59	18	u	8.09	8.78	17.08	2.92	1.51	125.7	109.9	107.7	256.0	149.8	217.3
OSCAR53996	0	5	scam_mpi	3.4e-03	0.55	18	u	8.98	8.98	16.41	2.81	1.55	139.6	113.0	102.9	244.9	150.1	192.8
OSCAR18011	0	3	scam_mpi	3.3e-04	0.59	18	v	-16.48	18.41	38.01	0.65	3.17	256.0	256.0	256.0	33.8	200.5	59.3

Table 16. Performance results for all qualifying models used to forecast Chilko timing based on jackknife analysis. Each row represents a single model tested, some columns include: year adjust (year of environmental data same as return year [0] or prior year [-1]), month, summary statistics (P value, adjusted R squared, sample size), data name, data variables (which are sorted by their relative influence in the model). As the NEPSTAR regression models comprise more than one variable, only year-month of the latest variable is presented. Latitude and longtitude of NEPSTAR variables are excluded due to space limitations. The PMs include mean raw error, mean absolute error, root mean squared error, Thiel's U-statistic, and MASE. The initial three PMs are in day units, the latter two are unit-less. All PMs are described in the methods section. All PMs, except MASE, are given a rank. The best rank has a value of zero. The last rank equals total number of models (n). The average of the PM ranks by model (row) is included, as is the average rank for the alternate performance test method. The rows are sorted by average rank of performance method listed in caption. The first row is the best model, the last row is the worst.

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
nepstar13	-1,-1,0,-1,-1,0,0	6,5,3,4,5,3,3	mlr	3.0e-08	0.89	25	nepstar	0.07	2.02	2.41	0.31	0.35	3.0	6.9	0.0	0.0	2.5	23.7
mlr8	0,-1,-1	5,12,11	mlr	1.2e-05	0.79	18	OSCAR62986; OSCAR63007; OSCAR18030	-0.07	1.90	2.49	0.33	0.33	3.3	0.0	2.2	4.9	2.6	29.7
nepstar3	-1,0,0,-1	7,2,3,5	mlr	2.5e-08	0.83	25	nepstar	0.10	2.11	2.53	0.32	0.36	4.3	11.9	3.2	2.7	5.5	4.7
nepstar11	0,-1,0,-1	2,5,3,5	mlr	7.3e-08	0.81	25	nepstar	0.02	2.20	2.53	0.31	0.38	0.7	17.3	3.2	1.7	5.7	12.3
nepstar9	0,-1,0,-1	3,5,3,5	mlr	2.6e-08	0.83	25	nepstar	0.22	2.19	2.41	0.32	0.37	10.1	16.7	0.1	2.0	7.2	8.2
nepstar4	-1,0,0,-1	7,4,3,5	mlr	2.4e-08	0.83	25	nepstar	-0.11	2.19	2.58	0.33	0.37	4.9	16.5	4.5	4.8	7.7	12.0
nepstar2	-1,0,-1	6,3,5	mlr	4.2e-09	0.84	25	nepstar	0.28	2.14	2.59	0.34	0.37	12.8	13.6	4.8	6.1	9.3	8.0
mlr17	0,-1,0	5,12,5	mlr	1.6e-05	0.78	18	OSCAR62986; OSCAR63007; OSCAR18038	-0.08	2.23	2.70	0.36	0.38	3.7	19.3	7.7	9.8	10.1	33.3
mlr4	0,-1,0	5,12,5	mlr	6.2e-06	0.81	18	OSCAR62986; OSCAR63007; OSCAR53996	0.28	2.06	2.71	0.36	0.35	12.5	9.2	8.0	10.7	10.1	36.8
mlr84	0,-1,0	5,12,1	mlr	5.4e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18021	-0.00	2.18	2.85	0.38	0.37	0.1	16.1	11.7	14.3	10.5	41.1
mlr12	0,-1,-1	5,12,12	mlr	1.3e-05	0.79	18	OSCAR62986; OSCAR63007; OSCAR27027	-0.13	2.23	2.75	0.35	0.38	5.9	19.3	8.9	9.1	10.8	24.5
nepstar7	-1,0,0,-1	6,3,3,5	mlr	7.0e-09	0.85	25	nepstar	0.32	2.14	2.70	0.35	0.37	14.3	13.8	7.6	8.7	11.1	16.8
mlr2	0,-1,0	5,12,4	mlr	3.2e-06	0.83	18	OSCAR62986; OSCAR63007; OSCAR27026	-0.12	2.22	2.81	0.36	0.38	5.3	18.7	10.5	11.2	11.4	22.2
mlr38	0,-1,0	5,12,1	mlr	3.5e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR18024	-0.10	2.13	2.90	0.38	0.36	4.2	13.2	12.9	15.5	11.5	44.3
mlr85	0,-1,0	5,12,1	mlr	5.4e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18041	0.03	2.21	2.88	0.38	0.38	1.5	18.1	12.4	15.0	11.7	42.0
nepstar5	-2,-1,0,0	7,5,3,3	mlr	1.1e-08	0.85	25	nepstar	0.21	2.28	2.68	0.35	0.39	9.3	22.1	7.2	8.9	11.9	11.7
mlr1	0,-1,0	5,12,4	mlr	2.8e-06	0.83	18	OSCAR62986; OSCAR63007; OSCAR27019	0.20	2.25	2.73	0.36	0.38	8.9	20.0	8.4	11.1	12.1	25.9
mlr77	0,-1,0	5,12,1	mlr	5.3e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18025	-0.07	2.21	2.88	0.38	0.38	3.3	18.0	12.2	14.8	12.1	42.7
nepstar14	-1,0,0,-1,0	7,3,3,5,3	mlr	9.5e-08	0.83	25	nepstar	0.18	2.28	2.75	0.36	0.39	7.9	21.8	8.9	10.1	12.2	4.3
mlr37	0,-1,0	5,12,1	mlr	3.4e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR18046	-0.10	2.15	2.96	0.39	0.37	4.3	14.4	14.6	17.3	12.6	47.6
mlr23	0,-1,0	5,12,6	mlr	2.1e-05	0.78	18	OSCAR62986; OSCAR63007; OSCAR63008	0.04	2.35	2.83	0.37	0.40	1.6	25.9	11.0	13.1	12.9	36.1
mlr28	0,-1,0	5,12,4	mlr	2.7e-05	0.77	18	OSCAR62986; OSCAR63007; OSCAR18007	0.00	2.30	2.90	0.39	0.39	0.1	23.4	12.9	15.6	13.0	32.3
mlr71	0,-1,-1	5,12,12	mlr	5.2e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR63004	0.11	2.23	2.90	0.38	0.38	4.8	19.3	12.8	15.0	13.0	33.8
mlr86	0,-1,0	5,12,1	mlr	5.4e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18039	-0.03	2.28	2.92	0.39	0.39	1.2	22.2	13.3	15.8	13.1	43.0
mlr9	0,-1	5,12	mlr	8.7e-06	0.76	18	OSCAR62986; OSCAR63007	0.04	2.31	2.87	0.38	0.40	2.0	24.0	12.2	14.5	13.2	38.8
mlr11	0,-1,0	5,12,6	mlr	1.3e-05	0.79	18	OSCAR62986; OSCAR63007; OSCAR36001	0.10	2.34	2.82	0.37	0.40	4.4	25.6	10.7	12.9	13.4	33.7
mlr55	0,-1,-1	5,12,11	mlr	4.6e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR54004	-0.11	2.33	2.84	0.38	0.40	4.7	24.7	11.3	13.7	13.6	37.7
mlr49	0,-1,0	5,12,6	mlr	4.2e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR62990	-0.01	2.33	2.92	0.39	0.40	0.4	25.2	13.5	15.6	13.7	41.4
mlr29	0,-1,0	5,12,1	mlr	2.7e-05	0.77	18	OSCAR62986; OSCAR63007; OSCAR18042	-0.06	2.23	3.00	0.40	0.38	2.5	19.1	15.5	18.2	13.8	48.6
mlr34	0,-1,0	5,12,6	mlr	3.3e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR62989	0.06	2.35	2.88	0.38	0.40	2.6	26.2	12.4	14.3	13.9	38.8

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
nepstar1	-1,0,-1	7,3,5	mlr	3.1e-08	0.80	25	nepstar	0.15	2.27	2.93	0.39	0.39	6.5	21.5	13.7	16.1	14.4	8.6
mlr82	0,-1,0	5,12,1	mlr	5.4e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18029	0.12	2.35	2.90	0.38	0.40	5.5	25.9	13.0	15.3	14.9	41.3
mlr15	0,-1,0	5,12,4	mlr	1.5e-05	0.79	18	OSCAR62986; OSCAR63007; OSCAR27008	-0.12	2.38	2.90	0.38	0.41	5.4	27.8	13.0	14.8	15.2	25.9
mlr44	0,-1,0	5,12,6	mlr	3.9e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR62992	0.04	2.39	2.96	0.39	0.41	1.7	28.6	14.6	16.7	15.4	41.5
mlr48	0,-1,0	5,12,4	mlr	4.1e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18035	0.02	2.37	3.01	0.40	0.41	0.8	27.3	15.7	18.3	15.5	40.7
mlr5	0,-1,0	5,12,5	mlr	6.8e-06	0.81	18	OSCAR62986; OSCAR63007; OSCAR53991	0.27	2.26	2.93	0.39	0.39	12.0	20.7	13.6	15.9	15.6	42.6
mlr19	0,-1,0	5,12,1	mlr	1.7e-05	0.78	18	OSCAR62986; OSCAR63007; OSCAR18019	0.02	2.44	2.95	0.39	0.42	0.7	31.3	14.1	16.7	15.7	33.4
mlr31	0,-1,-1	5,12,12	mlr	3.0e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR18028	0.13	2.38	2.95	0.38	0.41	5.9	28.2	14.1	15.4	15.9	39.9
mlr14	0,-1	5,12	mlr	1.1e-05	0.75	18	OSCAR62986; OSCAR62997	0.13	2.37	2.95	0.39	0.41	6.0	27.4	14.1	16.4	16.0	38.7
mlr39	0,-1,0	5,12,4	mlr	3.6e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR18010	-0.03	2.46	2.94	0.39	0.42	1.1	32.3	14.0	16.6	16.0	37.5
mlr16	0,-1,0	5,12,4	mlr	1.5e-05	0.79	18	OSCAR62986; OSCAR63007; OSCAR27011	-0.17	2.39	2.90	0.38	0.41	7.6	28.8	13.0	15.0	16.1	28.2
mlr53	0,-1,0	5,12,6	mlr	4.5e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR27025	0.07	2.36	3.03	0.40	0.40	3.0	26.6	16.3	18.8	16.2	43.4
mlr66	0,-1,-1	5,12,11	mlr	5.0e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR54003	0.10	2.38	2.99	0.39	0.41	4.3	28.0	15.2	17.4	16.2	42.5
nepstar6	0,-1,0,0	3,5,3,3	mlr	4.3e-09	0.86	25	nepstar	0.58	2.30	2.70	0.35	0.39	26.2	23.1	7.7	8.0	16.3	14.4
mlr41	0,-1,0	5,12,3	mlr	3.7e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR18013	0.04	2.40	3.04	0.40	0.41	1.6	29.1	16.5	18.8	16.5	43.5
mlr25	0,0	5,4	mlr	1.8e-05	0.74	18	OSCAR62986; OSCAR27008	0.06	2.35	3.11	0.41	0.40	2.4	26.4	18.5	20.0	16.8	20.2
nepstar12	0,-1,0,-1	3,4,3,5	mlr	7.1e-08	0.82	25	nepstar	-0.15	2.54	2.81	0.37	0.44	6.8	37.5	10.5	12.6	16.8	22.8
mlr13	0,-1,0	5,12,4	mlr	1.5e-05	0.79	18	OSCAR62986; OSCAR63007; OSCAR27015	0.12	2.45	2.96	0.39	0.42	5.3	32.2	14.5	16.3	17.1	31.7
mlr40	0,-1,0	5,12,3	mlr	3.6e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR18044	0.09	2.41	3.02	0.40	0.41	4.0	29.9	16.1	18.6	17.1	40.7
mlr63	0,-1,0	5,12,3	mlr	5.0e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18045	0.12	2.43	2.98	0.39	0.42	5.2	31.0	15.0	17.3	17.1	40.8
mlr26	0,-1,-1	5,12,11	mlr	2.4e-05	0.77	18	OSCAR62986; OSCAR63007; OSCAR53997	0.10	2.34	3.09	0.41	0.40	4.4	25.7	18.0	20.7	17.2	43.3
mlr35	0,0	5,4	mlr	2.7e-05	0.72	18	OSCAR62986; OSCAR27019	0.68	2.17	2.83	0.38	0.37	30.6	15.3	11.1	13.8	17.7	24.8
mlr74	0,-1,0	5,12,3	mlr	5.2e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18040	0.02	2.51	3.03	0.40	0.43	0.9	35.4	16.2	18.2	17.7	43.9
mlr10	0,0	5,6	mlr	9.0e-06	0.76	18	OSCAR62986; OSCAR36001	0.38	2.27	2.99	0.40	0.39	17.2	21.4	15.3	17.6	17.9	27.6
mlr60	0,-1,0	5,12,4	mlr	4.9e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18008	0.01	2.49	3.07	0.41	0.43	0.4	34.1	17.4	19.8	17.9	44.0
mlr46	0,-1,0	5,12,4	mlr	3.9e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR27013	0.00	2.49	3.11	0.41	0.43	0.0	34.6	18.4	20.5	18.4	45.2
mlr73	0,-1,0	5,12,3	mlr	5.2e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18048	0.13	2.48	3.02	0.40	0.42	5.9	33.6	16.0	18.2	18.4	40.6
mlr65	0,-1,0	5,12,3	mlr	5.0e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18012	0.11	2.48	3.04	0.40	0.42	5.0	33.8	16.6	19.0	18.6	42.0
mlr81	0,-1,-1	5,12,12	mlr	5.4e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR62997	0.05	2.50	3.06	0.41	0.43	2.4	35.2	17.2	19.6	18.6	43.4
mlr59	0,-1,0	5,12,6	mlr	4.9e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR62994	0.08	2.46	3.10	0.41	0.42	3.5	32.7	18.3	20.7	18.8	44.0
mlr72	0,0	5,4	mlr	4.3e-05	0.70	18	OSCAR62986; OSCAR27011	0.08	2.38	3.22	0.42	0.41	3.5	27.7	21.4	23.5	19.0	24.8
mlr80	0,-1,0	5,12,2	mlr	5.3e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR53998	0.14	2.48	3.06	0.40	0.42	6.2	33.8	17.1	19.4	19.1	41.8
mlr3	0,-1,0	5,12,4	mlr	4.0e-06	0.82	18	OSCAR62986; OSCAR63007; OSCAR27004	-0.14	2.54	3.01	0.40	0.43	6.3	37.0	15.8	17.8	19.2	19.8
mlr78	0,-1,0	5,12,2	mlr	5.3e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18049	0.16	2.53	2.99	0.40	0.43	7.2	36.9	15.4	17.9	19.3	34.1
mlr24	0,-1,0	5,12,5	mlr	2.2e-05	0.78	18	OSCAR62986; OSCAR63007; OSCAR36000	0.08	2.47	3.14	0.42	0.42	3.6	33.0	19.1	21.7	19.4	36.6
mlr36	0,-1,0	5,12,5	mlr	3.4e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR18022	0.20	2.43	3.07	0.41	0.42	9.2	30.7	17.5	20.1	19.4	37.6
mlr54	0,-1,0	5,12,3	mlr	4.6e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18033	0.07	2.53	3.09	0.41	0.43	3.1	37.0	17.9	20.1	19.5	43.0
mlr62	0,-1,0	5,12,3	mlr	5.0e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18020	0.13	2.51	3.07	0.41	0.43	6.0	35.7	17.4	19.8	19.7	42.2
mlr58	0,-1,0	5,12,6	mlr	4.8e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR62995	0.09	2.48	3.15	0.42	0.42	3.8	33.7	19.6	22.0	19.8	45.3
mlr18	0,-1,0	5,12,4	mlr	1.6e-05	0.78	18	OSCAR62986; OSCAR63007; OSCAR27002	-0.09	2.54	3.10	0.41	0.43	4.0	37.4	18.1	19.9	19.9	36.0
mlr33	0,-1,-1	5,12,4	mlr	3.3e-05	0.76	18	OSCAR62986; OSCAR63007; lighthouse72126	-0.02	2.51	3.18	0.42	0.43	1.0	35.3	20.4	22.9	19.9	45.3
mlr20	0,0	5,6	mlr	1.4e-05	0.75	18	OSCAR62986; OSCAR63008	0.34	2.45	3.02	0.40	0.42	15.4	32.0	16.0	17.9	20.3	31.1

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr56	0,-1,0	5,12,3	mlr	4.6e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18043	0.14	2.52	3.10	0.41	0.43	6.1	36.3	18.1	20.5	20.3	43.1
mlr6	0,-1,0	5,12,5	mlr	9.3e-06	0.80	18	OSCAR62986; OSCAR63007; OSCAR18047	-0.05	2.56	3.14	0.42	0.44	2.2	38.2	19.3	21.6	20.3	44.3
mlr7	0,-1,0	5,12,4	mlr	1.0e-05	0.80	18	OSCAR62986; OSCAR63007; OSCAR27005	-0.05	2.64	3.07	0.40	0.45	2.1	43.2	17.3	18.7	20.3	27.5
mlr70	0,-1,0	5,12,4	mlr	5.2e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18016	0.12	2.54	3.13	0.41	0.43	5.2	37.0	18.9	21.2	20.6	44.7
mlr79	0,-1,0	5,12,1	mlr	5.3e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR63011	0.15	2.51	3.13	0.41	0.43	6.9	35.7	19.0	21.5	20.8	43.1
mlr21	0,-1,0	5,12,4	mlr	1.9e-05	0.78	18	OSCAR62986; OSCAR63007; OSCAR27010	-0.25	2.52	3.07	0.40	0.43	11.2	35.8	17.3	19.1	20.9	33.9
mlr76	0,-1,0	5,12,1	mlr	5.2e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR62996	0.08	2.57	3.15	0.42	0.44	3.6	38.8	19.5	21.9	20.9	44.6
mlr22	0,-1,0	5,12,4	mlr	1.9e-05	0.78	18	OSCAR62986; OSCAR63007; OSCAR27012	-0.13	2.64	3.08	0.40	0.45	6.0	42.9	17.6	18.9	21.4	32.2
mlr101	0,0	5,4	mlr	9.5e-05	0.67	18	OSCAR62986; OSCAR18010	0.24	2.40	3.24	0.43	0.41	10.7	28.9	21.9	24.5	21.5	30.9
mlr50	0,-1,0	5,12,3	mlr	4.4e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18011	-0.07	2.53	3.25	0.43	0.43	3.2	36.9	22.2	24.6	21.7	51.3
mlr89	0,0	5,5	mlr	5.3e-05	0.70	18	OSCAR62986; OSCAR53996	0.61	2.34	3.01	0.40	0.40	27.6	25.4	15.8	18.4	21.8	23.2
mlr57	0,-1,0	5,12,5	mlr	4.7e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR35999	0.11	2.54	3.23	0.43	0.43	4.7	37.3	21.6	24.1	21.9	45.4
mlr69	0,-1,0	5,12,1	mlr	5.1e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR63002	0.13	2.60	3.17	0.42	0.44	5.9	40.7	20.0	22.4	22.2	44.0
mlr61	0,-1,0	5,12,6	mlr	4.9e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR54001	0.17	2.52	3.23	0.43	0.43	7.4	36.1	21.5	24.2	22.3	42.7
mlr83	0,-1,0	5,12,6	mlr	5.4e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR62998	0.04	2.59	3.28	0.43	0.44	1.8	40.4	22.9	25.3	22.6	48.2
mlr67	0,-1,0	5,12,1	mlr	5.1e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR63001	0.12	2.62	3.19	0.42	0.45	5.6	41.8	20.5	22.9	22.7	44.4
mlr75	0,-1,0	5,12,1	mlr	5.2e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR63010	0.14	2.61	3.19	0.42	0.45	6.2	41.2	20.6	23.0	22.7	44.6
mlr113	0,0	5,3	mlr	1.3e-04	0.66	18	OSCAR62986; OSCAR18013	0.40	2.40	3.20	0.42	0.41	18.0	29.2	20.8	23.2	22.8	35.6
mlr108	0,0	5,3	mlr	1.1e-04	0.66	18	OSCAR62986; OSCAR18044	0.41	2.37	3.28	0.44	0.41	18.4	27.3	23.0	25.6	23.6	33.1
mlr45	0,-1,0	5,12,5	mlr	3.9e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18031	0.28	2.53	3.22	0.43	0.43	12.7	36.5	21.2	23.9	23.6	40.6
mlr120	0,0	5,3	mlr	1.6e-04	0.65	18	OSCAR62986; OSCAR18011	0.36	2.49	3.26	0.43	0.43	16.4	34.1	22.5	25.0	24.5	42.1
mlr87	0,-1,0	5,12,1	mlr	5.4e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR63006	0.18	2.65	3.24	0.43	0.45	8.3	43.7	21.9	24.2	24.5	45.0
mlr47	0,-1,-1	5,12,12	mlr	4.0e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR63009	-0.09	2.56	3.43	0.45	0.44	4.1	38.5	26.9	29.1	24.7	53.0
OSCAR35998	0	5	lm	4.0e-05	0.64	18	u	0.54	2.37	3.26	0.43	0.41	24.6	27.3	22.3	24.8	24.7	36.5
mlr30	0,-1,0	5,12,5	mlr	2.9e-05	0.77	18	OSCAR62986; OSCAR63007; OSCAR62993	0.24	2.50	3.37	0.45	0.43	11.0	35.0	25.2	27.8	24.8	46.0
mlr64	0,-1,-1	5,12,11	mlr	5.0e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR54002	-0.10	2.62	3.37	0.45	0.45	4.3	42.0	25.3	27.6	24.8	53.5
mlr42	0,0	5,6	mlr	3.0e-05	0.72	18	OSCAR62986; OSCAR62989	0.41	2.61	3.16	0.41	0.45	18.4	41.4	19.6	21.1	25.1	35.9
mlr68	0,-1,0	5,12,1	mlr	5.1e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR63003	0.25	2.65	3.24	0.43	0.45	11.4	43.9	21.9	24.2	25.3	43.1
mlr118	0,0	5,3	mlr	1.5e-04	0.65	18	OSCAR62986; OSCAR18043	0.43	2.38	3.39	0.45	0.41	19.6	28.0	25.8	28.5	25.5	37.2
mlr133	0,-1	5,11	mlr	2.1e-04	0.63	18	OSCAR62986; OSCAR18030	0.48	2.41	3.37	0.45	0.41	21.8	29.9	25.3	27.9	26.2	39.5
mlr105	0,0	5,4	mlr	1.0e-04	0.67	18	OSCAR62986; OSCAR18007	0.38	2.57	3.32	0.44	0.44	17.0	38.9	24.1	26.6	26.7	28.6
mlr91	0,0	5,5	mlr	5.9e-05	0.69	18	OSCAR62986; OSCAR18038	0.36	2.63	3.30	0.44	0.45	16.3	42.7	23.4	25.7	27.0	31.9
mlr153	0,0	5,1	mlr	2.9e-04	0.62	18	OSCAR62986; OSCAR18024	0.58	2.43	3.33	0.44	0.42	26.4	31.0	24.3	26.8	27.1	37.5
mlr95	0,0	5,4	mlr	7.5e-05	0.68	18	OSCAR62986; OSCAR27010	0.06	2.75	3.45	0.45	0.47	2.6	49.8	27.3	29.1	27.2	29.5
mlr116	0,0	5,4	mlr	1.4e-04	0.65	18	OSCAR62986; OSCAR18008	0.40	2.55	3.39	0.45	0.44	18.1	37.7	25.7	28.3	27.5	36.4
mlr126	0,0	5,3	mlr	1.8e-04	0.64	18	OSCAR62986; OSCAR18012	0.47	2.57	3.33	0.44	0.44	21.5	39.1	24.1	26.5	27.8	36.5
mlr43	0,-1,0	5,12,3	mlr	3.7e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR54005	0.20	2.71	3.41	0.45	0.46	9.1	47.1	26.3	28.7	27.8	46.3
mlr97	0,0	5,6	mlr	8.0e-05	0.68	18	OSCAR62986; OSCAR62995	0.49	2.47	3.42	0.45	0.42	22.2	33.1	26.6	29.2	27.8	43.2
mlr147	0,0	5,3	mlr	2.8e-04	0.62	18	OSCAR62986; OSCAR18045	0.51	2.56	3.32	0.44	0.44	23.1	38.4	24.0	25.9	27.9	35.6
mlr146	0,0	5,1	mlr	2.7e-04	0.62	18	OSCAR62986; OSCAR18046	0.57	2.52	3.31	0.44	0.43	25.8	36.2	23.7	26.3	28.0	39.4
mlr52	0,-1,0	5,12,5	mlr	4.4e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR63000	0.25	2.64	3.45	0.46	0.45	11.2	43.2	27.5	30.0	28.0	49.1
mlr121	0,0	5,1	mlr	1.6e-04	0.65	18	OSCAR62986; OSCAR18019	0.60	2.43	3.40	0.45	0.41	27.2	30.5	26.2	28.8	28.2	33.1

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr96	0,0	5,6	mlr	7.6e-05	0.68	18	OSCAR62986; OSCAR62994	0.56	2.48	3.38	0.45	0.42	25.2	33.9	25.6	28.3	28.3	42.3
mlr124	0,0	5,4	mlr	1.8e-04	0.64	18	OSCAR62986; OSCAR27013	0.50	2.56	3.39	0.45	0.44	22.8	38.3	25.9	27.9	28.7	40.5
mlr148	0,0	5,3	mlr	2.8e-04	0.62	18	OSCAR62986; OSCAR18048	0.56	2.57	3.35	0.44	0.44	25.2	39.2	24.7	26.6	28.9	35.6
mlr32	0,0	5,5	mlr	2.6e-05	0.72	18	OSCAR62986; OSCAR53991	0.61	2.61	3.28	0.43	0.45	27.8	41.4	22.8	24.2	29.0	36.5
mlr144	0,0	5,5	mlr	2.6e-04	0.62	18	OSCAR62986; OSCAR35999	0.40	2.54	3.52	0.47	0.43	18.3	37.3	29.3	31.6	29.1	46.2
mlr27	0,0	5,4	mlr	1.9e-05	0.73	18	OSCAR62986; OSCAR27004	0.25	2.83	3.33	0.44	0.48	11.3	54.3	24.4	26.5	29.1	20.6
OSCAR35999	0	5	lm	7.6e-05	0.61	18	u	-0.05	2.74	3.62	0.48	0.47	2.0	48.9	31.9	33.7	29.1	49.3
mlr127	0,0	5,3	mlr	1.8e-04	0.64	18	OSCAR62986; OSCAR18040	0.50	2.56	3.41	0.45	0.44	22.6	38.5	26.4	29.1	29.2	40.6
mlr142	0,0	5,1	mlr	2.5e-04	0.62	18	OSCAR62986; OSCAR18025	0.54	2.56	3.39	0.45	0.44	24.3	38.4	25.8	28.3	29.2	38.4
mlr150	0,0	5,2	mlr	2.9e-04	0.62	18	OSCAR62986; OSCAR18049	0.68	2.44	3.41	0.45	0.42	31.0	31.2	26.2	28.8	29.3	35.5
mlr123	0,0	5,3	mlr	1.8e-04	0.64	18	OSCAR62986; OSCAR18020	0.51	2.60	3.40	0.45	0.44	22.9	40.7	26.1	28.4	29.5	36.1
mlr134	0,0	5,1	mlr	2.1e-04	0.63	18	OSCAR62986; OSCAR18041	0.54	2.60	3.37	0.44	0.44	24.5	40.8	25.2	27.4	29.5	35.4
mlr90	0,0	5,4	mlr	5.6e-05	0.69	18	OSCAR62986; OSCAR27015	0.74	2.61	3.20	0.42	0.45	33.4	41.6	20.9	22.6	29.6	28.2
mlr99	0,-1	5,4	mlr	9.1e-05	0.67	18	OSCAR62986; lighthouse72126	0.60	2.48	3.45	0.46	0.42	27.2	33.6	27.4	30.0	29.6	39.3
OSCAR62988	0	5	scam_mpd	5.0e-05	0.61	18	u	-0.00	2.78	3.65	0.48	0.48	0.1	51.4	32.6	34.3	29.6	49.7
mlr141	0,0	5,1	mlr	2.5e-04	0.63	18	OSCAR62986; OSCAR18042	0.60	2.58	3.36	0.45	0.44	27.3	39.4	25.1	27.7	29.9	40.4
mlr149	0,0	5,5	mlr	2.9e-04	0.62	18	OSCAR62986; OSCAR36000	0.45	2.55	3.55	0.47	0.44	20.1	37.8	30.0	32.4	30.1	45.7
mlr94	0,-1	5,11	mlr	7.4e-05	0.68	18	OSCAR62986; OSCAR53997	0.60	2.58	3.40	0.45	0.44	27.3	39.6	26.0	28.6	30.4	42.5
mlr110	0,0	5,4	mlr	1.1e-04	0.66	18	OSCAR62986; OSCAR27002	0.41	2.66	3.49	0.46	0.46	18.5	44.3	28.5	30.5	30.5	34.8
mlr119	0,0	5,4	mlr	1.5e-04	0.65	18	OSCAR62986; OSCAR27026	0.59	2.55	3.47	0.46	0.44	26.6	37.8	27.9	30.0	30.6	35.7
mlr138	0,-1	5,11	mlr	2.4e-04	0.63	18	OSCAR62986; OSCAR54003	0.57	2.53	3.53	0.47	0.43	25.7	37.0	29.4	31.9	31.0	42.0
mlr112	0,0	5,6	mlr	1.2e-04	0.66	18	OSCAR62986; OSCAR27025	0.69	2.70	3.24	0.43	0.46	31.0	46.6	22.0	24.6	31.1	39.6
mlr143	0,0	5,3	mlr	2.6e-04	0.62	18	OSCAR62986; OSCAR18033	0.64	2.59	3.41	0.45	0.44	28.9	40.4	26.3	28.6	31.1	37.3
mlr102	0,0	5,5	mlr	9.7e-05	0.67	18	OSCAR62986; OSCAR18022	0.66	2.60	3.39	0.45	0.45	29.8	40.9	25.8	28.2	31.2	32.0
mlr145	0,0	5,1	mlr	2.6e-04	0.62	18	OSCAR62986; OSCAR18029	0.72	2.56	3.40	0.45	0.44	32.8	38.6	26.1	28.6	31.5	37.1
mlr128	0,0	5,4	mlr	1.9e-04	0.64	18	OSCAR62986; OSCAR18035	0.56	2.72	3.38	0.45	0.46	25.1	47.6	25.5	28.2	31.6	36.9
mlr98	0,0	5,4	mlr	8.6e-05	0.67	18	OSCAR62986; OSCAR27012	0.32	2.89	3.42	0.45	0.49	14.5	57.6	26.6	27.9	31.6	29.5
OSCAR62986	0	5	scam_mpd	2.2e-05	0.64	18	u	0.09	2.80	3.70	0.49	0.48	3.9	52.6	33.9	36.4	31.7	36.5
mlr125	0,0	5,1	mlr	1.8e-04	0.64	18	OSCAR62986; OSCAR18021	0.50	2.73	3.44	0.45	0.47	22.7	48.7	27.2	29.2	31.9	35.4
mlr117	0,0	5,6	mlr	1.4e-04	0.65	18	OSCAR62986; OSCAR62998	0.50	2.59	3.61	0.48	0.44	22.6	40.2	31.6	34.1	32.1	47.7
mlr130	0,0	5,1	mlr	2.0e-04	0.64	18	OSCAR62986; OSCAR18039	0.54	2.73	3.44	0.46	0.47	24.2	48.5	27.3	29.5	32.4	35.0
mlr104	0,0	5,6	mlr	1.0e-04	0.67	18	OSCAR62986; OSCAR62990	0.43	2.88	3.37	0.45	0.49	19.6	57.4	25.4	27.6	32.5	38.2
mlr103	0,0	5,1	mlr	1.0e-04	0.67	18	OSCAR62986; OSCAR63011	0.56	2.75	3.44	0.45	0.47	25.6	49.4	27.1	28.2	32.6	40.3
mlr51	0,0	5,4	mlr	3.6e-05	0.71	18	OSCAR62986; OSCAR27005	0.38	2.95	3.38	0.44	0.50	17.1	61.0	25.5	26.7	32.6	23.9
mlr137	0,-1	5,11	mlr	2.3e-04	0.63	18	OSCAR62986; OSCAR54002	0.45	2.64	3.66	0.49	0.45	20.5	43.3	33.0	35.6	33.1	47.6
mlr140	0,0	5,4	mlr	2.5e-04	0.63	18	OSCAR62986; OSCAR18016	0.65	2.68	3.48	0.46	0.46	29.3	45.2	28.2	30.7	33.3	41.3
mlr92	0,-1	5,12	mlr	6.9e-05	0.68	18	OSCAR62986; OSCAR63004	0.56	2.75	3.47	0.46	0.47	25.3	49.7	27.8	30.4	33.3	47.5
OSCAR54002	-1	11	scam_mpi	4.5e-03	0.51	18	u	0.32	2.77	3.66	0.49	0.47	14.6	50.8	32.9	35.5	33.5	41.2
mlr151	0,-1	5,12	mlr	2.9e-04	0.62	18	OSCAR62986; OSCAR27027	0.63	2.62	3.68	0.49	0.45	28.4	41.7	33.6	36.0	34.9	41.7
mlr152	0,0	5,5	mlr	2.9e-04	0.62	18	OSCAR62986; OSCAR63000	0.59	2.63	3.70	0.49	0.45	26.7	42.6	34.0	36.5	34.9	47.0
mlr106	0,0	5,6	mlr	1.0e-04	0.67	18	OSCAR62986; OSCAR62992	0.62	2.93	3.36	0.44	0.50	28.2	60.0	25.1	27.1	35.1	37.6
mlr100	0,-1	5,12	mlr	9.2e-05	0.67	18	OSCAR62986; OSCAR18028	0.73	2.89	3.37	0.44	0.49	33.1	57.5	25.4	26.1	35.5	35.6

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr132	0,-1	5,11	mlr	2.1e-04	0.63	18	OSCAR62986; OSCAR54004	0.69	2.70	3.61	0.48	0.46	31.1	46.5	31.6	34.1	35.8	43.3
mlr131	0,-1	5,12	mlr	2.0e-04	0.64	18	OSCAR62986; OSCAR63009	0.38	2.87	3.71	0.49	0.49	17.1	56.6	34.3	36.9	36.2	55.6
mlr88	0,0	5,5	mlr	4.5e-05	0.70	18	OSCAR62986; OSCAR18047	0.41	2.99	3.59	0.48	0.51	18.7	63.3	31.1	33.5	36.7	43.7
OSCAR27015	0	4	scam_mpd	5.4e-03	0.54	18	v	0.26	3.00	3.76	0.49	0.51	11.7	64.3	35.5	35.8	36.8	43.1
OSCAR36000	0	5	lm	1.7e-04	0.57	18	u	0.70	2.91	3.46	0.46	0.50	31.7	58.7	27.6	30.2	37.1	36.2
mlr136	0,0	5,6	mlr	2.2e-04	0.63	18	OSCAR62986; OSCAR54001	0.70	2.90	3.51	0.47	0.50	31.6	58.2	29.1	31.6	37.6	37.2
mlr139	0,0	5,5	mlr	2.4e-04	0.63	18	OSCAR62986; OSCAR62993	0.72	2.69	3.73	0.50	0.46	32.8	45.8	34.8	37.4	37.7	45.6
mlr111	0,0	5,5	mlr	1.1e-04	0.66	18	OSCAR62986; OSCAR18031	0.77	2.81	3.57	0.47	0.48	35.0	53.2	30.7	33.1	38.0	37.0
nepstar10	-1,-1,-1,0	7,4,5,3	mlr	2.1e-06	0.74	25	nepstar	0.70	2.89	3.56	0.47	0.49	31.6	58.0	30.4	33.0	38.2	24.6
mlr114	0,0	5,1	mlr	1.3e-04	0.66	18	OSCAR62986; OSCAR62996	0.79	2.94	3.77	0.50	0.50	35.9	60.5	35.7	37.7	42.4	39.2
mlr135	0,0	5,2	mlr	2.2e-04	0.63	18	OSCAR62986; OSCAR53998	0.89	2.84	3.77	0.50	0.49	40.4	55.0	35.9	38.4	42.4	42.6
OSCAR62991	0	5	scam_mpd	1.3e-04	0.57	18	u	0.45	3.16	3.84	0.51	0.54	20.2	73.5	37.6	40.2	42.9	36.2
mlr93	0,0	5,1	mlr	7.3e-05	0.68	18	OSCAR62986; OSCAR63003	0.80	2.92	3.86	0.51	0.50	36.1	59.8	38.1	40.3	43.6	38.9
mlr115	0,0	5,1	mlr	1.4e-04	0.65	18	OSCAR62986; OSCAR63010	0.81	2.97	3.82	0.50	0.51	36.7	62.4	37.2	39.3	43.9	40.8
nepstar8	-1,-1,0	4,5,3	mlr	2.0e-06	0.71	25	nepstar	0.45	3.23	3.86	0.51	0.55	20.5	77.5	38.3	40.9	44.3	20.6
mlr109	0,0	5,1	mlr	1.1e-04	0.66	18	OSCAR62986; OSCAR63006	0.84	2.99	3.88	0.51	0.51	38.2	63.6	38.9	40.9	45.4	40.4
OSCAR27005	0	4	scam_mpd	3.8e-04	0.61	18	v	0.27	3.47	3.94	0.50	0.59	12.2	91.6	40.5	39.3	45.9	44.2
shore72126	-1	4	scam_mpi	4.8e-03	0.50	20	temperature.c.	0.06	3.21	4.35	0.58	0.55	2.7	76.4	51.1	53.6	45.9	67.5
mlr122	0,0	5,1	mlr	1.7e-04	0.64	18	OSCAR62986; OSCAR63002	0.90	3.06	3.91	0.52	0.52	40.7	67.8	39.7	41.8	47.5	40.5
mlr107	0,0	5,3	mlr	1.0e-04	0.67	18	OSCAR62986; OSCAR54005	0.85	3.12	3.96	0.53	0.53	38.5	71.4	40.9	43.5	48.6	45.9
mlr129	0,0	5,1	mlr	1.9e-04	0.64	18	OSCAR62986; OSCAR63001	0.97	3.12	4.00	0.53	0.53	44.0	71.5	41.9	44.1	50.3	39.9
OSCAR18042	0	1	scam_mpi	4.7e-04	0.51	18	v	-0.51	3.27	4.27	0.57	0.56	22.9	79.8	48.9	51.5	50.8	50.7
OSCAR18040	0	3	scam_mpi	2.2e-03	0.51	18	v	-0.16	3.35	4.49	0.60	0.57	7.0	84.8	54.8	57.3	51.0	59.5
OSCAR27019	0	4	scam_mpd	3.4e-03	0.52	18	v	0.27	3.32	4.43	0.59	0.57	12.2	82.8	53.2	55.8	51.0	43.4
OSCAR53997	-1	11	scam_mpi	1.3e-03	0.54	18	u	0.58	3.32	4.33	0.57	0.57	26.2	83.2	50.6	52.9	53.2	63.7
OSCAR27012	0	4	scam_mpd	5.5e-03	0.56	18	v	0.18	3.86	4.33	0.55	0.66	8.1	114.8	50.6	48.8	55.5	38.0
OSCAR27025	0	6	scam_mpd	1.6e-03	0.51	18	v	-0.19	3.60	4.56	0.61	0.62	8.7	99.4	56.8	59.3	56.0	49.9
OSCAR18038	0	5	scam_mpi	1.6e-03	0.51	18	v	-0.07	3.52	4.84	0.64	0.60	3.0	94.6	64.0	66.5	57.0	26.5
OSCAR18011	0	3	scam_mpi	3.3e-04	0.59	18	v	-0.84	3.34	4.57	0.60	0.57	38.0	83.9	56.9	58.6	59.3	40.7
OSCAR27002	0	4	scam_mpd	9.8e-05	0.64	18	v	-0.04	3.83	4.75	0.62	0.66	1.7	112.8	61.7	61.8	59.5	20.9
OSCAR36001	0	6	lm	5.0e-04	0.51	18	u	-0.07	3.84	4.69	0.62	0.66	3.3	113.4	60.0	61.8	59.6	35.0
OSCAR27008	0	4	scam_mpd	1.9e-03	0.59	18	v	-1.16	3.34	4.32	0.57	0.57	52.6	83.9	50.4	51.8	59.7	26.0
OSCAR63000	0	5	scam_mpd	4.2e-03	0.53	18	u	0.12	3.84	4.85	0.64	0.66	5.6	113.5	64.3	66.2	62.4	66.9
OSCAR18007	0	4	scam_mpi	9.8e-04	0.63	18	v	-0.18	3.83	4.82	0.64	0.65	7.9	112.5	63.6	66.1	62.5	48.3
OSCAR54001	0	6	scam_mpi	3.4e-04	0.52	18	u	-0.22	3.58	5.12	0.68	0.61	9.9	98.0	71.6	74.0	63.4	39.9
OSCAR62995	0	6	scam_mpd	2.2e-03	0.55	18	u	-0.74	3.35	4.94	0.66	0.57	33.7	84.8	66.8	69.3	63.6	45.6
OSCAR62998	0	6	scam_mpd	1.0e-03	0.54	18	u	-0.82	3.47	4.87	0.65	0.59	37.0	91.5	64.8	67.3	65.1	47.8
OSCAR18020	0	3	scam_mpi	4.4e-03	0.54	18	v	-0.56	3.59	5.07	0.67	0.61	25.5	99.0	70.1	72.0	66.7	37.3
OSCAR18008	0	4	scam_mpi	1.4e-03	0.62	18	v	-0.53	3.69	5.10	0.68	0.63	23.9	104.8	70.9	73.2	68.2	54.6
OSCAR18043	0	3	scam_mpi	5.4e-03	0.51	18	v	-0.61	3.66	5.07	0.67	0.63	27.7	102.9	70.1	72.4	68.3	41.9
OSCAR18010	0	4	scam_mpi	1.4e-03	0.62	18	v	-0.53	3.80	5.04	0.67	0.65	23.9	111.2	69.3	71.8	69.1	54.2
OSCAR27010	0	4	scam_mpd	3.7e-03	0.57	18	v	-0.75	3.91	4.77	0.62	0.67	34.1	117.8	62.4	63.1	69.3	28.4

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
OSCAR63009	-1	12	scam_mpd	4.1e-03	0.51	18	u	-0.19	3.73	5.49	0.73	0.64	8.5	107.1	81.3	83.8	70.2	74.6
OSCAR18044	0	3	scam_mpi	8.5e-03	0.51	18	v	-0.17	3.98	5.28	0.70	0.68	7.5	121.7	75.7	77.7	70.6	47.6
OSCAR18022	0	5	scam_mpi	5.3e-03	0.53	18	v	-0.29	3.86	5.30	0.70	0.66	13.2	114.8	76.1	78.5	70.7	56.2
OSCAR27013	0	4	scam_mpd	7.6e-04	0.55	18	v	-0.16	4.05	5.21	0.69	0.69	7.2	125.7	73.9	75.9	70.7	62.6
OSCAR18028	-1	12	scam_mpi	3.3e-03	0.52	18	v	-0.18	4.25	5.16	0.65	0.73	8.1	137.5	72.4	68.4	71.6	35.4
OSCAR18016	0	4	scam_mpi	6.6e-04	0.56	18	v	-0.11	4.03	5.41	0.72	0.69	4.8	124.6	79.1	81.2	72.4	62.2
OSCAR62992	0	6	scam_mpd	5.8e-04	0.57	18	u	0.31	4.19	5.09	0.67	0.72	13.9	133.7	70.6	72.1	72.6	40.1
OSCAR62994	0	6	scam_mpd	8.6e-04	0.55	18	u	-0.63	3.88	5.18	0.69	0.66	28.4	115.8	73.1	75.5	73.2	46.6
OSCAR18012	0	3	scam_mpi	9.6e-04	0.59	18	v	-0.74	4.05	5.00	0.66	0.69	33.7	125.6	68.4	70.1	74.5	63.2
OSCAR27011	0	4	scam_mpd	4.4e-03	0.56	18	v	-1.11	3.98	4.77	0.63	0.68	50.5	121.8	62.2	63.8	74.6	37.5
OSCAR63005	0	6	scam_mpd	4.2e-04	0.51	18	u	0.26	4.18	5.28	0.70	0.71	11.9	133.2	75.7	77.5	74.6	39.7
OSCAR62990	0	6	scam_mpd	1.2e-03	0.58	18	u	-0.12	4.30	5.29	0.70	0.73	5.5	140.1	76.0	78.3	75.0	45.9
OSCAR18013	0	3	scam_mpi	5.3e-04	0.57	18	v	-0.77	3.89	5.26	0.69	0.66	34.9	116.0	75.0	76.6	75.6	48.0
OSCAR27026	0	4	scam_mpd	1.7e-03	0.51	18	v	0.72	4.13	5.16	0.67	0.71	32.7	130.6	72.4	72.3	77.0	34.1
OSCAR18045	0	3	scam_mpi	4.9e-03	0.51	18	v	-0.95	3.90	5.35	0.71	0.67	42.9	117.1	77.6	79.6	79.3	50.8
OSCAR53998	0	2	scam_mpi	2.4e-04	0.54	18	u	-0.97	3.83	5.42	0.72	0.65	44.0	112.7	79.5	81.9	79.5	51.9
OSCAR27004	0	4	scam_mpd	6.2e-04	0.62	18	v	0.94	3.96	5.33	0.71	0.68	42.6	120.3	77.1	79.1	79.8	36.6
OSCAR63008	0	6	scam_mpd	1.8e-03	0.51	18	u	-0.43	4.35	5.35	0.71	0.74	19.4	143.2	77.7	79.1	79.8	34.3
OSCAR63011	0	1	scam_mpd	2.5e-03	0.50	18	u	-0.97	3.90	5.38	0.71	0.67	43.9	116.8	78.3	80.2	79.8	50.4
OSCAR18025	0	1	scam_mpi	3.3e-04	0.53	18	v	-1.08	3.67	5.54	0.74	0.63	49.0	103.6	82.5	85.0	80.0	45.4
OSCAR63003	0	1	scam_mpd	1.4e-03	0.52	18	u	-1.04	3.88	5.39	0.72	0.66	47.1	115.8	78.6	81.0	80.6	52.0
OSCAR54004	-1	11	scam_mpi	1.7e-03	0.51	18	u	-0.88	3.90	5.51	0.73	0.67	39.9	117.1	81.8	84.3	80.8	57.9
OSCAR62996	0	1	scam_mpd	2.4e-04	0.54	18	u	-1.06	3.80	5.48	0.73	0.65	48.0	110.8	80.9	83.4	80.8	50.4
OSCAR18039	0	1	scam_mpi	1.6e-03	0.51	18	v	-1.03	3.76	5.57	0.74	0.64	46.6	108.5	83.3	85.4	80.9	44.5
OSCAR63010	0	1	scam_mpd	5.6e-04	0.51	18	u	-1.07	3.82	5.48	0.73	0.65	48.3	112.5	81.0	83.4	81.3	50.6
OSCAR63007	-1	12	scam_mpd	7.2e-03	0.51	18	u	-0.90	4.28	5.15	0.68	0.73	40.8	139.1	72.2	74.0	81.5	55.2
OSCAR62989	0	6	scam_mpd	9.2e-04	0.60	18	u	-0.57	4.36	5.38	0.70	0.74	25.8	143.6	78.3	78.9	81.6	38.0
OSCAR62997	-1	12	scam_mpd	1.0e-03	0.54	18	u	-1.24	4.11	5.04	0.67	0.70	56.2	129.4	69.2	71.4	81.6	52.8
median8	0	0	median8	NA			median8	-0.32	4.39	5.74	0.71	0.75	14.5	145.8	87.9	79.5	81.9	70.4
OSCAR63004	-1	12	scam_mpd	3.9e-04	0.52	18	u	-1.20	3.87	5.38	0.71	0.66	54.3	115.3	78.3	80.8	82.2	52.4
OSCAR63006	0	1	scam_mpd	2.3e-03	0.51	18	u	-1.09	3.90	5.48	0.73	0.67	49.3	116.8	81.1	83.5	82.7	50.6
OSCAR54005	0	3	scam_mpi	1.8e-03	0.50	18	u	-0.82	4.03	5.63	0.75	0.69	37.0	124.8	85.0	87.5	83.6	56.7
OSCAR63002	0	1	scam_mpd	1.4e-03	0.52	18	u	-1.09	3.89	5.57	0.74	0.67	49.2	116.5	83.3	85.7	83.7	51.0
OSCAR54003	-1	11	scam_mpi	2.0e-03	0.51	18	u	-1.20	3.84	5.53	0.73	0.66	54.6	113.7	82.4	84.8	83.9	49.7
OSCAR18033	0	3	scam_mpi	1.4e-03	0.52	18	v	-0.90	4.10	5.54	0.73	0.70	41.0	128.4	82.5	84.2	84.0	44.2
OSCAR62993	0	5	scam_mpd	1.8e-03	0.56	18	u	0.07	4.48	5.84	0.77	0.77	3.2	150.7	90.6	92.7	84.3	90.0
OSCAR18029	0	1	scam_mpi	3.6e-04	0.52	18	v	-0.81	4.01	5.73	0.76	0.69	36.7	123.1	87.7	90.1	84.4	52.4
OSCAR63001	0	1	scam_mpd	1.3e-03	0.52	18	u	-0.79	4.05	5.70	0.76	0.69	35.9	125.4	86.9	89.3	84.4	55.6
OSCAR18048	0	3	scam_mpi	5.2e-04	0.50	18	v	-0.90	4.16	5.59	0.72	0.71	40.9	131.9	83.9	82.2	84.7	48.8
OSCAR18046	0	1	scam_mpi	2.2e-03	0.51	18	v	-1.03	3.97	5.64	0.75	0.68	46.6	121.1	85.2	87.5	85.1	53.4
OSCAR18019	0	1	scam_mpi	2.0e-03	0.55	18	v	-0.36	4.34	5.87	0.77	0.74	16.1	143.0	91.3	92.0	85.6	47.7
OSCAR27027	-1	12	scam_mpd	2.3e-03	0.51	18	v	-0.86	4.09	5.71	0.76	0.70	38.8	127.9	86.9	89.4	85.7	62.2

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
OSCAR18030	-1	11	scam_mpi	3.6e-04	0.52	18	v	-1.34	3.85	5.60	0.74	0.66	60.9	113.9	84.0	86.5	86.3	47.8
OSCAR18049	0	2	scam_mpi	5.3e-04	0.50	18	v	-0.75	4.24	5.94	0.79	0.73	34.1	137.1	93.0	95.4	89.9	50.7
OSCAR18031	0	5	scam_mpi	7.1e-03	0.52	18	v	-0.07	4.75	6.15	0.81	0.81	3.3	166.4	98.5	99.6	92.0	82.7
median4	0	0	median4	NA			median4	-0.96	4.89	6.65	0.82	0.84	43.7	175.1	111.8	101.7	108.1	70.9
OSCAR18021	0	1	scam_mpi	3.1e-04	0.53	18	v	-1.34	4.63	6.52	0.86	0.79	61.0	159.8	108.4	110.5	109.9	50.4
OSCAR18047	0	5	scam_mpi	2.7e-03	0.50	18	v	1.22	4.59	6.79	0.90	0.78	55.2	157.2	115.6	117.9	111.5	132.7
OSCAR18035	0	4	scam_mpi	7.9e-03	0.51	18	v	-2.47	6.02	8.98	1.19	1.03	111.8	240.9	173.3	175.5	175.4	64.6
OSCAR53996	0	5	scam_mpi	3.4e-03	0.55	18	u	2.74	5.13	11.06	1.47	0.88	124.4	188.8	228.1	229.9	192.8	233.1
median.all	0	0	median.all	NA			median.all	-5.64	6.07	7.81	0.96	1.04	256.0	244.1	142.4	129.9	193.1	89.9
OSCAR18041	0	1	scam_mpi	5.8e-04	0.51	18	v	2.97	6.06	11.37	1.51	1.04	134.9	243.6	236.2	237.9	213.1	52.4
OSCAR53991	0	5	scam_mpi	1.3e-03	0.59	18	u	2.31	6.27	12.12	1.58	1.07	104.9	256.0	256.0	252.5	217.3	252.0
OSCAR18024	0	1	scam_mpi	3.1e-04	0.53	18	v	3.14	5.91	12.04	1.60	1.01	142.3	234.4	254.1	256.0	221.7	51.3

Table 17. Performance results for all qualifying models used to forecast Chilko timing based on jackknife.short analysis. Each row represents a single model tested, some columns include: year adjust (year of environmental data same as return year [0] or prior year [-1]), month, summary statistics (P value, adjusted R squared, sample size), data name, data variables (which are sorted by their relative influence in the model). As the NEPSTAR regression models comprise more than one variable, only year-month of the latest variable is presented. Latitude and longtitude of NEPSTAR variables are excluded due to space limitations. The PMs include mean raw error, mean absolute error, root mean squared error, Thiel's U-statistic, and MASE. The initial three PMs are in day units, the latter two are unit-less. All PMs are described in the methods section. All PMs, except MASE, are given a rank. The best rank has a value of zero. The last rank equals total number of models (n). The average of the PM ranks by model (row) is included, as is the average rank for the alternate performance test method. The rows are sorted by average rank of performance method listed in caption. The first row is the best model, the last row is the worst.

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
nepstar14	-1,0,0,-1,0	7,3,3,5,3	mlr	9.5e-08	0.83	25	nepstar	-0.34	1.78	2.13	0.36	0.31	9.8	3.8	1.9	1.9	4.3	12.2
nepstar3	-1,0,0,-1	7,2,3,5	mlr	2.5e-08	0.83	25	nepstar	-0.62	1.68	2.01	0.34	0.29	18.8	0.0	0.0	0.0	4.7	5.5
nepstar2	-1,0,-1	6,3,5	mlr	4.2e-09	0.84	25	nepstar	-0.21	1.95	2.53	0.43	0.34	5.6	9.8	8.4	8.4	8.0	9.3
nepstar9	0,-1,0,-1	3,5,3,5	mlr	2.6e-08	0.83	25	nepstar	-0.41	2.05	2.24	0.38	0.35	12.0	13.1	3.8	3.8	8.2	7.2
nepstar1	-1,0,-1	7,3,5	mlr	3.1e-08	0.80	25	nepstar	-0.67	1.93	2.18	0.37	0.33	20.2	8.8	2.7	2.7	8.6	14.4
nepstar5	-2,-1,0,0	7,5,3,3	mlr	1.1e-08	0.85	25	nepstar	-0.07	2.43	2.58	0.44	0.42	1.4	26.7	9.3	9.3	11.7	11.9
nepstar4	-1,0,0,-1	7,4,3,5	mlr	2.4e-08	0.83	25	nepstar	-0.98	1.96	2.25	0.38	0.34	30.1	10.1	3.9	3.9	12.0	7.7
nepstar11	0,-1,0,-1	2,5,3,5	mlr	7.3e-08	0.81	25	nepstar	-1.11	1.96	2.17	0.37	0.34	34.0	9.9	2.6	2.6	12.3	5.7
nepstar6	0,-1,0,0	3,5,3,3	mlr	4.3e-09	0.86	25	nepstar	0.61	2.07	2.78	0.48	0.36	18.4	13.8	12.6	12.6	14.4	16.3
nepstar7	-1,0,0,-1	6,3,3,5	mlr	7.0e-09	0.85	25	nepstar	-0.02	2.45	3.24	0.55	0.42	0.0	27.2	20.1	20.1	16.8	11.1
mlr3	0,-1,0	5,12,4	mlr	4.0e-06	0.82	18	OSCAR62986; OSCAR63007; OSCAR27004	-0.38	2.63	3.08	0.53	0.45	11.0	33.6	17.4	17.4	19.8	19.2
mlr25	0,0	5,4	mlr	1.8e-05	0.74	18	OSCAR62986; OSCAR27008	-0.76	2.22	3.19	0.55	0.38	23.0	19.1	19.2	19.2	20.2	16.8
mlr27	0,0	5,4	mlr	1.9e-05	0.73	18	OSCAR62986; OSCAR27004	-0.28	2.63	3.26	0.56	0.45	8.1	33.7	20.3	20.3	20.6	29.1
nepstar8	-1,-1,0	4,5,3	mlr	2.0e-06	0.71	25	nepstar	-0.14	2.68	3.34	0.57	0.46	3.5	35.5	21.6	21.6	20.6	44.3
OSCAR27002	0	4	scam_mpd	9.8e-05	0.64	18	v	0.73	2.33	3.19	0.55	0.40	21.9	23.2	19.2	19.2	20.9	59.5
mlr2	0,-1,0	5,12,4	mlr	3.2e-06	0.83	18	OSCAR62986; OSCAR63007; OSCAR27026	-0.44	2.70	3.23	0.55	0.47	13.1	36.3	19.8	19.8	22.2	11.4
nepstar12	0,-1,0,-1	3,4,3,5	mlr	7.1e-08	0.82	25	nepstar	-1.35	2.47	2.67	0.46	0.43	41.6	27.9	10.7	10.7	22.8	16.8
mlr89	0,0	5,5	mlr	5.3e-05	0.70	18	OSCAR62986; OSCAR53996	0.32	2.68	3.49	0.60	0.46	9.2	35.4	24.1	24.1	23.2	21.8
nepstar13	-1,-1,0,-1,-1,0,0	6,5,3,4,5,3,3	mlr	3.0e-08	0.89	25	nepstar	-1.08	2.55	2.96	0.51	0.44	32.9	31.0	15.4	15.4	23.7	2.5
mlr51	0,0	5,4	mlr	3.6e-05	0.71	18	OSCAR62986; OSCAR27005	-0.37	2.74	3.46	0.59	0.47	10.7	37.5	23.7	23.7	23.9	32.6
mlr12	0,-1,-1	5,12,12	mlr	1.3e-05	0.79	18	OSCAR62986; OSCAR63007; OSCAR27027	-0.64	2.72	3.29	0.56	0.47	19.4	36.8	20.9	20.9	24.5	10.8
nepstar10	-1,-1,-1,0	7,4,5,3	mlr	2.1e-06	0.74	25	nepstar	0.85	2.64	3.20	0.55	0.45	25.8	34.0	19.3	19.3	24.6	38.2
mlr35	0,0	5,4	mlr	2.7e-05	0.72	18	OSCAR62986; OSCAR27019	-0.14	2.90	3.61	0.62	0.50	3.7	43.4	26.1	26.1	24.8	17.7
mlr72	0,0	5,4	mlr	4.3e-05	0.70	18	OSCAR62986; OSCAR27011	-0.79	2.43	3.49	0.60	0.42	24.0	26.7	24.2	24.2	24.8	19.0
mlr1	0,-1,0	5,12,4	mlr	2.8e-06	0.83	18	OSCAR62986; OSCAR63007; OSCAR27019	-0.20	3.12	3.46	0.59	0.54	5.5	50.9	23.7	23.7	25.9	12.1
mlr15	0,-1,0	5,12,4	mlr	1.5e-05	0.79	18	OSCAR62986; OSCAR63007; OSCAR27008	-0.64	2.82	3.36	0.57	0.49	19.2	40.4	22.0	22.0	25.9	15.2
OSCAR27008	0	4	scam_mpd	1.9e-03	0.59	18	v	0.17	3.02	3.60	0.62	0.52	4.5	47.5	25.9	25.9	26.0	59.7
OSCAR18038	0	5	scam_mpi	1.6e-03	0.51	18	v	0.22	2.93	3.72	0.64	0.50	6.2	44.2	27.9	27.9	26.5	57.0
mlr7	0,-1,0	5,12,4	mlr	1.0e-05	0.80	18	OSCAR62986; OSCAR63007; OSCAR27005	-0.47	3.03	3.49	0.60	0.52	13.8	47.9	24.2	24.2	27.5	20.3
mlr10	0,0	5,6	mlr	9.0e-06	0.76	18	OSCAR62986; OSCAR36001	-0.19	3.14	3.64	0.62	0.54	5.1	51.8	26.6	26.6	27.6	17.9

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr16	0,-1,0	5,12,4	mlr	1.5e-05	0.79	18	OSCAR62986; OSCAR63007; OSCAR27011	-0.66	2.97	3.46	0.59	0.51	19.8	45.8	23.6	23.6	28.2	16.1
mlr90	0,0	5,4	mlr	5.6e-05	0.69	18	OSCAR62986; OSCAR27015	-0.06	3.17	3.81	0.65	0.55	1.2	52.9	29.3	29.3	28.2	29.6
OSCAR27010	0	4	scam_mpd	3.7e-03	0.57	18	v	-0.10	3.16	3.81	0.65	0.55	2.2	52.6	29.3	29.3	28.4	69.3
mlr105	0,0	5,4	mlr	1.0e-04	0.67	18	OSCAR62986; OSCAR18007	-0.12	3.16	3.81	0.65	0.54	3.0	52.4	29.4	29.4	28.6	26.7
mlr95	0,0	5,4	mlr	7.5e-05	0.68	18	OSCAR62986; OSCAR27010	-0.55	2.95	3.74	0.64	0.51	16.4	45.1	28.3	28.3	29.5	27.2
mlr98	0,0	5,4	mlr	8.6e-05	0.67	18	OSCAR62986; OSCAR27012	-0.51	2.99	3.75	0.64	0.52	15.1	46.4	28.3	28.3	29.5	31.6
mlr8	0,-1,-1	5,12,11	mlr	1.2e-05	0.79	18	OSCAR62986; OSCAR63007; OSCAR18030	-0.46	3.20	3.58	0.61	0.55	13.6	54.0	25.6	25.6	29.7	2.6
mlr101	0,0	5,4	mlr	9.5e-05	0.67	18	OSCAR62986; OSCAR18010	-0.29	3.19	3.91	0.67	0.55	8.2	53.3	30.9	30.9	30.9	21.5
mlr20	0,0	5,6	mlr	1.4e-05	0.75	18	OSCAR62986; OSCAR63008	-0.25	3.36	3.78	0.65	0.58	7.0	59.6	28.8	28.8	31.1	20.3
mlr13	0,-1,0	5,12,4	mlr	1.5e-05	0.79	18	OSCAR62986; OSCAR63007; OSCAR27015	-0.38	3.33	3.76	0.64	0.57	11.2	58.6	28.5	28.5	31.7	17.1
mlr91	0,0	5,5	mlr	5.9e-05	0.69	18	OSCAR62986; OSCAR18038	-0.49	3.15	3.88	0.66	0.54	14.6	52.0	30.5	30.5	31.9	27.0
mlr102	0,0	5,5	mlr	9.7e-05	0.67	18	OSCAR62986; OSCAR18022	-0.19	3.23	4.09	0.70	0.56	5.1	55.1	34.0	34.0	32.0	31.2
mlr22	0,-1,0	5,12,4	mlr	1.9e-05	0.78	18	OSCAR62986; OSCAR63007; OSCAR27012	-0.56	3.28	3.69	0.63	0.57	16.9	56.8	27.4	27.4	32.2	21.4
mlr28	0,-1,0	5,12,4	mlr	2.7e-05	0.77	18	OSCAR62986; OSCAR63007; OSCAR18007	-0.29	3.41	3.84	0.66	0.59	8.4	61.2	29.8	29.8	32.3	13.0
mlr108	0,0	5,3	mlr	1.1e-04	0.66	18	OSCAR62986; OSCAR18044	-0.93	2.91	3.86	0.66	0.50	28.5	43.6	30.1	30.1	33.1	23.6
mlr121	0,0	5,1	mlr	1.6e-04	0.65	18	OSCAR62986; OSCAR18019	-0.42	3.21	4.04	0.69	0.55	12.3	54.1	33.0	33.0	33.1	28.2
mlr17	0,-1,0	5,12,5	mlr	1.6e-05	0.78	18	OSCAR62986; OSCAR63007; OSCAR18038	-0.54	3.40	3.74	0.64	0.59	16.0	60.9	28.2	28.2	33.3	10.1
mlr19	0,-1,0	5,12,1	mlr	1.7e-05	0.78	18	OSCAR62986; OSCAR63007; OSCAR18019	-0.47	3.40	3.80	0.65	0.59	14.1	61.0	29.2	29.2	33.4	15.7
mlr11	0,-1,0	5,12,6	mlr	1.3e-05	0.79	18	OSCAR62986; OSCAR63007; OSCAR36001	-0.34	3.53	3.83	0.65	0.61	9.9	65.7	29.7	29.7	33.7	13.4
mlr71	0,-1,-1	5,12,12	mlr	5.2e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR63004	-0.49	3.38	3.86	0.66	0.58	14.6	60.2	30.2	30.2	33.8	13.0
mlr21	0,-1,0	5,12,4	mlr	1.9e-05	0.78	18	OSCAR62986; OSCAR63007; OSCAR27010	-0.53	3.42	3.79	0.65	0.59	15.7	61.8	29.0	29.0	33.9	20.9
mlr78	0,-1,0	5,12,2	mlr	5.3e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18049	-0.34	3.51	3.91	0.67	0.60	9.8	64.7	30.9	30.9	34.1	19.3
OSCAR27026	0	4	scam_mpd	1.7e-03	0.51	18	v	1.16	3.07	3.59	0.61	0.53	35.7	49.1	25.7	25.7	34.1	77.0
OSCAR63008	0	6	scam_mpd	1.8e-03	0.51	18	u	0.55	3.40	3.84	0.66	0.59	16.4	61.1	29.8	29.8	34.3	79.8
mlr110	0,0	5,4	mlr	1.1e-04	0.66	18	OSCAR62986; OSCAR27002	-0.34	3.32	4.19	0.72	0.57	9.8	58.1	35.6	35.6	34.8	30.5
mlr130	0,0	5,1	mlr	2.0e-04	0.64	18	OSCAR62986; OSCAR18039	-0.38	3.32	4.18	0.71	0.57	11.3	58.2	35.3	35.3	35.0	32.4
OSCAR36001	0	6	lm	5.0e-04	0.51	18	u	1.30	3.11	3.52	0.60	0.54	40.1	50.8	24.6	24.6	35.0	59.6
mlr125	0,0	5,1	mlr	1.8e-04	0.64	18	OSCAR62986; OSCAR18021	-0.44	3.35	4.13	0.71	0.58	13.1	59.2	34.6	34.6	35.4	31.9
mlr134	0,0	5,1	mlr	2.1e-04	0.63	18	OSCAR62986; OSCAR18041	-0.41	3.35	4.16	0.71	0.58	12.2	59.3	35.0	35.0	35.4	29.5
OSCAR18028	-1	12	scam_mpi	3.3e-03	0.52	18	v	0.18	3.51	4.22	0.72	0.60	4.8	64.8	36.1	36.1	35.4	71.6
mlr150	0,0	5,2	mlr	2.9e-04	0.62	18	OSCAR62986; OSCAR18049	-0.31	3.43	4.19	0.72	0.59	9.0	61.9	35.5	35.5	35.5	29.3
mlr100	0,-1	5,12	mlr	9.2e-05	0.67	18	OSCAR62986; OSCAR18028	-0.50	3.42	4.03	0.69	0.59	15.0	61.7	32.9	32.9	35.6	35.5
mlr113	0,0	5,3	mlr	1.3e-04	0.66	18	OSCAR62986; OSCAR18013	-1.12	3.03	3.85	0.66	0.52	34.4	47.8	30.0	30.0	35.6	22.8
mlr147	0,0	5,3	mlr	2.8e-04	0.62	18	OSCAR62986; OSCAR18045	-0.51	3.30	4.15	0.71	0.57	15.1	57.6	34.8	34.8	35.6	27.9
mlr148	0,0	5,3	mlr	2.8e-04	0.62	18	OSCAR62986; OSCAR18048	-0.47	3.33	4.16	0.71	0.57	13.9	58.4	35.1	35.1	35.6	28.9
mlr119	0,0	5,4	mlr	1.5e-04	0.65	18	OSCAR62986; OSCAR27026	-0.50	3.30	4.17	0.71	0.57	14.9	57.5	35.2	35.2	35.7	30.6
mlr42	0,0	5,6	mlr	3.0e-05	0.72	18	OSCAR62986; OSCAR62989	-0.41	3.52	4.05	0.69	0.61	12.1	65.2	33.2	33.2	35.9	25.1
mlr18	0,-1,0	5,12,4	mlr	1.6e-05	0.78	18	OSCAR62986; OSCAR63007; OSCAR27002	-0.40	3.57	4.02	0.69	0.61	11.8	66.9	32.7	32.7	36.0	19.9
mlr123	0,0	5,3	mlr	1.8e-04	0.64	18	OSCAR62986; OSCAR18020	-0.83	3.17	4.04	0.69	0.55	25.2	52.9	33.1	33.1	36.1	29.5
mlr23	0,-1,0	5,12,6	mlr	2.1e-05	0.78	18	OSCAR62986; OSCAR63007; OSCAR63008	-0.41	3.65	3.93	0.67	0.63	12.0	69.7	31.3	31.3	36.1	12.9
OSCAR36000	0	5	lm	1.7e-04	0.57	18	u	0.94	3.28	3.83	0.66	0.57	28.6	56.8	29.7	29.7	36.2	37.1
OSCAR62991	0	5	scam_mpd	1.3e-04	0.57	18	u	0.94	3.28	3.83	0.66	0.57	28.6	56.8	29.7	29.7	36.2	42.9

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr116	0,0	5,4	mlr	1.4e-04	0.65	18	OSCAR62986; OSCAR18008	-0.34	3.47	4.24	0.72	0.60	9.8	63.3	36.3	36.3	36.4	27.5
mlr126	0,0	5,3	mlr	1.8e-04	0.64	18	OSCAR62986; OSCAR18012	-0.88	3.21	4.01	0.69	0.55	26.7	54.1	32.6	32.6	36.5	27.8
mlr32	0,0	5,5	mlr	2.6e-05	0.72	18	OSCAR62986; OSCAR53991	0.82	3.21	4.06	0.69	0.55	25.1	54.1	33.4	33.4	36.5	29.0
OSCAR35998	0	5	lm	4.0e-05	0.64	18	u	-0.44	3.41	4.21	0.72	0.59	12.9	61.4	35.9	35.9	36.5	24.7
OSCAR62986	0	5	scam_mpd	2.2e-05	0.64	18	u	-0.44	3.41	4.21	0.72	0.59	12.9	61.4	35.9	35.9	36.5	31.7
mlr24	0,-1,0	5,12,5	mlr	2.2e-05	0.78	18	OSCAR62986; OSCAR63007; OSCAR36000	-0.04	3.72	4.26	0.73	0.64	0.6	72.4	36.6	36.6	36.6	19.4
OSCAR27004	0	4	scam_mpd	6.2e-04	0.62	18	v	1.52	2.96	3.67	0.63	0.51	46.8	45.5	27.0	27.0	36.6	79.8
mlr4	0,-1,0	5,12,5	mlr	6.2e-06	0.81	18	OSCAR62986; OSCAR63007; OSCAR53996	0.51	3.64	3.92	0.67	0.63	15.3	69.4	31.2	31.2	36.8	10.1
mlr128	0,0	5,4	mlr	1.9e-04	0.64	18	OSCAR62986; OSCAR18035	-0.11	3.66	4.30	0.74	0.63	2.8	70.1	37.4	37.4	36.9	31.6
mlr111	0,0	5,5	mlr	1.1e-04	0.66	18	OSCAR62986; OSCAR18031	0.08	3.58	4.43	0.76	0.62	1.8	67.2	39.4	39.4	37.0	38.0
mlr145	0,0	5,1	mlr	2.6e-04	0.62	18	OSCAR62986; OSCAR18029	-0.37	3.49	4.27	0.73	0.60	10.7	64.0	36.8	36.8	37.1	31.5
mlr118	0,0	5,3	mlr	1.5e-04	0.65	18	OSCAR62986; OSCAR18043	-0.75	3.27	4.16	0.71	0.56	22.6	56.2	35.0	35.0	37.2	25.5
mlr136	0,0	5,6	mlr	2.2e-04	0.63	18	OSCAR62986; OSCAR54001	-0.20	3.62	4.30	0.74	0.62	5.5	68.7	37.3	37.3	37.2	37.6
mlr143	0,0	5,3	mlr	2.6e-04	0.62	18	OSCAR62986; OSCAR18033	-0.51	3.46	4.19	0.72	0.60	15.1	62.9	35.5	35.5	37.3	31.1
OSCAR18020	0	3	scam_mpi	4.4e-03	0.54	18	v	-0.45	3.23	4.49	0.77	0.56	13.5	54.8	40.4	40.4	37.3	66.7
mlr153	0,0	5,1	mlr	2.9e-04	0.62	18	OSCAR62986; OSCAR18024	-0.46	3.46	4.26	0.73	0.60	13.7	63.0	36.7	36.7	37.5	27.1
mlr39	0,-1,0	5,12,4	mlr	3.6e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR18010	-0.41	3.69	4.05	0.69	0.64	12.1	71.1	33.3	33.3	37.5	16.0
OSCAR27011	0	4	scam_mpd	4.4e-03	0.56	18	v	-0.04	3.80	4.29	0.73	0.66	0.5	75.1	37.2	37.2	37.5	74.6
mlr106	0,0	5,6	mlr	1.0e-04	0.67	18	OSCAR62986; OSCAR62992	-0.45	3.65	4.08	0.70	0.63	13.3	69.7	33.8	33.8	37.6	35.1
mlr36	0,-1,0	5,12,5	mlr	3.4e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR18022	-0.26	3.73	4.17	0.71	0.64	7.3	72.5	35.3	35.3	37.6	19.4
mlr55	0,-1,-1	5,12,11	mlr	4.6e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR54004	-0.91	3.47	3.84	0.66	0.60	27.7	63.3	29.8	29.8	37.7	13.6
OSCAR27012	0	4	scam_mpd	5.5e-03	0.56	18	v	0.38	3.66	4.19	0.72	0.63	11.1	70.0	35.5	35.5	38.0	55.5
OSCAR62989	0	6	scam_mpd	9.2e-04	0.60	18	u	0.19	3.57	4.46	0.76	0.62	5.1	67.1	39.9	39.9	38.0	81.6
mlr104	0,0	5,6	mlr	1.0e-04	0.67	18	OSCAR62986; OSCAR62990	-0.53	3.65	4.08	0.70	0.63	15.7	69.7	33.8	33.8	38.2	32.5
mlr142	0,0	5,1	mlr	2.5e-04	0.62	18	OSCAR62986; OSCAR18025	-0.49	3.48	4.31	0.74	0.60	14.5	64.0	37.5	37.5	38.4	29.2
mlr14	0,-1	5,12	mlr	1.1e-05	0.75	18	OSCAR62986; OSCAR62997	-0.37	3.81	4.11	0.70	0.66	10.8	75.6	34.3	34.3	38.7	16.0
mlr34	0,-1,0	5,12,6	mlr	3.3e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR62989	-0.46	3.77	4.09	0.70	0.65	13.7	73.9	33.8	33.8	38.8	13.9
mlr9	0,-1	5,12	mlr	8.7e-06	0.76	18	OSCAR62986; OSCAR63007	-0.50	3.73	4.08	0.70	0.64	15.0	72.6	33.7	33.7	38.8	13.2
mlr93	0,0	5,1	mlr	7.3e-05	0.68	18	OSCAR62986; OSCAR63003	-0.64	3.37	4.36	0.75	0.58	19.2	59.9	38.3	38.3	38.9	43.6
mlr114	0,0	5,1	mlr	1.3e-04	0.66	18	OSCAR62986; OSCAR62996	-0.61	3.42	4.37	0.75	0.59	18.3	61.5	38.4	38.4	39.2	42.4
mlr99	0,-1	5,4	mlr	9.1e-05	0.67	18	OSCAR62986; lighthouse72126	-0.35	3.50	4.54	0.78	0.60	10.2	64.5	41.3	41.3	39.3	29.6
mlr146	0,0	5,1	mlr	2.7e-04	0.62	18	OSCAR62986; OSCAR18046	-0.64	3.52	4.25	0.73	0.61	19.2	65.3	36.5	36.5	39.4	28.0
mlr133	0,-1	5,11	mlr	2.1e-04	0.63	18	OSCAR62986; OSCAR18030	-0.55	3.48	4.40	0.75	0.60	16.3	63.7	39.0	39.0	39.5	26.2
mlr112	0,0	5,6	mlr	1.2e-04	0.66	18	OSCAR62986; OSCAR27025	-0.33	3.82	4.25	0.73	0.66	9.5	75.8	36.5	36.5	39.6	31.1
OSCAR63005	0	6	scam_mpd	4.2e-04	0.51	18	u	1.49	3.30	3.71	0.64	0.57	45.9	57.4	27.8	27.8	39.7	74.6
mlr129	0,0	5,1	mlr	1.9e-04	0.64	18	OSCAR62986; OSCAR63001	-0.41	3.58	4.47	0.76	0.62	12.1	67.4	40.1	40.1	39.9	50.3
mlr31	0,-1,-1	5,12,12	mlr	3.0e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR18028	-0.57	3.76	4.12	0.71	0.65	16.9	73.8	34.5	34.5	39.9	15.9
OSCAR54001	0	6	scam_mpi	3.4e-04	0.52	18	u	1.93	2.81	3.85	0.66	0.48	59.6	40.0	30.1	30.1	39.9	63.4
OSCAR62992	0	6	scam_mpd	5.8e-04	0.57	18	u	0.85	3.61	4.03	0.69	0.62	25.8	68.5	33.0	33.0	40.1	72.6
mlr103	0,0	5,1	mlr	1.0e-04	0.67	18	OSCAR62986; OSCAR63011	-0.90	3.36	4.29	0.73	0.58	27.4	59.5	37.2	37.2	40.3	32.6
mlr109	0,0	5,1	mlr	1.1e-04	0.66	18	OSCAR62986; OSCAR63006	-0.54	3.52	4.47	0.76	0.61	16.2	65.2	40.1	40.1	40.4	45.4
mlr141	0,0	5,1	mlr	2.5e-04	0.63	18	OSCAR62986; OSCAR18042	-0.65	3.58	4.31	0.74	0.62	19.5	67.2	37.5	37.5	40.4	29.9

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr122	0,0	5,1	mlr	1.7e-04	0.64	18	OSCAR62986; OSCAR63002	-0.46	3.57	4.50	0.77	0.62	13.8	67.0	40.6	40.6	40.5	47.5
mlr124	0,0	5,4	mlr	1.8e-04	0.64	18	OSCAR62986; OSCAR27013	-0.38	3.68	4.46	0.76	0.64	11.2	71.0	40.0	40.0	40.5	28.7
mlr127	0,0	5,3	mlr	1.8e-04	0.64	18	OSCAR62986; OSCAR18040	-0.47	3.66	4.41	0.75	0.63	13.9	70.1	39.1	39.1	40.6	29.2
mlr45	0,-1,0	5,12,5	mlr	3.9e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18031	-0.08	3.97	4.44	0.76	0.69	1.8	81.3	39.7	39.7	40.6	23.6
mlr73	0,-1,0	5,12,3	mlr	5.2e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18048	-0.30	3.95	4.25	0.73	0.68	8.6	80.5	36.6	36.6	40.6	18.4
mlr40	0,-1,0	5,12,3	mlr	3.6e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR18044	-0.62	3.75	4.19	0.72	0.65	18.5	73.5	35.5	35.5	40.7	17.1
mlr48	0,-1,0	5,12,4	mlr	4.1e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18035	-0.36	3.90	4.27	0.73	0.67	10.5	78.8	36.8	36.8	40.7	15.5
OSCAR18011	0	3	scam_mpi	3.3e-04	0.59	18	v	-1.26	3.35	4.01	0.69	0.58	38.7	59.1	32.6	32.6	40.7	59.3
mlr115	0,0	5,1	mlr	1.4e-04	0.65	18	OSCAR62986; OSCAR63010	-0.52	3.54	4.51	0.77	0.61	15.6	66.0	40.8	40.8	40.8	43.9
mlr63	0,-1,0	5,12,3	mlr	5.0e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18045	-0.33	3.96	4.25	0.73	0.68	9.7	80.7	36.5	36.5	40.8	17.1
mlr84	0,-1,0	5,12,1	mlr	5.4e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18021	-0.49	3.89	4.20	0.72	0.67	14.7	78.3	35.7	35.7	41.1	10.5
OSCAR54002	-1	11	scam_mpi	4.5e-03	0.51	18	u	2.10	2.77	3.88	0.66	0.48	65.1	38.6	30.6	30.6	41.2	33.5
mlr140	0,0	5,4	mlr	2.5e-04	0.63	18	OSCAR62986; OSCAR18016	-0.32	3.80	4.49	0.77	0.65	9.3	74.9	40.4	40.4	41.3	33.3
mlr82	0,-1,0	5,12,1	mlr	5.4e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18029	-0.57	3.86	4.18	0.72	0.67	17.0	77.3	35.4	35.4	41.3	14.9
mlr49	0,-1,0	5,12,6	mlr	4.2e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR62990	-0.56	3.88	4.18	0.72	0.67	16.9	77.8	35.5	35.5	41.4	13.7
mlr44	0,-1,0	5,12,6	mlr	3.9e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR62992	-0.56	3.89	4.18	0.72	0.67	16.8	78.2	35.5	35.5	41.5	15.4
mlr151	0,-1	5,12	mlr	2.9e-04	0.62	18	OSCAR62986; OSCAR27027	-0.53	3.60	4.55	0.78	0.62	15.7	68.1	41.5	41.5	41.7	34.9
mlr80	0,-1,0	5,12,2	mlr	5.3e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR53998	-0.55	3.89	4.24	0.73	0.67	16.4	78.2	36.4	36.4	41.8	19.1
OSCAR18043	0	3	scam_mpi	5.4e-03	0.51	18	v	0.31	3.53	4.86	0.83	0.61	9.0	65.5	46.5	46.5	41.9	68.3
mlr138	0,-1	5,11	mlr	2.4e-04	0.63	18	OSCAR62986; OSCAR54003	-0.33	3.73	4.65	0.79	0.64	9.5	72.6	43.0	43.0	42.0	31.0
mlr65	0,-1,0	5,12,3	mlr	5.0e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18012	-0.44	3.96	4.28	0.73	0.68	13.1	80.7	37.1	37.1	42.0	18.6
mlr85	0,-1,0	5,12,1	mlr	5.4e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18041	-0.54	3.92	4.23	0.72	0.68	16.0	79.4	36.2	36.2	42.0	11.7
mlr120	0,0	5,3	mlr	1.6e-04	0.65	18	OSCAR62986; OSCAR18011	-1.07	3.54	4.15	0.71	0.61	32.7	65.9	35.0	35.0	42.1	24.5
mlr62	0,-1,0	5,12,3	mlr	5.0e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18020	-0.43	3.97	4.31	0.74	0.69	12.8	81.3	37.4	37.4	42.2	19.7
mlr96	0,0	5,6	mlr	7.6e-05	0.68	18	OSCAR62986; OSCAR62994	-0.94	3.43	4.42	0.76	0.59	28.7	62.1	39.3	39.3	42.3	28.3
mlr66	0,-1,-1	5,12,11	mlr	5.0e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR54003	-0.76	3.79	4.23	0.72	0.65	23.1	74.7	36.2	36.2	42.5	16.2
mlr94	0,-1	5,11	mlr	7.4e-05	0.68	18	OSCAR62986; OSCAR53997	0.18	3.95	4.61	0.79	0.68	4.8	80.3	42.4	42.4	42.5	30.4
mlr135	0,0	5,2	mlr	2.2e-04	0.63	18	OSCAR62986; OSCAR53998	-0.25	3.88	4.62	0.79	0.67	7.2	78.1	42.6	42.6	42.6	42.4
mlr5	0,-1,0	5,12,5	mlr	6.8e-06	0.81	18	OSCAR62986; OSCAR63007; OSCAR53991	0.68	3.87	4.22	0.72	0.67	20.6	77.6	36.0	36.0	42.6	15.6
mlr61	0,-1,0	5,12,6	mlr	4.9e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR54001	-0.37	3.97	4.43	0.76	0.68	10.7	81.1	39.5	39.5	42.7	22.3
mlr77	0,-1,0	5,12,1	mlr	5.3e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18025	-0.69	3.91	4.20	0.72	0.67	20.7	78.9	35.7	35.7	42.7	12.1
mlr54	0,-1,0	5,12,3	mlr	4.6e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18033	-0.60	3.94	4.28	0.73	0.68	18.1	79.9	37.1	37.1	43.0	19.5
mlr86	0,-1,0	5,12,1	mlr	5.4e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18039	-0.61	3.96	4.26	0.73	0.68	18.2	80.7	36.6	36.6	43.0	13.1
mlr56	0,-1,0	5,12,3	mlr	4.6e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18043	-0.40	4.04	4.37	0.75	0.70	11.9	83.6	38.5	38.5	43.1	20.3
mlr68	0,-1,0	5,12,1	mlr	5.1e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR63003	-0.48	4.00	4.33	0.74	0.69	14.4	82.2	37.8	37.8	43.1	25.3
mlr79	0,-1,0	5,12,1	mlr	5.3e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR63011	-0.17	4.14	4.48	0.77	0.71	4.5	87.2	40.3	40.3	43.1	20.8
OSCAR27015	0	4	scam_mpd	5.4e-03	0.54	18	v	0.97	3.54	4.36	0.75	0.61	29.5	66.0	38.4	38.4	43.1	36.8
mlr97	0,0	5,6	mlr	8.0e-05	0.68	18	OSCAR62986; OSCAR62995	-0.97	3.41	4.52	0.77	0.59	29.7	61.3	40.9	40.9	43.2	27.8
mlr132	0,-1	5,11	mlr	2.1e-04	0.63	18	OSCAR62986; OSCAR54004	-0.22	3.93	4.70	0.80	0.68	6.0	79.6	43.8	43.8	43.3	35.8
mlr26	0,-1,-1	5,12,11	mlr	2.4e-05	0.77	18	OSCAR62986; OSCAR63007; OSCAR53997	-0.15	4.15	4.52	0.77	0.72	3.9	87.4	40.9	40.9	43.3	17.2
mlr53	0,-1,0	5,12,6	mlr	4.5e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR27025	-0.53	3.99	4.33	0.74	0.69	15.9	82.0	37.9	37.9	43.4	16.2
mlr81	0,-1,-1	5,12,12	mlr	5.4e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR62997	-0.65	3.94	4.27	0.73	0.68	19.7	80.2	36.8	36.8	43.4	18.6

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
OSCAR27019	0	4	scam_mpd	3.4e-03	0.52	18	v	2.10	3.06	3.84	0.66	0.53	64.9	48.9	29.9	29.9	43.4	51.0
mlr41	0,-1,0	5,12,3	mlr	3.7e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR18013	-0.78	3.84	4.27	0.73	0.66	23.7	76.4	36.9	36.9	43.5	16.5
mlr88	0,0	5,5	mlr	4.5e-05	0.70	18	OSCAR62986; OSCAR18047	-0.60	3.78	4.54	0.78	0.65	18.0	74.3	41.3	41.3	43.7	36.7
mlr74	0,-1,0	5,12,3	mlr	5.2e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18040	-0.55	4.06	4.31	0.74	0.70	16.4	84.4	37.5	37.5	43.9	17.7
mlr59	0,-1,0	5,12,6	mlr	4.9e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR62994	-0.55	3.98	4.41	0.75	0.69	16.5	81.4	39.1	39.1	44.0	18.8
mlr60	0,-1,0	5,12,4	mlr	4.9e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18008	-0.59	3.98	4.35	0.74	0.69	17.8	81.6	38.2	38.2	44.0	17.9
mlr69	0,-1,0	5,12,1	mlr	5.1e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR63002	-0.56	4.00	4.36	0.75	0.69	16.9	82.3	38.4	38.4	44.0	22.2
OSCAR18033	0	3	scam_mpi	1.4e-03	0.52	18	v	-0.76	3.74	4.48	0.77	0.64	23.0	72.9	40.4	40.4	44.2	84.0
OSCAR27005	0	4	scam_mpd	8.8e-04	0.61	18	v	2.17	3.18	3.75	0.64	0.55	67.2	53.1	28.3	28.3	44.2	45.9
mlr38	0,-1,0	5,12,1	mlr	3.5e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR18024	-0.76	3.95	4.28	0.73	0.68	23.0	80.3	37.0	37.0	44.3	11.5
mlr6	0,-1,0	5,12,5	mlr	9.3e-06	0.80	18	OSCAR62986; OSCAR63007; OSCAR18047	-0.66	4.00	4.32	0.74	0.69	19.8	82.0	37.8	37.8	44.3	20.3
mlr67	0,-1,0	5,12,1	mlr	5.1e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR63001	-0.60	4.01	4.37	0.75	0.69	18.0	82.6	38.5	38.5	44.4	22.7
OSCAR18039	0	1	scam_mpi	1.6e-03	0.51	18	v	0.53	3.58	4.91	0.84	0.62	15.8	67.2	47.4	47.4	44.5	80.9
mlr75	0,-1,0	5,12,1	mlr	5.2e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR63010	-0.55	4.05	4.41	0.75	0.70	16.4	83.9	39.2	39.2	44.6	22.7
mlr76	0,-1,0	5,12,1	mlr	5.2e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR62996	-0.57	4.03	4.39	0.75	0.70	17.2	83.4	38.8	38.8	44.6	20.9
mlr70	0,-1,0	5,12,4	mlr	5.2e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR18016	-0.42	4.14	4.44	0.76	0.71	12.4	87.1	39.6	39.6	44.7	20.6
mlr87	0,-1,0	5,12,1	mlr	5.4e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR63006	-0.56	4.06	4.42	0.76	0.70	16.8	84.4	39.4	39.4	45.0	24.5
mlr46	0,-1,0	5,12,4	mlr	3.9e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR27013	-0.54	4.08	4.45	0.76	0.70	16.2	84.9	39.9	39.9	45.2	18.4
mlr33	0,-1,-1	5,12,4	mlr	3.3e-05	0.76	18	OSCAR62986; OSCAR63007; lighthouse72126	-0.72	3.92	4.46	0.76	0.68	21.9	79.4	40.0	40.0	45.3	19.9
mlr58	0,-1,0	5,12,6	mlr	4.8e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR62995	-0.53	4.06	4.50	0.77	0.70	15.7	84.2	40.6	40.6	45.3	19.8
mlr57	0,-1,0	5,12,5	mlr	4.7e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR35999	-0.28	4.19	4.62	0.79	0.72	7.9	88.7	42.6	42.6	45.4	21.9
OSCAR18025	0	1	scam_mpi	3.3e-04	0.53	18	v	0.56	3.67	4.91	0.84	0.63	16.8	70.4	47.3	47.3	45.4	80.0
mlr139	0,0	5,5	mlr	2.4e-04	0.63	18	OSCAR62986; OSCAR62993	-0.07	4.01	5.02	0.86	0.69	1.6	82.5	49.2	49.2	45.6	37.7
OSCAR62995	0	6	scam_mpd	2.2e-03	0.55	18	u	-0.17	3.73	5.23	0.90	0.64	4.6	72.5	52.6	52.6	45.6	63.6
mlr149	0,0	5,5	mlr	2.9e-04	0.62	18	OSCAR62986; OSCAR36000	-0.73	3.74	4.69	0.80	0.65	22.1	73.1	43.8	43.8	45.7	30.1
mlr107	0,0	5,3	mlr	1.0e-04	0.67	18	OSCAR62986; OSCAR54005	-0.28	4.07	4.79	0.82	0.70	8.1	84.8	45.4	45.4	45.9	48.6
OSCAR62990	0	6	scam_mpd	1.2e-03	0.58	18	u	0.18	4.12	4.83	0.83	0.71	4.9	86.5	46.0	46.0	45.9	75.0
mlr30	0,-1,0	5,12,5	mlr	2.9e-05	0.77	18	OSCAR62986; OSCAR63007; OSCAR62993	-0.04	4.26	4.82	0.83	0.73	0.5	91.5	45.9	45.9	46.0	24.8
mlr144	0,0	5,5	mlr	2.6e-04	0.62	18	OSCAR62986; OSCAR35999	-0.83	3.73	4.68	0.80	0.64	25.2	72.5	43.6	43.6	46.2	29.1
mlr43	0,-1,0	5,12,3	mlr	3.7e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR54005	-0.49	4.19	4.51	0.77	0.72	14.7	88.8	40.8	40.8	46.3	27.8
OSCAR62994	0	6	scam_mpd	8.6e-04	0.55	18	u	-0.30	3.83	5.13	0.88	0.66	8.5	76.1	50.9	50.9	46.6	73.2
mlr152	0,0	5,5	mlr	2.9e-04	0.62	18	OSCAR62986; OSCAR63000	-0.33	4.00	4.97	0.85	0.69	9.7	82.0	48.2	48.2	47.0	34.9
mlr92	0,-1	5,12	mlr	6.9e-05	0.68	18	OSCAR62986; OSCAR63004	-0.37	4.32	4.64	0.79	0.74	10.7	93.5	42.9	42.9	47.5	33.3
mlr137	0,-1	5,11	mlr	2.3e-04	0.63	18	OSCAR62986; OSCAR54002	-0.50	4.05	4.82	0.82	0.70	15.0	83.9	45.8	45.8	47.6	33.1
mlr37	0,-1,0	5,12,1	mlr	3.4e-05	0.76	18	OSCAR62986; OSCAR63007; OSCAR18046	-0.95	4.03	4.42	0.76	0.69	28.9	83.1	39.3	39.3	47.6	12.6
OSCAR18044	0	3	scam_mpi	8.5e-03	0.51	18	v	-0.06	4.24	5.02	0.86	0.73	1.2	90.7	49.2	49.2	47.6	70.6
mlr117	0,0	5,6	mlr	1.4e-04	0.65	18	OSCAR62986; OSCAR62998	-0.87	3.70	4.85	0.83	0.64	26.3	71.6	46.4	46.4	47.7	32.1
OSCAR18019	0	1	scam_mpi	2.0e-03	0.55	18	v	0.97	3.97	4.46	0.76	0.68	29.7	81.1	39.9	39.9	47.7	85.6
OSCAR18030	-1	11	scam_mpi	3.6e-04	0.52	18	v	0.03	4.18	5.15	0.88	0.72	0.3	88.4	51.3	51.3	47.8	86.3
OSCAR62998	0	6	scam_mpd	1.0e-03	0.54	18	u	-0.12	3.98	5.28	0.90	0.69	3.0	81.3	53.4	53.4	47.8	65.1
OSCAR18013	0	3	scam_mpi	5.3e-04	0.57	18	v	-1.16	3.83	4.47	0.76	0.66	35.6	76.3	40.1	40.1	48.0	75.6
mlr83	0,-1,0	5,12,6	mlr	5.4e-05	0.74	18	OSCAR62986; OSCAR63007; OSCAR62998	-0.50	4.23	4.69	0.80	0.73	14.8	90.4	43.8	43.8	48.2	22.6

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
OSCAR18007	0	4	scam_mpi	9.8e-04	0.63	18	v	0.71	4.08	4.67	0.80	0.70	21.6	85.0	43.3	43.3	48.3	62.5
mlr29	0,-1,0	5,12,1	mlr	2.7e-05	0.77	18	OSCAR62986; OSCAR63007; OSCAR18042	-0.96	4.09	4.45	0.76	0.71	29.2	85.4	39.8	39.8	48.6	13.8
OSCAR18048	0	3	scam_mpi	5.2e-04	0.50	18	v	0.10	4.21	5.17	0.88	0.73	2.4	89.8	51.5	51.5	48.8	84.7
mlr52	0,-1,0	5,12,5	mlr	4.4e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR63000	-0.07	4.45	4.98	0.85	0.77	1.3	98.2	48.5	48.5	49.1	28.0
OSCAR35999	0	5	lm	7.6e-05	0.61	18	u	-1.35	3.56	4.73	0.81	0.61	41.7	66.6	44.4	44.4	49.3	29.1
OSCAR54003	-1	11	scam_mpi	2.0e-03	0.51	18	u	0.16	4.25	5.18	0.89	0.73	4.3	90.9	51.7	51.7	49.7	83.9
OSCAR62988	0	5	scam_mpd	5.0e-05	0.61	18	u	-1.26	3.66	4.78	0.82	0.63	38.6	70.1	45.1	45.1	49.7	29.6
OSCAR27025	0	6	scam_mpd	1.6e-03	0.51	18	v	1.06	3.92	4.70	0.80	0.68	32.3	79.4	43.9	43.9	49.9	56.0
OSCAR18021	0	1	scam_mpi	3.1e-04	0.53	18	v	0.34	4.22	5.13	0.88	0.73	9.8	89.9	50.9	50.9	50.4	109.9
OSCAR62996	0	1	scam_mpd	2.4e-04	0.54	18	u	0.25	4.26	5.17	0.88	0.73	7.2	91.4	51.6	51.6	50.4	80.8
OSCAR63011	0	1	scam_mpd	2.5e-03	0.50	18	u	0.21	4.25	5.22	0.89	0.73	5.9	91.0	52.3	52.3	50.4	79.8
OSCAR63006	0	1	scam_mpd	2.3e-03	0.51	18	u	0.29	4.26	5.16	0.88	0.73	8.2	91.5	51.4	51.4	50.6	82.7
OSCAR63010	0	1	scam_mpd	5.6e-04	0.51	18	u	0.28	4.26	5.16	0.88	0.73	8.1	91.4	51.4	51.4	50.6	81.3
OSCAR18042	0	1	scam_mpi	4.7e-04	0.51	18	v	0.29	4.27	5.16	0.88	0.74	8.2	91.6	51.5	51.5	50.7	50.8
OSCAR18049	0	2	scam_mpi	5.3e-04	0.50	18	v	0.14	4.32	5.24	0.90	0.74	3.7	93.5	52.8	52.8	50.7	89.9
OSCAR18045	0	3	scam_mpi	4.9e-03	0.51	18	v	0.26	4.27	5.20	0.89	0.74	7.3	91.8	52.1	52.1	50.8	79.3
OSCAR63002	0	1	scam_mpd	1.4e-03	0.52	18	u	0.31	4.27	5.16	0.88	0.74	9.1	91.8	51.5	51.5	51.0	83.7
mlr50	0,-1,0	5,12,3	mlr	4.4e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR18011	-0.91	4.24	4.68	0.80	0.73	27.7	90.6	43.5	43.5	51.3	21.7
OSCAR18024	0	1	scam_mpi	3.1e-04	0.53	18	v	0.35	4.28	5.16	0.88	0.74	10.3	92.1	51.4	51.4	51.3	221.7
OSCAR53998	0	2	scam_mpi	2.4e-04	0.54	18	u	0.36	4.32	5.18	0.89	0.74	10.6	93.5	51.7	51.7	51.9	79.5
OSCAR63003	0	1	scam_mpd	1.4e-03	0.52	18	u	0.33	4.32	5.23	0.89	0.74	9.5	93.4	52.5	52.5	52.0	80.6
OSCAR18029	0	1	scam_mpi	3.6e-04	0.52	18	v	0.40	4.32	5.21	0.89	0.74	11.9	93.4	52.2	52.2	52.4	84.4
OSCAR18041	0	1	scam_mpi	5.8e-04	0.51	18	v	0.43	4.31	5.18	0.89	0.74	12.7	93.3	51.7	51.7	52.4	213.1
OSCAR63004	-1	12	scam_mpd	3.9e-04	0.52	18	u	0.22	4.39	5.30	0.91	0.76	6.0	96.0	53.7	53.7	52.4	82.2
OSCAR62997	-1	12	scam_mpd	1.0e-03	0.54	18	u	0.67	4.32	5.00	0.85	0.74	20.2	93.4	48.7	48.7	52.8	81.6
mlr47	0,-1,-1	5,12,12	mlr	4.0e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR63009	-0.90	4.16	4.96	0.85	0.72	27.5	87.9	48.2	48.2	53.0	24.7
OSCAR18046	0	1	scam_mpi	2.2e-03	0.51	18	v	0.40	4.39	5.25	0.90	0.76	11.8	96.0	52.9	52.9	53.4	85.1
mlr64	0,-1,-1	5,12,11	mlr	5.0e-05	0.75	18	OSCAR62986; OSCAR63007; OSCAR54002	-0.86	4.36	4.85	0.83	0.75	26.3	95.0	46.4	46.4	53.5	24.8
OSCAR18010	0	4	scam_mpi	1.4e-03	0.62	18	v	0.76	4.37	5.02	0.86	0.75	23.2	95.4	49.2	49.2	54.2	69.1
OSCAR18008	0	4	scam_mpi	1.4e-03	0.62	18	v	0.77	4.36	5.08	0.87	0.75	23.3	95.1	50.1	50.1	54.6	68.2
OSCAR63007	-1	12	scam_mpd	7.2e-03	0.51	18	u	0.90	4.33	5.06	0.87	0.75	27.5	93.7	49.7	49.7	55.2	81.5
mlr131	0,-1	5,12	mlr	2.0e-04	0.64	18	OSCAR62986; OSCAR63009	-0.39	4.75	5.14	0.88	0.82	11.5	108.8	51.1	51.1	55.6	36.2
OSCAR63001	0	1	scam_mpd	1.3e-03	0.52	18	u	0.50	4.48	5.34	0.91	0.77	14.8	99.3	54.3	54.3	55.6	84.4
OSCAR18022	0	5	scam_mpi	5.3e-03	0.53	18	v	1.13	4.32	4.98	0.85	0.74	34.5	93.5	48.4	48.4	56.2	70.7
OSCAR54005	0	3	scam_mpi	1.8e-03	0.50	18	u	0.60	4.41	5.45	0.93	0.76	18.1	96.7	56.1	56.1	56.7	83.6
OSCAR54004	-1	11	scam_mpi	1.7e-03	0.51	18	u	0.90	4.34	5.37	0.92	0.75	27.6	94.4	54.9	54.9	57.9	80.8
OSCAR18040	0	3	scam_mpi	2.2e-03	0.51	18	v	1.33	4.19	5.33	0.91	0.72	40.8	88.9	54.2	54.2	59.5	51.0
OSCAR18016	0	4	scam_mpi	6.6e-04	0.56	18	v	1.09	4.74	5.30	0.91	0.82	33.2	108.3	53.7	53.7	62.2	72.4
OSCAR27027	-1	12	scam_mpd	2.3e-03	0.51	18	v	0.80	4.86	5.44	0.93	0.84	24.3	112.4	56.0	56.0	62.2	85.7
OSCAR27013	0	4	scam_mpd	7.6e-04	0.55	18	v	0.98	4.83	5.34	0.91	0.83	29.8	111.7	54.4	54.4	62.6	70.7
OSCAR18012	0	3	scam_mpi	9.6e-04	0.59	18	v	-1.20	4.86	5.19	0.89	0.84	36.8	112.5	51.8	51.8	63.2	74.5
OSCAR53997	-1	11	scam_mpi	1.3e-03	0.54	18	u	2.51	3.91	5.01	0.86	0.67	77.9	78.9	48.9	48.9	63.7	53.2

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
OSCAR18035	0	4	scam_mpi	7.9e-03	0.51	18	v	0.91	4.88	5.60	0.96	0.84	27.7	113.4	58.6	58.6	64.6	175.4
OSCAR63000	0	5	scam_mpd	4.2e-03	0.53	18	u	0.25	5.29	6.07	1.04	0.91	7.1	128.0	66.3	66.3	66.9	62.4
shore72126	-1	4	scam_mpi	4.8e-03	0.50	20	temperature.c.	1.31	4.69	5.78	0.99	0.81	40.1	106.7	61.6	61.6	67.5	45.9
median8	0	0	median8	NA			0	0.92	5.25	5.91	1.01	0.91	27.9	126.4	63.7	63.7	70.4	81.9
median4	0	0	median4	NA			0	0.42	5.42	6.27	1.07	0.93	12.3	132.3	69.5	69.5	70.9	108.1
OSCAR63009	-1	12	scam_mpd	4.1e-03	0.51	18	u	2.57	4.24	5.94	1.02	0.73	79.7	90.7	64.1	64.1	74.6	70.2
OSCAR18031	0	5	scam_mpi	7.1e-03	0.52	18	v	1.84	5.36	6.41	1.10	0.92	56.9	130.3	71.8	71.8	82.7	92.0
median.all	0	0	median.all	NA			0	-3.58	4.92	6.10	1.04	0.85	111.5	114.6	66.8	66.8	89.9	193.1
OSCAR62993	0	5	scam_mpd	1.8e-03	0.56	18	u	1.65	6.05	6.73	1.15	1.04	51.0	154.9	77.1	77.1	90.0	84.3
OSCAR18047	0	5	scam_mpi	2.7e-03	0.50	18	v	4.42	6.25	9.09	1.56	1.08	137.8	161.7	115.7	115.7	132.7	111.5
OSCAR53996	0	5	scam_mpi	3.4e-03	0.55	18	u	7.95	7.95	16.16	2.76	1.37	248.3	221.9	231.0	231.0	233.1	192.8
OSCAR53991	0	5	scam_mpi	1.3e-03	0.59	18	u	8.07	8.80	17.44	2.98	1.52	252.0	252.0	252.0	252.0	252.0	217.3

APPENDIX C: DIVERSION MODEL PERFORMANCE RESULTS

Table 18. Performance results for all qualifying models used to forecast Fraser diversion based on retrospective analysis. Each row represents a single model tested, some columns include: year adjust (year of environmental data same as return year [0] or prior year [-1]), month, summary statistics (P value, adjusted R squared, sample size), data name, data variables (which are sorted by their relative influence in the model). As the NEPSTAR regression models comprise more than one variable, only year-month of the latest variable is presented. Latitude and longtitude of NEPSTAR variables are excluded due to space limitations. The PMs include mean raw error, mean absolute error, root mean squared error, Thiel's U-statistic, and MASE. The initial three PMs are in percent diversion units, the latter two are unit-less. All PMs are described in the methods section. All PMs, except MASE, are given a rank. The best rank has a value of zero. The last rank equals total number of models (n). The average of the PM ranks by model (row) is included, as is the average rank for the alternate performance test method. The rows are sorted by average rank of performance method listed in caption. The first row is the best model, the last row is the worst.

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
nepstar7	-1,-1,0	6,1,1	mlr	1.1e-07	0.71	30	nepstar	-0.00	0.07	0.09	0.31	0.22	0.3	0.0	0.0	3.1	0.8	5.3
nepstar3	-1,0,-1,0	1,4,4,1	mlr	2.1e-08	0.77	30	nepstar	-0.01	0.08	0.10	0.32	0.25	13.1	7.7	2.0	5.5	7.1	3.6
nepstar8	-1,-1,0,0	7,1,4,1	mlr	4.0e-08	0.75	30	nepstar	-0.01	0.08	0.10	0.33	0.26	4.9	10.0	8.5	7.2	7.6	5.0
nepstar10	-1,-1,0	1,4,1	mlr	6.2e-08	0.72	30	nepstar	0.01	0.08	0.10	0.30	0.28	12.7	13.9	4.5	0.0	7.8	6.5
nepstar1	-1,-1,0	1,4,1	mlr	1.9e-08	0.74	30	nepstar	0.01	0.09	0.11	0.33	0.31	7.5	21.8	12.4	6.8	12.1	10.7
nepstar5	-1,-1,0,0	6,1,4,1	mlr	5.5e-08	0.75	30	nepstar	-0.03	0.09	0.11	0.32	0.30	31.3	20.6	11.0	3.3	16.5	6.1
nepstar4	-1,-1,0	7,1,1	mlr	4.8e-08	0.72	30	nepstar	0.02	0.08	0.11	0.38	0.26	21.7	10.1	15.7	19.8	16.8	3.0
nepstar14	-1,-1,-1,0	7,1,4,1	mlr	5.7e-08	0.75	30	nepstar	0.02	0.08	0.11	0.38	0.25	23.9	7.6	16.7	20.4	17.1	3.8
nepstar12	-1,-1,0,0	6,1,4,1	mlr	1.5e-07	0.73	30	nepstar	-0.02	0.10	0.11	0.34	0.32	22.3	26.0	15.6	9.7	18.4	5.4
nepstar13	-1,-1,0,0	6,1,3,1	mlr	1.1e-07	0.73	30	nepstar	-0.00	0.10	0.12	0.41	0.32	2.7	24.3	24.5	28.5	20.0	11.3
nepstar2	-1,-1,-1,0	7,1,4,1	mlr	2.2e-08	0.77	30	nepstar	0.02	0.09	0.12	0.39	0.30	19.2	20.4	19.6	22.5	20.4	7.4
nepstar6	-1,-1,0	6,1,3	mlr	1.2e-07	0.70	30	nepstar	0.00	0.10	0.14	0.46	0.34	3.3	29.8	36.0	40.4	27.4	19.2
nepstar11	-1,-1,0,0	7,1,3,1	mlr	6.4e-08	0.75	30	nepstar	0.02	0.09	0.14	0.46	0.31	16.8	21.4	34.9	39.2	28.1	6.6
nepstar15	-1,-1,0,0,0	6,1,4,3,1	mlr	1.4e-07	0.75	30	nepstar	-0.02	0.10	0.13	0.42	0.34	23.0	30.9	28.3	31.2	28.4	9.7
mlr57	0,0,0	5,1,6	mlr	2.0e-04	0.62	21	OISST23402; OSCAR213625; OISST23353	-0.00	0.13	0.14	0.46	0.42	3.4	50.0	37.3	40.6	32.8	19.8
mlr67	0,0,0	5,1,5	mlr	2.6e-04	0.61	21	OISST23402; OSCAR213625; OISST23400	0.01	0.12	0.14	0.48	0.40	4.6	45.0	39.8	44.9	33.6	28.7
mlr73	0,0,0	5,1,6	mlr	2.9e-04	0.60	21	OISST23402; OSCAR213625; OISST23364	0.00	0.13	0.14	0.47	0.41	3.8	48.6	39.4	44.2	34.0	22.2
mlr58	0,0,0	5,1,5	mlr	2.1e-04	0.62	21	OISST23402; OSCAR213625; OISST23390	0.01	0.12	0.14	0.48	0.41	6.5	46.8	39.4	44.6	34.3	27.6
mlr66	0,0,0	5,1,6	mlr	2.6e-04	0.61	21	OISST23402; OSCAR213625; OISST23374	0.01	0.12	0.14	0.47	0.41	8.3	47.1	38.5	43.5	34.4	22.1
mlr78	0,0,0	5,1,6	mlr	3.2e-04	0.60	21	OISST23402; OSCAR213625; OISST23384	-0.00	0.13	0.14	0.48	0.41	3.5	48.7	40.6	45.3	34.5	22.5
mlr1	0,0	5,1	mlr	8.0e-05	0.61	21	OISST23402; OSCAR213625	0.01	0.12	0.14	0.48	0.39	12.9	41.8	39.6	44.7	34.7	20.6
mlr61	0,0,0	5,1,6	mlr	2.3e-04	0.61	21	OISST23402; OSCAR213625; OISST23344	-0.01	0.13	0.14	0.46	0.42	8.6	50.4	38.4	41.3	34.7	19.9
mlr80	0,0,0	5,1,6	mlr	3.3e-04	0.60	21	OISST23402; OSCAR213625; OISST23386	0.00	0.13	0.14	0.48	0.42	3.5	49.0	40.7	45.8	34.7	23.1
mlr65	0,0,0	5,1,6	mlr	2.5e-04	0.61	21	OISST23402; OSCAR213625; OISST23405	0.01	0.12	0.14	0.47	0.40	13.2	44.3	38.2	43.3	34.8	22.7
mlr68	0,0,0	5,1,6	mlr	2.8e-04	0.60	21	OISST23402; OSCAR213625; OISST23356	-0.01	0.13	0.14	0.47	0.42	7.0	49.7	39.2	43.1	34.8	21.0
mlr71	0,0,0	5,1,5	mlr	2.8e-04	0.60	21	OISST23402; OSCAR213625; OISST23367	0.01	0.12	0.14	0.47	0.40	12.7	44.7	39.1	44.1	35.2	28.1
mlr77	0,0,0	5,1,5	mlr	3.1e-04	0.60	21	OISST23402; OSCAR213625; OISST23380	0.01	0.12	0.14	0.48	0.40	11.4	44.9	40.2	45.3	35.5	29.1
mlr82	0,0,0	5,1,5	mlr	3.3e-04	0.59	21	OISST23402; OSCAR213625; OISST23403	0.01	0.12	0.14	0.48	0.40	11.2	44.9	41.1	46.3	35.9	29.9

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
mlr72	0,0,0	5,1,5	mlr	2.8e-04	0.60	21	OISST23402; OSCAR213625; OISST23378	0.01	0.12	0.14	0.48	0.39	14.5	43.4	41.4	46.5	36.4	27.7
mlr81	0,0,0	5,1,5	mlr	3.3e-04	0.60	21	OISST23402; OSCAR213625; OISST23355	0.02	0.12	0.14	0.48	0.40	15.2	44.1	40.6	45.7	36.4	28.4
mlr75	0,0,0	5,1,6	mlr	3.1e-04	0.60	21	OISST23402; OSCAR213625; OISST23395	0.01	0.12	0.14	0.48	0.40	14.1	46.1	40.4	45.6	36.6	23.4
mlr76	0,0,0	5,1,5	mlr	3.1e-04	0.60	21	OISST23402; OSCAR213625; OISST23362	0.01	0.12	0.14	0.49	0.40	12.1	44.0	42.5	47.7	36.6	27.9
mlr70	0,0,0	5,1,6	mlr	2.8e-04	0.60	21	OISST23402; OSCAR213625; OISST23369	-0.02	0.13	0.14	0.47	0.41	14.9	48.7	40.2	44.0	37.0	20.9
mlr83	0,0,0	5,1,6	mlr	3.3e-04	0.59	21	OISST23402; OSCAR213625; OISST23396	0.01	0.12	0.14	0.48	0.41	12.3	47.5	41.5	46.8	37.0	23.7
mlr86	0,0,0	5,1,5	mlr	3.6e-04	0.59	21	OISST23402; OSCAR213625; OISST23346	0.02	0.12	0.14	0.49	0.39	15.1	43.1	42.6	47.7	37.1	28.5
mlr85	0,0,0	5,1,5	mlr	3.5e-04	0.59	21	OISST23402; OSCAR213625; OISST23365	0.02	0.12	0.14	0.48	0.40	15.8	44.9	41.7	46.8	37.3	29.4
OSCAR213625	0	1	lm	1.5e-04	0.51	21	v	0.05	0.10	0.13	0.43	0.35	56.2	31.3	28.5	33.2	37.3	26.8
mlr84	0,0,0	5,1,5	mlr	3.4e-04	0.59	21	OISST23402; OSCAR213625; OISST23354	0.01	0.12	0.15	0.49	0.41	9.1	47.2	44.0	49.2	37.4	27.8
mlr74	0,0,0	5,1,6	mlr	3.0e-04	0.60	21	OISST23402; OSCAR213625; OISST23398	-0.02	0.12	0.14	0.48	0.41	17.2	47.4	41.1	45.5	37.8	21.6
mlr62	0,0,0	5,1,6	mlr	2.4e-04	0.61	21	OISST23402; OSCAR213625; OISST23349	-0.02	0.13	0.14	0.47	0.42	20.1	50.7	39.9	41.8	38.1	19.3
mlr89	0,0,0	5,1,5	mlr	3.7e-04	0.59	21	OISST23402; OSCAR213625; OISST23347	0.01	0.13	0.15	0.50	0.42	4.9	50.5	45.9	51.3	38.2	27.5
mlr69	0,0,0	5,1,6	mlr	2.8e-04	0.60	21	OISST23402; OSCAR213625; OISST23410	-0.02	0.12	0.14	0.48	0.41	22.0	47.8	41.0	44.7	38.9	20.8
mlr88	0,0,0	5,1,5	mlr	3.7e-04	0.59	21	OISST23402; OSCAR213625; OISST23385	0.02	0.12	0.15	0.49	0.40	17.9	45.9	43.7	48.9	39.1	30.4
mlr56	0,0,0	5,1,6	mlr	2.0e-04	0.62	21	OISST23402; OSCAR213625; OISST23345	-0.02	0.13	0.14	0.46	0.43	24.4	52.6	40.3	40.0	39.3	18.0
mlr90	0,0,0	5,1,5	mlr	3.7e-04	0.59	21	OISST23402; OSCAR213625; OISST23358	0.02	0.12	0.15	0.50	0.40	18.2	44.6	44.7	50.0	39.4	29.7
mlr92	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23342	0.01	0.12	0.15	0.50	0.41	11.9	48.0	46.3	51.6	39.4	28.4
mlr64	0,0,0	5,1,6	mlr	2.5e-04	0.61	21	OISST23402; OSCAR213625; OISST23372	-0.03	0.13	0.14	0.47	0.42	26.2	50.1	41.2	43.5	40.3	19.6
mlr100	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23343	0.01	0.13	0.15	0.52	0.43	6.1	51.8	49.1	54.6	40.4	27.9
mlr95	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23348	-0.00	0.13	0.15	0.52	0.44	0.0	55.5	50.2	55.8	40.4	27.1
mlr96	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23350	0.02	0.12	0.15	0.51	0.41	16.5	46.4	46.6	52.0	40.4	29.4
nepstar9	-1,-1,0	7,1,3	mlr	7.1e-08	0.72	30	nepstar	0.03	0.11	0.15	0.51	0.36	27.9	34.0	47.8	52.5	40.5	16.2
mlr63	0,0,0	5,1,6	mlr	2.4e-04	0.61	21	OISST23402; OSCAR213625; OISST23391	-0.03	0.13	0.14	0.47	0.42	30.7	50.8	41.7	43.2	41.6	19.1
mlr101	0,0,0	5,1,5	mlr	3.9e-04	0.59	21	OISST23402; OSCAR213625; OISST23361	-0.00	0.14	0.16	0.53	0.45	0.3	58.4	51.9	57.3	42.0	27.2
mlr60	0,0,0	5,1,6	mlr	2.2e-04	0.61	21	OISST23402; OSCAR213625; OISST23363	-0.03	0.13	0.14	0.47	0.43	32.7	52.6	42.0	41.8	42.3	18.4
mlr59	0,0,0	5,1,6	mlr	2.2e-04	0.62	21	OISST23402; OSCAR213625; OISST23399	-0.04	0.13	0.14	0.47	0.43	36.7	53.1	42.8	42.0	43.6	18.3
mlr55	0,0,0	5,1,6	mlr	1.9e-04	0.62	21	OISST23402; OSCAR213625; OISST23381	-0.04	0.13	0.15	0.46	0.44	39.5	55.2	43.8	40.5	44.8	17.5
mlr102	0,0,0	5,1,5	mlr	3.9e-04	0.59	21	OISST23402; OSCAR213625; OISST23352	-0.01	0.14	0.16	0.53	0.46	7.4	60.8	53.1	58.7	45.0	26.6
mlr91	0,0,0	5,1,5	mlr	3.7e-04	0.59	21	OISST23402; OSCAR213625; OISST23375	-0.01	0.14	0.16	0.54	0.48	12.6	64.6	55.2	60.8	48.3	26.8
mlr103	0,0,0	5,1,5	mlr	3.9e-04	0.59	21	OISST23402; OSCAR213625; OISST23371	-0.01	0.15	0.16	0.54	0.48	14.3	65.2	55.0	60.4	48.7	26.2
mlr87	0,0,0	5,1,5	mlr	3.6e-04	0.59	21	OISST23402; OSCAR213625; OISST23376	-0.01	0.15	0.16	0.55	0.49	6.6	69.0	58.5	63.7	49.5	27.2
mlr98	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23370	-0.02	0.14	0.16	0.55	0.47	18.4	64.0	56.6	62.5	50.4	26.3
mlr99	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23407	-0.02	0.15	0.16	0.54	0.49	19.4	67.2	55.6	60.4	50.6	25.6
OISST23405	0	6	lm	3.2e-06	0.50	32	truetemp	-0.03	0.14	0.16	0.54	0.46	34.0	59.7	56.7	61.0	52.8	32.1
mlr105	0,0,0	5,1,5	mlr	3.9e-04	0.59	21	OISST23402; OSCAR213625; OISST23373	-0.02	0.15	0.16	0.55	0.49	23.4	67.3	57.7	63.5	53.0	25.8
OISST23400	0	5	lm	2.8e-06	0.51	32	truetemp	-0.05	0.14	0.15	0.51	0.47	49.2	63.4	48.8	52.8	53.5	35.5
mlr94	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23408	-0.02	0.15	0.17	0.56	0.50	18.4	71.3	60.6	65.8	54.0	26.6
OISST23403	0	5	lm	3.0e-06	0.51	32	truetemp	-0.03	0.15	0.16	0.54	0.49	31.4	68.8	55.4	60.4	54.0	37.5
mlr97	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23404	-0.03	0.15	0.16	0.56	0.49	25.4	67.8	59.2	65.0	54.3	26.2
mlr107	0,0,0	5,1,5	mlr	3.9e-04	0.59	21	OISST23402; OSCAR213625; OISST23389	-0.03	0.15	0.16	0.55	0.50	26.7	69.5	57.9	63.3	54.4	25.5
mlr93	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23383	0.01	0.16	0.18	0.58	0.53	4.5	77.9	68.7	72.4	55.9	27.1

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
mlr104	0,0,0	5,1,5	mlr	3.9e-04	0.59	21	OISST23402; OSCAR213625; OISST23397	-0.03	0.15	0.17	0.56	0.49	31.3	67.8	59.8	65.7	56.1	25.7
OISST23380	0	5	lm	1.8e-06	0.52	32	truetemp	-0.05	0.15	0.16	0.53	0.49	49.8	67.5	53.1	57.3	56.9	36.0
mlr106	0,0,0	5,1,5	mlr	3.9e-04	0.59	21	OISST23402; OSCAR213625; OISST23406	-0.03	0.15	0.17	0.56	0.50	34.4	70.6	59.5	65.1	57.4	25.3
OISST23385	0	5	lm	2.0e-06	0.52	32	truetemp	-0.03	0.16	0.17	0.55	0.51	34.5	73.2	59.9	64.8	58.1	37.5
mlr17	0,0	5,6	mlr	1.3e-04	0.59	21	OISST23402; OISST23405	-0.08	0.12	0.16	0.51	0.41	79.5	47.7	51.9	54.0	58.3	35.0
mlr19	0,0	5,5	mlr	1.4e-04	0.59	21	OISST23402; OISST23400	-0.06	0.15	0.16	0.52	0.48	61.1	65.1	53.3	56.8	59.1	39.0
OISST23395	0	6	lm	2.6e-06	0.51	32	truetemp	-0.05	0.14	0.17	0.55	0.46	55.1	59.3	59.8	62.3	59.1	34.9
OISST23390	0	5	lm	2.3e-06	0.51	32	truetemp	-0.07	0.14	0.15	0.51	0.47	71.3	61.9	50.6	53.5	59.4	35.0
OISST23374	0	6	lm	1.5e-06	0.53	32	truetemp	-0.05	0.14	0.17	0.54	0.46	55.0	60.9	60.1	62.2	59.6	32.3
mlr28	0,0	5,5	mlr	1.5e-04	0.58	21	OISST23402; OISST23403	-0.05	0.15	0.16	0.53	0.49	57.4	67.0	55.1	59.1	59.7	39.3
mlr11	0,0	5,5	mlr	1.2e-04	0.59	21	OISST23402; OISST23390	-0.06	0.15	0.16	0.52	0.48	64.7	65.6	53.5	56.7	60.1	38.4
mlr27	0,0	5,5	mlr	1.5e-04	0.58	21	OISST23402; OISST23380	-0.05	0.15	0.16	0.53	0.49	56.6	68.7	55.7	59.7	60.2	39.0
mlr16	0,0	5,6	mlr	1.3e-04	0.59	21	OISST23402; OISST23374	-0.08	0.12	0.16	0.52	0.41	85.8	46.7	55.3	56.3	61.0	34.8
mlr22	0,0	5,6	mlr	1.4e-04	0.58	21	OISST23402; OISST23395	-0.08	0.12	0.16	0.52	0.41	85.8	47.6	55.1	56.4	61.2	36.6
mlr37	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23385	-0.05	0.15	0.16	0.54	0.50	55.2	70.2	57.7	61.8	61.2	38.9
OISST23353	0	6	lm	9.6e-07	0.54	32	truetemp	-0.05	0.15	0.17	0.55	0.48	55.3	64.9	62.1	63.8	61.5	29.8
OISST23365	0	5	lm	1.3e-06	0.53	32	truetemp	-0.05	0.15	0.16	0.54	0.51	53.4	72.6	58.1	62.2	61.6	36.5
OISST23367	0	5	lm	1.4e-06	0.53	32	truetemp	-0.07	0.15	0.16	0.53	0.48	71.4	66.2	54.1	57.3	62.2	35.1
mlr79	0,0,0	5,1,5	mlr	3.3e-04	0.60	21	OISST23402; OSCAR213625; OISST23394	0.02	0.16	0.18	0.60	0.52	24.9	75.3	73.3	75.9	62.3	25.8
mlr6	0,0	5,6	mlr	1.2e-04	0.59	21	OISST23402; OISST23353	-0.08	0.13	0.16	0.52	0.41	87.2	48.6	56.7	57.0	62.4	32.6
mlr24	0,0	5,5	mlr	1.4e-04	0.58	21	OISST23402; OISST23367	-0.06	0.15	0.16	0.55	0.51	60.5	72.0	58.7	62.5	63.4	38.8
mlr34	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23365	-0.06	0.15	0.16	0.55	0.51	58.7	72.7	59.3	63.3	63.5	39.0
OISST23402	0	5	lm	3.0e-06	0.51	32	truetemp	-0.08	0.14	0.16	0.53	0.46	86.6	59.7	55.8	58.7	65.2	37.1
mlr25	0,0	5,6	mlr	1.5e-04	0.58	21	OISST23402; OISST23396	-0.09	0.13	0.17	0.54	0.41	94.0	48.1	60.1	60.3	65.6	37.2
mlr18	0,0	5,6	mlr	1.3e-04	0.59	21	OISST23402; OISST23364	-0.09	0.13	0.17	0.54	0.41	94.0	48.8	60.5	60.2	65.9	35.3
OISST23355	0	5	lm	9.9e-07	0.54	32	truetemp	-0.07	0.15	0.16	0.54	0.50	72.0	71.1	58.6	62.2	66.0	35.5
mlr9	0,0	5,6	mlr	1.2e-04	0.59	21	OISST23402; OISST23344	-0.09	0.13	0.17	0.54	0.42	94.5	50.2	61.2	60.6	66.6	33.0
OISST23358	0	5	lm	1.1e-06	0.54	32	truetemp	-0.06	0.16	0.17	0.57	0.53	57.9	78.2	64.0	67.8	67.0	36.9
OISST23364	0	6	lm	1.3e-06	0.53	32	truetemp	-0.07	0.14	0.17	0.56	0.47	73.4	62.1	67.0	67.2	67.4	34.3
OISST23344	0	6	lm	8.0e-07	0.55	32	truetemp	-0.07	0.15	0.17	0.57	0.48	71.2	64.8	67.3	67.5	67.7	31.7
mlr43	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23358	-0.06	0.16	0.17	0.57	0.53	62.3	77.4	63.9	67.5	67.8	38.9
OISST23378	0	5	lm	1.8e-06	0.52	32	truetemp	-0.08	0.14	0.16	0.54	0.48	86.9	64.3	58.5	61.7	67.9	36.5
OISST23396	0	6	lm	2.7e-06	0.51	32	truetemp	-0.07	0.14	0.17	0.57	0.47	74.3	62.2	67.8	68.3	68.1	37.2
mlr30	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23355	-0.06	0.16	0.17	0.57	0.53	63.6	77.1	64.0	68.1	68.2	39.0
mlr2	0,0	5,6	mlr	1.1e-04	0.60	21	OISST23402; OISST23345	-0.09	0.13	0.17	0.55	0.43	98.3	52.4	63.8	62.7	69.3	31.9
mlr23	0,0	5,6	mlr	1.4e-04	0.58	21	OISST23402; OISST23386	-0.09	0.13	0.17	0.55	0.43	99.9	52.2	64.9	64.6	70.4	36.1
mlr15	0,0	5,6	mlr	1.3e-04	0.59	21	OISST23402; OISST23356	-0.09	0.13	0.17	0.55	0.43	99.4	53.4	65.3	64.8	70.7	34.0
OISST23345	0	6	lm	8.3e-07	0.55	32	truetemp	-0.07	0.15	0.18	0.58	0.50	71.7	70.0	70.8	70.8	70.8	31.8
OISST23346	0	5	lm	8.4e-07	0.55	32	truetemp	-0.07	0.16	0.17	0.57	0.53	76.0	76.9	64.4	67.8	71.3	36.1
mlr48	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23350	-0.07	0.16	0.17	0.58	0.54	68.7	80.6	67.1	70.3	71.7	38.6
OISST23362	0	5	lm	1.2e-06	0.53	32	truetemp	-0.08	0.15	0.17	0.56	0.50	89.1	69.6	62.5	65.8	71.7	36.2
OISST23350	0	5	lm	9.5e-07	0.54	32	truetemp	-0.06	0.17	0.18	0.58	0.55	63.7	82.8	68.6	72.0	71.8	36.8

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
mlr8	0,0	5,6	mlr	1.2e-04	0.59	21	OISST23402; OISST23349	-0.10	0.13	0.17	0.56	0.44	102.0	54.0	66.9	66.0	72.2	33.0
OISST23356	0	6	lm	1.1e-06	0.54	32	truetemp	-0.08	0.15	0.18	0.59	0.49	79.9	66.7	73.2	73.5	73.3	34.4
mlr39	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23346	-0.07	0.17	0.18	0.59	0.54	71.7	81.8	69.0	72.8	73.8	39.2
OISST23394	0	5	lm	2.6e-06	0.51	32	truetemp	-0.09	0.15	0.17	0.58	0.49	92.1	66.9	66.6	70.8	74.1	39.6
mlr21	0,0	5,6	mlr	1.4e-04	0.59	21	OISST23402; OISST23384	-0.10	0.14	0.18	0.57	0.45	102.6	56.6	68.4	69.1	74.2	35.1
OISST23349	0	6	lm	9.3e-07	0.54	32	truetemp	-0.08	0.15	0.18	0.60	0.49	79.2	69.1	74.9	75.2	74.6	33.8
OISST23386	0	6	lm	2.1e-06	0.52	32	truetemp	-0.08	0.15	0.18	0.59	0.49	83.2	68.7	74.3	74.4	75.1	36.9
mlr3	0,0	5,6	mlr	1.1e-04	0.60	21	OISST23402; OISST23381	-0.10	0.13	0.18	0.57	0.44	107.5	55.5	69.6	67.9	75.2	32.2
mlr13	0,0	5,6	mlr	1.3e-04	0.59	21	OISST23402; OISST23369	-0.10	0.14	0.18	0.57	0.45	104.9	57.5	69.5	69.8	75.4	34.1
mlr4	0,0	5,6	mlr	1.1e-04	0.59	21	OISST23402; OISST23363	-0.10	0.13	0.18	0.57	0.44	107.9	54.7	70.2	69.0	75.5	32.7
OISST23354	0	5	lm	9.8e-07	0.54	32	truetemp	-0.09	0.16	0.17	0.58	0.52	92.5	75.5	67.8	71.2	76.7	36.2
mlr20	0,0	5,5	mlr	1.4e-04	0.59	21	OISST23402; OISST23378	-0.07	0.17	0.18	0.61	0.55	71.8	84.1	73.9	79.0	77.2	40.3
mlr10	0,0	5,6	mlr	1.2e-04	0.59	21	OISST23402; OISST23372	-0.10	0.14	0.18	0.58	0.45	109.4	57.4	71.8	71.4	77.5	33.5
OISST23342	0	5	lm	7.8e-07	0.55	32	truetemp	-0.08	0.17	0.18	0.59	0.55	80.7	83.5	71.4	74.5	77.5	36.8
mlr5	0,0	5,6	mlr	1.1e-04	0.59	21	OISST23402; OISST23399	-0.11	0.13	0.18	0.58	0.44	112.9	55.7	72.8	71.2	78.2	33.3
OISST23381	0	6	lm	1.8e-06	0.52	32	truetemp	-0.07	0.16	0.19	0.61	0.54	75.5	79.3	78.9	79.1	78.2	34.7
mlr35	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23394	-0.09	0.15	0.18	0.61	0.50	92.2	70.4	72.7	78.0	78.3	41.2
mlr7	0,0	5,6	mlr	1.2e-04	0.59	21	OISST23402; OISST23391	-0.11	0.13	0.18	0.58	0.44	112.5	56.1	72.9	72.0	78.3	33.6
OISST23363	0	6	lm	1.3e-06	0.53	32	truetemp	-0.08	0.16	0.19	0.61	0.52	80.5	75.7	79.3	79.6	78.8	34.9
OISST23383	0	5	lm	2.0e-06	0.52	32	truetemp	-0.09	0.15	0.18	0.60	0.51	96.8	72.7	70.8	75.1	78.8	39.0
OISST23369	0	6	lm	1.5e-06	0.53	32	truetemp	-0.08	0.15	0.19	0.62	0.51	83.4	72.1	79.4	81.1	79.0	35.8
OISST23384	0	6	lm	2.0e-06	0.52	32	truetemp	-0.08	0.15	0.19	0.62	0.51	83.4	72.9	79.0	81.0	79.0	36.7
mlr14	0,0	5,6	mlr	1.3e-04	0.59	21	OISST23402; OISST23398	-0.10	0.14	0.18	0.59	0.46	111.1	59.1	72.9	73.7	79.2	34.6
mlr46	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23342	-0.08	0.17	0.18	0.61	0.57	79.2	86.9	74.5	77.8	79.6	39.3
mlr12	0,0	5,6	mlr	1.2e-04	0.59	21	OISST23402; OISST23410	-0.11	0.14	0.18	0.59	0.45	114.1	57.9	73.5	73.6	79.8	34.5
OISST23372	0	6	lm	1.5e-06	0.53	32	truetemp	-0.08	0.15	0.19	0.63	0.51	84.8	72.9	81.7	82.9	80.6	36.1
mlr26	0,0	5,5	mlr	1.5e-04	0.58	21	OISST23402; OISST23362	-0.08	0.17	0.19	0.62	0.56	81.7	86.6	77.3	82.3	82.0	39.9
OISST23391	0	6	lm	2.4e-06	0.51	32	truetemp	-0.08	0.16	0.19	0.63	0.52	84.6	76.8	83.4	84.4	82.3	37.4
OISST23347	0	5	lm	8.8e-07	0.54	32	truetemp	-0.09	0.17	0.18	0.60	0.55	96.4	81.9	73.9	77.2	82.4	36.7
OISST23399	0	6	lm	2.8e-06	0.51	32	truetemp	-0.08	0.16	0.19	0.63	0.54	82.4	80.4	83.3	83.6	82.4	37.4
OISST23343	0	5	lm	8.0e-07	0.55	32	truetemp	-0.08	0.17	0.19	0.61	0.57	85.2	89.0	77.1	79.8	82.8	37.3
mlr53	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23343	-0.08	0.18	0.19	0.61	0.58	86.3	89.6	77.4	80.2	83.4	39.3
OISST23410	0	6	lm	3.5e-06	0.50	32	truetemp	-0.08	0.16	0.20	0.64	0.51	88.4	73.2	85.2	87.2	83.5	38.9
OISST23398	0	6	lm	2.7e-06	0.51	32	truetemp	-0.08	0.16	0.20	0.64	0.52	87.6	75.0	84.7	87.5	83.7	38.0
OISST23376	0	5	lm	1.7e-06	0.52	32	truetemp	-0.10	0.16	0.19	0.62	0.53	103.1	79.1	76.6	80.9	84.9	38.4
mlr33	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23354	-0.09	0.17	0.19	0.64	0.58	90.2	89.5	80.9	85.7	86.6	40.0
mlr51	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23361	-0.09	0.18	0.19	0.62	0.58	94.5	91.4	79.8	81.8	86.9	39.6
OISST23348	0	5	lm	8.9e-07	0.54	32	truetemp	-0.10	0.17	0.19	0.63	0.57	100.9	89.4	81.5	84.5	89.1	37.5
OISST23361	0	5	lm	1.2e-06	0.54	32	truetemp	-0.09	0.18	0.19	0.64	0.60	90.3	96.0	84.1	86.3	89.2	38.7
mlr41	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23347	-0.09	0.18	0.19	0.65	0.59	97.6	92.2	83.9	88.0	90.4	40.1
mlr32	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23383	-0.10	0.17	0.20	0.66	0.55	104.3	84.3	85.8	92.0	91.6	42.6
OISST23375	0	5	lm	1.5e-06	0.53	32	truetemp	-0.10	0.17	0.19	0.64	0.56	109.8	86.2	83.5	87.6	91.8	38.3

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	retro rank	jackk rank
OISST23352	0	5	lm	9.6e-07	0.54	32	truetemp	-0.10	0.18	0.20	0.65	0.60	104.1	95.6	87.3	90.0	94.2	38.5
mlr49	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23348	-0.10	0.18	0.20	0.66	0.60	104.1	96.2	88.0	91.4	94.9	40.3
mlr50	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23352	-0.10	0.18	0.20	0.66	0.61	108.0	97.7	89.1	91.8	96.6	40.3
mlr52	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23371	-0.10	0.18	0.20	0.65	0.61	110.5	97.8	88.6	90.4	96.8	40.5
mlr40	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23407	-0.11	0.18	0.20	0.65	0.61	114.1	97.9	88.9	89.8	97.7	41.5
OISST23408	0	5	lm	3.5e-06	0.50	32	truetemp	-0.11	0.18	0.20	0.68	0.58	112.2	90.0	91.8	97.5	97.9	41.4
mlr31	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23376	-0.11	0.18	0.20	0.68	0.58	114.0	91.0	91.3	97.1	98.4	41.8
OISST23370	0	5	lm	1.5e-06	0.53	32	truetemp	-0.11	0.18	0.20	0.67	0.59	114.6	94.3	91.1	94.9	98.7	39.2
OISST23371	0	5	lm	1.5e-06	0.53	32	truetemp	-0.10	0.19	0.21	0.67	0.63	106.0	102.4	93.1	95.3	99.2	40.6
mlr29	0,0	5,5	mlr	1.5e-04	0.58	21	OISST23402; OISST23408	-0.12	0.17	0.20	0.68	0.57	122.3	87.2	91.4	97.4	99.6	42.3
mlr38	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23375	-0.11	0.18	0.21	0.69	0.60	121.2	94.6	94.0	99.2	102.2	41.4
OISST23373	0	5	lm	1.5e-06	0.53	32	truetemp	-0.11	0.19	0.21	0.69	0.62	117.4	100.9	96.7	100.0	103.8	40.4
mlr47	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23389	-0.12	0.19	0.21	0.68	0.62	123.7	101.2	95.1	97.2	104.3	41.5
OISST23404	0	5	lm	3.1e-06	0.51	32	truetemp	-0.11	0.18	0.21	0.71	0.61	119.5	97.8	99.2	104.5	105.2	41.8
mlr45	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23370	-0.12	0.19	0.21	0.70	0.61	124.3	98.9	96.9	101.1	105.3	41.3
OISST23407	0	5	lm	3.4e-06	0.50	32	truetemp	-0.10	0.20	0.21	0.70	0.66	108.7	110.3	100.4	101.9	105.3	43.9
mlr54	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23373	-0.12	0.19	0.21	0.69	0.62	124.8	100.8	96.8	100.2	105.6	41.2
mlr36	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23404	-0.12	0.18	0.21	0.70	0.59	129.8	94.5	97.5	103.0	106.2	42.3
OISST23389	0	5	lm	2.2e-06	0.52	32	truetemp	-0.11	0.20	0.22	0.71	0.65	118.1	107.7	101.5	104.1	107.9	42.5
mlr42	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23406	-0.12	0.19	0.21	0.70	0.62	131.5	101.8	98.8	101.9	108.5	42.3
mlr44	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23397	-0.12	0.19	0.21	0.71	0.61	132.2	99.3	99.7	104.2	108.9	42.2
OISST23397	0	5	lm	2.7e-06	0.51	32	truetemp	-0.12	0.19	0.22	0.73	0.63	123.8	104.4	104.1	108.7	110.3	42.5
mean.all	0	0	mean.all	NA			mean.all	-0.08	0.22	0.24	0.77	0.71	79.8	124.2	119.9	120.0	111.0	134.9
OISST23406	0	5	lm	3.2e-06	0.50	32	truetemp	-0.12	0.20	0.22	0.74	0.66	125.5	111.1	107.9	111.5	114.0	44.1
mean8	0	0	mean8	NA			mean8	0.11	0.20	0.25	0.81	0.64	114.8	106.8	129.5	129.6	120.2	77.0
mean4	0	0	mean4	NA			mean4	0.10	0.26	0.30	0.98	0.86	100.7	161.8	174.4	174.4	152.8	95.4
median.all	0	0	median.all	NA			median.all	-0.16	0.25	0.27	0.89	0.81	165.9	148.7	151.0	151.0	154.2	184.0
lly	0	0	lly	NA			lly	0.08	0.29	0.31	1.00	0.95	82.8	184.0	179.1	179.1	156.3	89.1
median8	0	0	median8	NA			median8	0.17	0.22	0.28	0.92	0.74	184.0	130.6	158.5	158.5	157.9	96.8
median4	0	0	median4	NA			median4	0.13	0.28	0.31	1.02	0.91	137.4	173.6	184.0	184.0	169.8	101.9

Table 19. Performance results for all qualifying models used to forecast Fraser diversion based on jackknife analysis. Each row represents a single model tested, some columns include: year adjust (year of environmental data same as return year [0] or prior year [-1]), month, summary statistics (P value, adjusted R squared, sample size), data name, data variables (which are sorted by their relative influence in the model). As the NEPSTAR regression models comprise more than one variable, only year-month of the latest variable is presented. Latitude and longtitude of NEPSTAR variables are excluded due to space limitations. The PMs include mean raw error, mean absolute error, root mean squared error, Thiel's U-statistic, and MASE. The initial three PMs are in percent diversion units, the latter two are unit-less. All PMs are described in the methods section. All PMs, except MASE, are given a rank. The best rank has a value of zero. The last rank equals total number of models (n). The average of the PM ranks by model (row) is included, as is the average rank for the alternate performance test method. The rows are sorted by average rank of performance method listed in caption. The first row is the best model, the last row is the worst.

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
nepstar4	-1,-1,0	7,1,1	mlr	4.8e-08	0.72	30	nepstar	0.01	0.09	0.11	0.43	0.40	4.0	0.0	0.0	8.2	3.0	13.0
nepstar3	-1,0,-1,0	1,4,4,1	mlr	2.1e-08	0.77	30	nepstar	-0.00	0.10	0.12	0.39	0.44	1.1	7.3	6.1	0.0	3.6	11.3
nepstar14	-1,-1,-1,0	7,1,4,1	mlr	5.7e-08	0.75	30	nepstar	0.00	0.09	0.11	0.43	0.42	2.5	3.7	1.7	7.3	3.8	15.8
nepstar8	-1,-1,0,0	7,1,4,1	mlr	4.0e-08	0.75	30	nepstar	0.01	0.09	0.12	0.41	0.44	3.9	6.3	5.9	3.9	5.0	12.6
nepstar7	-1,-1,0	6,1,1	mlr	1.1e-07	0.71	30	nepstar	0.01	0.09	0.12	0.44	0.41	6.6	1.8	3.6	9.2	5.3	1.4
nepstar12	-1,-1,0,0	6,1,4,1	mlr	1.5e-07	0.73	30	nepstar	0.01	0.09	0.12	0.40	0.44	5.5	6.9	7.7	1.6	5.4	16.4
nepstar5	-1,-1,0,0	6,1,4,1	mlr	5.5e-08	0.75	30	nepstar	0.01	0.10	0.12	0.40	0.46	4.5	10.2	7.6	2.3	6.1	17.5
nepstar10	-1,-1,0	1,4,1	mlr	6.2e-08	0.72	30	nepstar	-0.00	0.10	0.12	0.44	0.45	0.9	9.1	6.4	9.5	6.5	8.3
nepstar11	-1,-1,0,0	7,1,3,1	mlr	6.4e-08	0.75	30	nepstar	-0.00	0.09	0.12	0.47	0.43	0.3	4.4	6.0	15.6	6.6	25.5
nepstar2	-1,-1,-1,0	7,1,4,1	mlr	2.2e-08	0.77	30	nepstar	0.00	0.10	0.12	0.45	0.45	1.9	9.5	5.6	12.7	7.4	20.2
nepstar15	-1,-1,0,0,0	6,1,4,3,1	mlr	1.4e-07	0.75	30	nepstar	0.00	0.10	0.13	0.44	0.49	0.0	15.7	12.4	10.9	9.7	27.6
nepstar1	-1,-1,0	1,4,1	mlr	1.9e-08	0.74	30	nepstar	-0.00	0.10	0.12	0.47	0.48	1.3	14.4	10.9	16.1	10.7	13.1
nepstar13	-1,-1,0,0	6,1,3,1	mlr	1.1e-07	0.73	30	nepstar	0.00	0.10	0.12	0.48	0.48	1.2	15.3	10.4	18.3	11.3	19.9
nepstar9	-1,-1,0	7,1,3	mlr	7.1e-08	0.72	30	nepstar	-0.00	0.11	0.13	0.53	0.50	0.2	18.3	18.3	27.9	16.2	40.9
mlr55	0,0,0	5,1,6	mlr	1.9e-04	0.62	21	OISST23402; OSCAR213625; OISST23381	0.00	0.12	0.13	0.51	0.54	0.7	26.7	18.9	23.6	17.5	38.1
mlr56	0,0,0	5,1,6	mlr	2.0e-04	0.62	21	OISST23402; OSCAR213625; OISST23345	0.00	0.12	0.13	0.51	0.55	1.8	27.3	19.0	23.8	18.0	35.7
mlr59	0,0,0	5,1,6	mlr	2.2e-04	0.62	21	OISST23402; OSCAR213625; OISST23399	0.00	0.12	0.14	0.52	0.54	1.5	26.7	20.2	24.6	18.3	37.5
mlr60	0,0,0	5,1,6	mlr	2.2e-04	0.61	21	OISST23402; OSCAR213625; OISST23363	0.00	0.12	0.14	0.52	0.55	1.8	27.2	20.0	24.4	18.4	36.9
mlr63	0,0,0	5,1,6	mlr	2.4e-04	0.61	21	OISST23402; OSCAR213625; OISST23391	0.00	0.12	0.14	0.52	0.55	2.4	27.5	21.3	25.4	19.1	36.7
nepstar6	-1,-1,0	6,1,3	mlr	1.2e-07	0.70	30	nepstar	0.00	0.11	0.14	0.54	0.53	2.4	23.7	21.5	29.1	19.2	26.2
mlr62	0,0,0	5,1,6	mlr	2.4e-04	0.61	21	OISST23402; OSCAR213625; OISST23349	0.00	0.12	0.14	0.52	0.55	2.8	28.7	20.6	24.9	19.3	35.1
mlr64	0,0,0	5,1,6	mlr	2.5e-04	0.61	21	OISST23402; OSCAR213625; OISST23372	0.00	0.12	0.14	0.52	0.55	2.8	28.3	21.6	25.7	19.6	36.2
mlr57	0,0,0	5,1,6	mlr	2.0e-04	0.62	21	OISST23402; OSCAR213625; OISST23353	0.01	0.12	0.14	0.52	0.56	3.3	30.5	20.0	25.3	19.8	32.7
mlr61	0,0,0	5,1,6	mlr	2.3e-04	0.61	21	OISST23402; OSCAR213625; OISST23344	0.01	0.12	0.14	0.52	0.56	3.4	30.3	20.5	25.4	19.9	33.6
mlr1	0,0	5,1	mlr	8.0e-05	0.61	21	OISST23402; OSCAR213625	0.01	0.12	0.14	0.52	0.56	5.5	29.9	21.2	25.9	20.6	24.3
mlr69	0,0,0	5,1,6	mlr	2.8e-04	0.60	21	OISST23402; OSCAR213625; OISST23410	0.01	0.12	0.14	0.53	0.56	3.6	29.5	23.1	27.0	20.8	35.7
mlr70	0,0,0	5,1,6	mlr	2.8e-04	0.60	21	OISST23402; OSCAR213625; OISST23369	0.01	0.12	0.14	0.53	0.56	3.8	30.5	22.5	26.6	20.9	34.9
mlr68	0,0,0	5,1,6	mlr	2.8e-04	0.60	21	OISST23402; OSCAR213625; OISST23356	0.01	0.12	0.14	0.53	0.57	4.0	31.5	22.0	26.5	21.0	33.6
mlr74	0,0,0	5,1,6	mlr	3.0e-04	0.60	21	OISST23402; OSCAR213625; OISST23398	0.01	0.12	0.14	0.53	0.57	4.1	30.8	23.7	27.7	21.6	35.5
mlr66	0,0,0	5,1,6	mlr	2.6e-04	0.61	21	OISST23402; OSCAR213625; OISST23374	0.01	0.12	0.14	0.53	0.58	4.6	33.4	22.6	27.9	22.1	30.4
mlr73	0,0,0	5,1,6	mlr	2.9e-04	0.60	21	OISST23402; OSCAR213625; OISST23364	0.01	0.12	0.14	0.53	0.58	4.8	33.4	22.9	27.9	22.2	31.9

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr78	0,0,0	5,1,6	mlr	3.2e-04	0.60	21	OISST23402; OSCAR213625; OISST23384	0.01	0.12	0.14	0.54	0.58	4.7	33.1	24.0	28.4	22.5	33.7
mlr65	0,0,0	5,1,6	mlr	2.5e-04	0.61	21	OISST23402; OSCAR213625; OISST23405	0.01	0.13	0.14	0.54	0.58	4.5	34.3	23.3	28.7	22.7	28.1
mlr80	0,0,0	5,1,6	mlr	3.3e-04	0.60	21	OISST23402; OSCAR213625; OISST23386	0.01	0.13	0.14	0.54	0.58	5.1	34.3	24.2	28.9	23.1	32.3
mlr75	0,0,0	5,1,6	mlr	3.1e-04	0.60	21	OISST23402; OSCAR213625; OISST23395	0.01	0.13	0.14	0.54	0.59	4.9	34.8	24.4	29.5	23.4	29.3
mlr83	0,0,0	5,1,6	mlr	3.3e-04	0.59	21	OISST23402; OSCAR213625; OISST23396	0.01	0.13	0.14	0.54	0.59	5.2	35.1	24.7	29.7	23.7	30.8
mlr106	0,0,0	5,1,5	mlr	3.9e-04	0.59	21	OISST23402; OSCAR213625; OISST23406	0.01	0.13	0.14	0.55	0.59	6.8	35.8	26.9	31.7	25.3	31.5
mlr107	0,0,0	5,1,5	mlr	3.9e-04	0.59	21	OISST23402; OSCAR213625; OISST23389	0.01	0.13	0.14	0.56	0.59	7.2	35.8	27.0	31.9	25.5	31.0
mlr99	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23407	0.01	0.13	0.14	0.56	0.59	7.4	35.9	27.1	32.0	25.6	30.5
mlr104	0,0,0	5,1,5	mlr	3.9e-04	0.59	21	OISST23402; OSCAR213625; OISST23397	0.01	0.13	0.14	0.56	0.59	6.6	36.2	27.5	32.3	25.7	32.7
mlr105	0,0,0	5,1,5	mlr	3.9e-04	0.59	21	OISST23402; OSCAR213625; OISST23373	0.01	0.13	0.14	0.56	0.59	7.2	36.1	27.5	32.4	25.8	31.8
mlr79	0,0,0	5,1,5	mlr	3.3e-04	0.60	21	OISST23402; OSCAR213625; OISST23394	0.01	0.13	0.15	0.56	0.59	4.8	35.9	28.9	33.8	25.8	34.3
mlr103	0,0,0	5,1,5	mlr	3.9e-04	0.59	21	OISST23402; OSCAR213625; OISST23371	0.01	0.13	0.14	0.56	0.59	8.0	36.3	27.8	32.7	26.2	31.0
mlr97	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23404	0.01	0.13	0.15	0.56	0.60	6.3	37.3	28.3	33.0	26.2	33.8
mlr98	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23370	0.01	0.13	0.15	0.56	0.60	7.1	36.8	28.2	33.1	26.3	32.7
mlr102	0,0,0	5,1,5	mlr	3.9e-04	0.59	21	OISST23402; OSCAR213625; OISST23352	0.01	0.13	0.15	0.56	0.60	8.1	36.5	28.4	33.3	26.6	31.3
mlr94	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23408	0.01	0.13	0.15	0.56	0.60	5.4	38.3	29.2	33.7	26.6	33.8
mlr91	0,0,0	5,1,5	mlr	3.7e-04	0.59	21	OISST23402; OSCAR213625; OISST23375	0.01	0.13	0.15	0.56	0.60	6.4	38.1	29.0	33.8	26.8	32.9
OSCAR213625	0	1	lm	1.5e-04	0.51	21	v	0.02	0.12	0.15	0.57	0.58	10.5	33.1	29.4	34.4	26.8	22.9
mlr93	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23383	0.01	0.13	0.15	0.57	0.61	3.3	39.0	30.9	35.2	27.1	29.8
mlr95	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23348	0.01	0.13	0.15	0.57	0.60	8.1	37.2	29.1	34.1	27.1	31.4
mlr101	0,0,0	5,1,5	mlr	3.9e-04	0.59	21	OISST23402; OSCAR213625; OISST23361	0.01	0.13	0.15	0.57	0.60	8.8	37.0	29.0	34.0	27.2	30.7
mlr87	0,0,0	5,1,5	mlr	3.6e-04	0.59	21	OISST23402; OSCAR213625; OISST23376	0.01	0.13	0.15	0.57	0.61	5.1	39.1	30.1	34.6	27.2	31.8
mlr89	0,0,0	5,1,5	mlr	3.7e-04	0.59	21	OISST23402; OSCAR213625; OISST23347	0.01	0.13	0.15	0.57	0.60	7.6	38.2	29.7	34.7	27.5	30.7
mlr58	0,0,0	5,1,5	mlr	2.1e-04	0.62	21	OISST23402; OSCAR213625; OISST23390	0.01	0.13	0.15	0.57	0.61	6.2	38.7	29.9	35.6	27.6	28.4
mlr72	0,0,0	5,1,5	mlr	2.8e-04	0.60	21	OISST23402; OSCAR213625; OISST23378	0.01	0.13	0.15	0.57	0.61	4.2	40.2	30.8	35.7	27.7	25.5
mlr84	0,0,0	5,1,5	mlr	3.4e-04	0.59	21	OISST23402; OSCAR213625; OISST23354	0.01	0.13	0.15	0.57	0.61	6.7	39.0	30.2	35.1	27.8	29.8
mlr100	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23343	0.01	0.13	0.15	0.57	0.60	9.1	37.3	30.1	35.0	27.9	30.5
mlr76	0,0,0	5,1,5	mlr	3.1e-04	0.60	21	OISST23402; OSCAR213625; OISST23362	0.01	0.13	0.15	0.57	0.61	5.6	39.7	30.6	35.5	27.9	28.2
mlr71	0,0,0	5,1,5	mlr	2.8e-04	0.60	21	OISST23402; OSCAR213625; OISST23367	0.01	0.13	0.15	0.58	0.61	6.9	39.1	30.5	35.8	28.1	26.6
mlr81	0,0,0	5,1,5	mlr	3.3e-04	0.60	21	OISST23402; OSCAR213625; OISST23355	0.01	0.13	0.15	0.58	0.61	7.6	38.9	31.0	36.1	28.4	27.3
mlr92	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23342	0.01	0.13	0.15	0.58	0.60	9.1	38.0	30.9	35.8	28.4	29.8
mlr86	0,0,0	5,1,5	mlr	3.6e-04	0.59	21	OISST23402; OSCAR213625; OISST23346	0.01	0.13	0.15	0.58	0.61	8.4	38.6	31.0	36.1	28.5	28.4
mlr67	0,0,0	5,1,5	mlr	2.6e-04	0.61	21	OISST23402; OSCAR213625; OISST23400	0.01	0.13	0.15	0.58	0.61	7.3	38.9	31.5	37.0	28.7	28.8
mlr77	0,0,0	5,1,5	mlr	3.1e-04	0.60	21	OISST23402; OSCAR213625; OISST23380	0.01	0.13	0.15	0.58	0.61	7.9	39.1	32.1	37.4	29.1	27.1
mlr85	0,0,0	5,1,5	mlr	3.5e-04	0.59	21	OISST23402; OSCAR213625; OISST23365	0.01	0.13	0.15	0.58	0.61	8.7	39.1	32.4	37.6	29.4	26.8
mlr96	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23350	0.01	0.13	0.15	0.58	0.60	9.9	38.3	32.2	37.2	29.4	29.3
mlr90	0,0,0	5,1,5	mlr	3.7e-04	0.59	21	OISST23402; OSCAR213625; OISST23358	0.01	0.13	0.15	0.59	0.61	9.6	38.8	32.7	37.7	29.7	28.4
OISST23353	0	6	lm	9.6e-07	0.54	32	truetemp	-0.02	0.13	0.15	0.58	0.60	16.0	37.6	28.6	36.9	29.8	58.7
mlr82	0,0,0	5,1,5	mlr	3.3e-04	0.59	21	OISST23402; OSCAR213625; OISST23403	0.01	0.13	0.15	0.59	0.61	8.5	39.3	33.3	38.6	29.9	27.5
mlr88	0,0,0	5,1,5	mlr	3.7e-04	0.59	21	OISST23402; OSCAR213625; OISST23385	0.01	0.13	0.15	0.59	0.61	9.5	39.3	33.8	38.9	30.4	27.1
OISST23344	0	6	lm	8.0e-07	0.55	32	truetemp	-0.03	0.13	0.15	0.59	0.61	18.8	38.9	30.7	38.5	31.7	63.7
OISST23345	0	6	lm	8.3e-07	0.55	32	truetemp	-0.02	0.13	0.15	0.59	0.62	15.2	41.5	31.7	38.8	31.8	67.0

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr2	0,0	5,6	mlr	1.1e-04	0.60	21	OISST23402; OISST23345	-0.04	0.12	0.15	0.58	0.57	28.2	31.9	29.9	37.6	31.9	63.0
OISST23405	0	6	lm	3.2e-06	0.50	32	truetemp	-0.03	0.13	0.15	0.60	0.61	18.3	39.0	30.8	40.4	32.1	50.7
mlr3	0,0	5,6	mlr	1.1e-04	0.60	21	OISST23402; OISST23381	-0.04	0.12	0.15	0.59	0.58	27.9	32.8	30.3	37.8	32.2	67.5
OISST23374	0	6	lm	1.5e-06	0.53	32	truetemp	-0.03	0.13	0.15	0.60	0.60	20.8	38.2	30.6	39.6	32.3	56.6
mlr6	0,0	5,6	mlr	1.2e-04	0.59	21	OISST23402; OISST23353	-0.04	0.13	0.15	0.59	0.58	28.7	33.8	29.8	38.2	32.6	57.3
mlr4	0,0	5,6	mlr	1.1e-04	0.59	21	OISST23402; OISST23363	-0.04	0.13	0.15	0.59	0.58	28.3	33.6	30.9	38.1	32.7	67.6
mlr8	0,0	5,6	mlr	1.2e-04	0.59	21	OISST23402; OISST23349	-0.04	0.12	0.15	0.59	0.58	29.3	33.3	31.2	38.4	33.0	64.8
mlr9	0,0	5,6	mlr	1.2e-04	0.59	21	OISST23402; OISST23344	-0.04	0.12	0.15	0.59	0.57	29.9	32.5	30.8	38.8	33.0	60.8
mlr5	0,0	5,6	mlr	1.1e-04	0.59	21	OISST23402; OISST23399	-0.04	0.12	0.15	0.59	0.58	29.3	33.5	31.5	38.7	33.3	69.6
mlr10	0,0	5,6	mlr	1.2e-04	0.59	21	OISST23402; OISST23372	-0.04	0.13	0.15	0.59	0.58	29.3	34.0	32.0	38.9	33.5	68.2
mlr7	0,0	5,6	mlr	1.2e-04	0.59	21	OISST23402; OISST23391	-0.04	0.13	0.15	0.59	0.58	29.6	33.8	32.0	38.9	33.6	69.2
OISST23349	0	6	lm	9.3e-07	0.54	32	truetemp	-0.02	0.14	0.15	0.60	0.63	17.0	43.5	34.2	40.6	33.8	69.7
mlr15	0,0	5,6	mlr	1.3e-04	0.59	21	OISST23402; OISST23356	-0.04	0.12	0.15	0.60	0.57	31.4	32.6	32.1	39.7	34.0	63.4
mlr13	0,0	5,6	mlr	1.3e-04	0.59	21	OISST23402; OISST23369	-0.04	0.12	0.15	0.59	0.58	30.9	33.5	32.5	39.5	34.1	66.1
OISST23364	0	6	lm	1.3e-06	0.53	32	truetemp	-0.03	0.13	0.15	0.60	0.61	23.9	39.7	32.5	41.0	34.3	63.1
OISST23356	0	6	lm	1.1e-06	0.54	32	truetemp	-0.03	0.13	0.15	0.60	0.62	20.8	42.0	33.8	40.8	34.4	67.9
mlr12	0,0	5,6	mlr	1.2e-04	0.59	21	OISST23402; OISST23410	-0.04	0.12	0.15	0.60	0.58	31.1	33.5	33.3	40.0	34.5	69.1
mlr14	0,0	5,6	mlr	1.3e-04	0.59	21	OISST23402; OISST23398	-0.04	0.12	0.15	0.60	0.58	31.3	33.4	33.4	40.1	34.6	68.2
OISST23381	0	6	lm	1.8e-06	0.52	32	truetemp	-0.02	0.14	0.16	0.62	0.64	12.5	44.6	37.3	44.2	34.7	74.1
mlr16	0,0	5,6	mlr	1.3e-04	0.59	21	OISST23402; OISST23374	-0.05	0.13	0.15	0.60	0.59	31.9	35.0	31.8	40.6	34.8	56.1
OISST23363	0	6	lm	1.3e-06	0.53	32	truetemp	-0.02	0.14	0.16	0.62	0.64	14.0	44.9	37.2	43.6	34.9	73.9
OISST23395	0	6	lm	2.6e-06	0.51	32	truetemp	-0.04	0.13	0.15	0.61	0.61	24.6	39.1	33.2	42.7	34.9	56.1
mlr17	0,0	5,6	mlr	1.3e-04	0.59	21	OISST23402; OISST23405	-0.05	0.13	0.15	0.60	0.59	31.8	35.3	32.0	41.1	35.0	52.5
OISST23390	0	5	lm	2.3e-06	0.51	32	truetemp	-0.05	0.13	0.15	0.59	0.59	34.6	36.2	30.9	38.3	35.0	54.3
mlr21	0,0	5,6	mlr	1.4e-04	0.59	21	OISST23402; OISST23384	-0.05	0.12	0.15	0.60	0.58	33.3	32.8	33.6	40.9	35.1	65.1
OISST23367	0	5	lm	1.4e-06	0.53	32	truetemp	-0.05	0.13	0.15	0.59	0.60	33.6	37.0	31.1	38.6	35.1	57.3
mlr18	0,0	5,6	mlr	1.3e-04	0.59	21	OISST23402; OISST23364	-0.05	0.13	0.15	0.60	0.58	33.2	34.2	32.6	41.0	35.3	60.2
OISST23355	0	5	lm	9.9e-07	0.54	32	truetemp	-0.05	0.13	0.15	0.59	0.61	32.4	38.6	31.8	39.3	35.5	61.2
OISST23400	0	5	lm	2.8e-06	0.51	32	truetemp	-0.04	0.13	0.15	0.59	0.61	30.9	39.1	32.7	39.2	35.5	50.1
OISST23369	0	6	lm	1.5e-06	0.53	32	truetemp	-0.03	0.14	0.16	0.61	0.64	18.6	44.5	37.0	42.9	35.8	72.0
OISST23380	0	5	lm	1.8e-06	0.52	32	truetemp	-0.04	0.13	0.15	0.60	0.61	30.0	40.3	33.4	40.1	36.0	53.6
mlr23	0,0	5,6	mlr	1.4e-04	0.58	21	OISST23402; OISST23386	-0.05	0.13	0.15	0.61	0.58	35.1	33.7	33.8	41.9	36.1	63.1
OISST23346	0	5	lm	8.4e-07	0.55	32	truetemp	-0.05	0.13	0.15	0.60	0.61	31.7	40.0	32.7	40.0	36.1	66.4
OISST23372	0	6	lm	1.5e-06	0.53	32	truetemp	-0.02	0.14	0.16	0.62	0.64	15.5	45.4	38.7	44.6	36.1	74.8
OISST23354	0	5	lm	9.8e-07	0.54	32	truetemp	-0.05	0.13	0.15	0.60	0.59	36.1	36.0	32.1	40.6	36.2	69.9
OISST23362	0	5	lm	1.2e-06	0.53	32	truetemp	-0.05	0.13	0.15	0.60	0.59	37.3	35.2	31.8	40.4	36.2	65.0
OISST23365	0	5	lm	1.3e-06	0.53	32	truetemp	-0.04	0.13	0.15	0.60	0.62	29.4	41.6	34.1	40.9	36.5	58.3
OISST23378	0	5	lm	1.8e-06	0.52	32	truetemp	-0.05	0.13	0.15	0.60	0.59	38.3	35.4	31.9	40.5	36.5	61.2
mlr22	0,0	5,6	mlr	1.4e-04	0.58	21	OISST23402; OISST23395	-0.05	0.13	0.15	0.61	0.59	34.7	35.7	33.5	42.6	36.6	55.9
OISST23347	0	5	lm	8.8e-07	0.54	32	truetemp	-0.05	0.13	0.15	0.60	0.60	34.9	38.0	32.9	41.1	36.7	75.3
OISST23384	0	6	lm	2.0e-06	0.52	32	truetemp	-0.03	0.14	0.16	0.62	0.63	22.4	43.6	37.1	43.7	36.7	71.2
OISST23342	0	5	lm	7.8e-07	0.55	32	truetemp	-0.04	0.13	0.15	0.60	0.62	30.9	41.5	33.5	41.1	36.8	72.4

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
OISST23350	0	5	lm	9.5e-07	0.54	32	truetemp	-0.04	0.14	0.15	0.61	0.63	27.8	43.6	34.4	41.5	36.8	68.1
OISST23358	0	5	lm	1.1e-06	0.54	32	truetemp	-0.04	0.14	0.15	0.61	0.63	28.7	42.8	34.4	41.5	36.9	63.6
OISST23386	0	6	lm	2.1e-06	0.52	32	truetemp	-0.04	0.13	0.15	0.62	0.63	26.2	42.3	35.7	43.5	36.9	68.5
OISST23402	0	5	lm	3.0e-06	0.51	32	truetemp	-0.06	0.13	0.15	0.60	0.59	39.5	35.9	32.1	40.7	37.1	58.4
mlr25	0,0	5,6	mlr	1.5e-04	0.58	21	OISST23402; OISST23396	-0.05	0.13	0.15	0.61	0.59	36.4	35.3	34.2	43.0	37.2	60.1
OISST23396	0	6	lm	2.7e-06	0.51	32	truetemp	-0.04	0.13	0.15	0.62	0.62	28.3	41.5	34.9	44.0	37.2	63.7
OISST23343	0	5	lm	8.0e-07	0.55	32	truetemp	-0.04	0.14	0.15	0.61	0.63	30.1	42.6	34.3	42.0	37.3	77.3
OISST23391	0	6	lm	2.4e-06	0.51	32	truetemp	-0.02	0.14	0.16	0.64	0.65	14.6	46.3	41.3	47.2	37.4	76.8
OISST23399	0	6	lm	2.8e-06	0.51	32	truetemp	-0.02	0.14	0.16	0.64	0.65	13.9	46.4	41.4	47.7	37.4	77.5
OISST23348	0	5	lm	8.9e-07	0.54	32	truetemp	-0.05	0.13	0.15	0.61	0.61	33.7	39.9	34.2	42.4	37.5	81.6
OISST23385	0	5	lm	2.0e-06	0.52	32	truetemp	-0.04	0.14	0.16	0.61	0.63	26.9	43.6	36.4	43.2	37.5	55.7
OISST23403	0	5	lm	3.0e-06	0.51	32	truetemp	-0.04	0.14	0.16	0.61	0.63	28.0	42.5	36.6	42.9	37.5	51.6
OISST23398	0	6	lm	2.7e-06	0.51	32	truetemp	-0.03	0.14	0.16	0.63	0.64	17.5	45.7	41.6	47.0	38.0	75.5
OISST23375	0	5	lm	1.5e-06	0.53	32	truetemp	-0.05	0.13	0.15	0.62	0.59	38.3	36.3	34.9	43.9	38.3	82.6
mlr11	0,0	5,5	mlr	1.2e-04	0.59	21	OISST23402; OISST23390	-0.05	0.13	0.15	0.61	0.62	33.8	41.5	35.7	42.4	38.4	57.8
OISST23376	0	5	lm	1.7e-06	0.52	32	truetemp	-0.06	0.13	0.15	0.62	0.59	39.7	35.7	34.6	43.7	38.4	76.4
OISST23352	0	5	lm	9.6e-07	0.54	32	truetemp	-0.05	0.13	0.15	0.62	0.62	32.7	42.0	35.5	43.8	38.5	86.5
mlr48	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23350	-0.04	0.14	0.15	0.61	0.64	31.5	44.3	35.6	43.1	38.6	67.6
OISST23361	0	5	lm	1.2e-06	0.54	32	truetemp	-0.04	0.14	0.15	0.62	0.64	30.1	44.7	36.0	44.0	38.7	83.3
mlr24	0,0	5,5	mlr	1.4e-04	0.58	21	OISST23402; OISST23367	-0.05	0.14	0.16	0.62	0.63	32.6	43.0	36.4	43.5	38.8	61.5
mlr37	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23385	-0.05	0.14	0.16	0.62	0.63	32.6	43.0	36.3	43.8	38.9	59.0
mlr43	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23358	-0.05	0.14	0.15	0.62	0.63	32.0	44.1	36.1	43.5	38.9	64.9
OISST23410	0	6	lm	3.5e-06	0.50	32	truetemp	-0.02	0.14	0.16	0.64	0.65	16.5	46.6	43.6	48.9	38.9	76.9
mlr19	0,0	5,5	mlr	1.4e-04	0.59	21	OISST23402; OISST23400	-0.05	0.13	0.16	0.62	0.62	34.3	41.6	36.7	43.4	39.0	56.8
mlr27	0,0	5,5	mlr	1.5e-04	0.58	21	OISST23402; OISST23380	-0.05	0.14	0.16	0.62	0.63	33.0	42.8	36.7	43.7	39.0	58.4
mlr30	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23355	-0.05	0.14	0.16	0.62	0.63	32.2	43.6	36.6	43.9	39.0	65.5
mlr34	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23365	-0.05	0.14	0.16	0.62	0.63	32.5	43.5	36.5	43.6	39.0	61.4
OISST23383	0	5	lm	2.0e-06	0.52	32	truetemp	-0.06	0.13	0.15	0.62	0.60	40.8	36.8	34.7	43.8	39.0	70.9
mlr39	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23346	-0.05	0.14	0.16	0.62	0.63	32.6	43.8	36.4	43.8	39.2	69.6
OISST23370	0	5	lm	1.5e-06	0.53	32	truetemp	-0.05	0.13	0.15	0.62	0.61	36.2	39.5	36.1	44.9	39.2	89.1
mlr28	0,0	5,5	mlr	1.5e-04	0.58	21	OISST23402; OISST23403	-0.05	0.13	0.16	0.62	0.62	34.0	42.1	36.9	44.1	39.3	57.4
mlr46	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23342	-0.05	0.14	0.16	0.62	0.64	32.7	44.2	36.4	44.0	39.3	73.5
mlr53	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23343	-0.05	0.14	0.15	0.62	0.64	32.8	44.1	36.1	44.0	39.3	75.8
mlr51	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23361	-0.05	0.14	0.16	0.62	0.63	34.1	43.7	36.1	44.3	39.6	77.5
OISST23394	0	5	lm	2.6e-06	0.51	32	truetemp	-0.06	0.13	0.15	0.62	0.60	41.7	37.5	34.9	44.1	39.6	66.4
mlr26	0,0	5,5	mlr	1.5e-04	0.58	21	OISST23402; OISST23362	-0.05	0.13	0.16	0.63	0.62	35.5	40.8	37.5	45.9	39.9	74.4
mlr33	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23354	-0.05	0.13	0.16	0.63	0.62	35.6	41.5	37.2	45.5	40.0	77.3
mlr41	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23347	-0.05	0.13	0.16	0.63	0.63	35.7	42.3	37.1	45.2	40.1	79.7
mlr20	0,0	5,5	mlr	1.4e-04	0.59	21	OISST23402; OISST23378	-0.05	0.13	0.16	0.63	0.62	34.9	40.7	38.6	47.0	40.3	71.1
mlr49	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23348	-0.05	0.14	0.16	0.63	0.63	35.5	43.0	37.3	45.5	40.3	82.3
mlr50	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23352	-0.05	0.14	0.16	0.63	0.63	35.5	43.1	37.2	45.5	40.3	83.3
OISST23373	0	5	lm	1.5e-06	0.53	32	truetemp	-0.05	0.14	0.16	0.63	0.63	34.7	43.2	37.5	46.4	40.4	93.9

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr52	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23371	-0.05	0.14	0.16	0.63	0.63	36.3	43.0	37.2	45.7	40.5	82.9
OISST23371	0	5	lm	1.5e-06	0.53	32	truetemp	-0.05	0.14	0.16	0.63	0.64	32.5	46.0	37.7	46.2	40.6	91.3
mlr35	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23394	-0.06	0.13	0.16	0.63	0.61	42.4	39.5	37.2	45.9	41.2	68.0
mlr54	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23373	-0.05	0.13	0.16	0.63	0.62	38.3	41.8	38.1	46.9	41.2	86.6
mlr45	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23370	-0.06	0.13	0.16	0.63	0.62	38.9	41.2	38.3	47.0	41.3	85.6
mlr38	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23375	-0.06	0.13	0.16	0.63	0.62	40.2	40.3	38.2	47.0	41.4	83.2
OISST23408	0	5	lm	3.5e-06	0.50	32	truetemp	-0.06	0.13	0.16	0.64	0.61	40.0	38.9	38.6	48.0	41.4	87.8
mlr40	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23407	-0.05	0.14	0.16	0.63	0.63	38.0	43.7	37.8	46.4	41.5	82.5
mlr47	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23389	-0.05	0.14	0.16	0.63	0.63	38.4	42.6	38.1	46.8	41.5	85.9
mlr31	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23376	-0.06	0.13	0.16	0.64	0.61	41.2	39.6	38.8	47.7	41.8	80.9
OISST23404	0	5	lm	3.1e-06	0.51	32	truetemp	-0.05	0.13	0.16	0.64	0.62	37.6	41.6	39.3	48.6	41.8	94.3
mlr44	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23397	-0.06	0.13	0.16	0.64	0.62	39.9	41.9	39.0	47.9	42.2	86.1
mlr29	0,0	5,5	mlr	1.5e-04	0.58	21	OISST23402; OISST23408	-0.06	0.13	0.16	0.64	0.62	41.9	40.5	38.9	47.8	42.3	78.5
mlr36	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23404	-0.06	0.13	0.16	0.64	0.62	40.8	41.2	39.1	48.0	42.3	83.0
mlr42	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23406	-0.06	0.14	0.16	0.64	0.63	39.7	42.8	38.9	47.7	42.3	86.6
OISST23389	0	5	lm	2.2e-06	0.52	32	truetemp	-0.05	0.14	0.16	0.64	0.65	34.2	47.3	39.7	48.6	42.5	98.0
OISST23397	0	5	lm	2.7e-06	0.51	32	truetemp	-0.05	0.14	0.16	0.65	0.64	35.8	44.5	40.2	49.4	42.5	98.8
mlr32	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23383	-0.06	0.13	0.16	0.64	0.61	42.6	40.3	39.3	48.3	42.6	77.0
OISST23407	0	5	lm	3.4e-06	0.50	32	truetemp	-0.05	0.14	0.16	0.65	0.67	33.8	50.4	41.4	50.1	43.9	97.0
OISST23406	0	5	lm	3.2e-06	0.50	32	truetemp	-0.05	0.14	0.16	0.66	0.66	35.2	48.4	42.0	51.0	44.1	102.5
median8	0	0	median8	NA			median8	0.07	0.20	0.25	1.01	0.95	51.0	104.3	113.7	118.3	96.8	174.6
median4	0	0	median4	NA			median4	0.06	0.22	0.26	1.05	1.02	41.7	118.4	121.8	125.8	101.9	141.0
median.all	0	0	median.all	NA			median.all	-0.26	0.30	0.33	1.35	1.37	184.0	184.0	184.0	184.0	184.0	150.1

Table 20. *Performance results for all qualifying models used to forecast Fraser diversion based on jackknife.short analysis. Each row represents a single model tested, some columns include: year adjust (year of environmental data same as return year [0] or prior year [-1]), month, summary statistics (P value, adjusted R squared, sample size), data name, data variables (which are sorted by their relative influence in the model). As the NEPSTAR regression models comprise more than one variable, only year-month of the latest variable is presented. Latitude and longtitude of NEPSTAR variables are excluded due to space limitations. The PMs include mean raw error, mean absolute error, root mean squared error, Thiel's U-statistic, and MASE. The initial three PMs are in percent diversion units, the latter two are unit-less. All PMs are described in the methods section. All PMs, except MASE, are given a rank. The best rank has a value of zero. The last rank equals total number of models (n). The average of the PM ranks by model (row) is included, as is the average rank for the alternate performance test method. The rows are sorted by average rank of performance method listed in caption. The first row is the best model, the last row is the worst.*

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
nepstar7	-1,-1,0	6,1,1	mlr	1.1e-07	0.71	30	nepstar	-0.01	0.07	0.10	0.33	0.24	5.8	0.0	0.0	0.0	1.4	5.3
nepstar10	-1,-1,0	1,4,1	mlr	6.2e-08	0.72	30	nepstar	0.01	0.09	0.10	0.35	0.30	5.7	17.2	5.2	5.2	8.3	6.5
nepstar3	-1,0,-1,0	1,4,4,1	mlr	2.1e-08	0.77	30	nepstar	-0.02	0.09	0.10	0.35	0.29	21.5	14.4	4.7	4.7	11.3	3.6
nepstar8	-1,-1,0,0	7,1,4,1	mlr	4.0e-08	0.75	30	nepstar	-0.02	0.09	0.11	0.36	0.29	16.0	15.4	9.5	9.5	12.6	5.0
nepstar4	-1,-1,0	7,1,1	mlr	4.8e-08	0.72	30	nepstar	0.02	0.08	0.11	0.39	0.26	15.0	6.8	15.1	15.1	13.0	3.0
nepstar1	-1,-1,0	1,4,1	mlr	1.9e-08	0.74	30	nepstar	0.00	0.10	0.11	0.38	0.32	0.3	23.4	14.4	14.4	13.1	10.7
nepstar14	-1,-1,-1,0	7,1,4,1	mlr	5.7e-08	0.75	30	nepstar	0.02	0.08	0.12	0.40	0.28	15.5	11.0	18.2	18.2	15.8	3.8
nepstar12	-1,-1,0,0	6,1,4,1	mlr	1.5e-07	0.73	30	nepstar	-0.03	0.09	0.11	0.37	0.30	25.8	17.5	11.1	11.1	16.4	5.4
nepstar5	-1,-1,0,0	6,1,4,1	mlr	5.5e-08	0.75	30	nepstar	-0.03	0.10	0.11	0.36	0.31	35.0	20.6	7.2	7.2	17.5	6.1
nepstar13	-1,-1,0,0	6,1,3,1	mlr	1.1e-07	0.73	30	nepstar	-0.01	0.10	0.13	0.42	0.33	7.3	25.3	23.6	23.6	19.9	11.3
nepstar2	-1,-1,-1,0	7,1,4,1	mlr	2.2e-08	0.77	30	nepstar	0.01	0.10	0.12	0.42	0.33	10.7	24.4	22.9	22.9	20.2	7.4
OSCAR213625	0	1	lm	1.5e-04	0.51	21	v	0.03	0.10	0.12	0.40	0.33	30.2	24.6	18.4	18.4	22.9	26.8
mlr1	0,0	5,1	mlr	8.0e-05	0.61	21	OISST23402; OSCAR213625	-0.00	0.12	0.13	0.44	0.38	1.5	38.2	28.7	28.7	24.3	20.6
mlr72	0,0,0	5,1,5	mlr	2.8e-04	0.60	21	OISST23402; OSCAR213625; OISST23378	0.00	0.12	0.13	0.44	0.40	4.3	41.9	27.9	27.9	25.5	27.7
nepstar11	-1,-1,0,0	7,1,3,1	mlr	6.4e-08	0.75	30	nepstar	0.01	0.10	0.14	0.47	0.32	11.0	22.6	34.2	34.2	25.5	6.6
nepstar6	-1,-1,0	6,1,3	mlr	1.2e-07	0.70	30	nepstar	0.00	0.11	0.14	0.48	0.35	0.0	31.0	36.8	36.8	26.2	19.2
mlr71	0,0,0	5,1,5	mlr	2.8e-04	0.60	21	OISST23402; OSCAR213625; OISST23367	0.00	0.12	0.13	0.45	0.40	0.9	44.0	30.7	30.7	26.6	28.1
mlr85	0,0,0	5,1,5	mlr	3.5e-04	0.59	21	OISST23402; OSCAR213625; OISST23365	0.00	0.12	0.13	0.46	0.40	1.2	43.1	31.5	31.5	26.8	29.4
mlr77	0,0,0	5,1,5	mlr	3.1e-04	0.60	21	OISST23402; OSCAR213625; OISST23380	-0.00	0.12	0.13	0.45	0.40	2.1	43.5	31.3	31.3	27.1	29.1
mlr88	0,0,0	5,1,5	mlr	3.7e-04	0.59	21	OISST23402; OSCAR213625; OISST23385	0.00	0.12	0.14	0.46	0.40	0.6	42.8	32.6	32.6	27.1	30.4
mlr81	0,0,0	5,1,5	mlr	3.3e-04	0.60	21	OISST23402; OSCAR213625; OISST23355	0.00	0.12	0.13	0.45	0.40	3.4	43.8	31.0	31.0	27.3	28.4
mlr82	0,0,0	5,1,5	mlr	3.3e-04	0.59	21	OISST23402; OSCAR213625; OISST23403	-0.00	0.12	0.14	0.46	0.40	3.5	42.9	31.7	31.7	27.5	29.9
nepstar15	-1,-1,0,0,0	6,1,4,3,1	mlr	1.4e-07	0.75	30	nepstar	-0.03	0.11	0.13	0.43	0.36	26.2	31.3	26.5	26.5	27.6	9.7
mlr65	0,0,0	5,1,6	mlr	2.5e-04	0.61	21	OISST23402; OSCAR213625; OISST23405	-0.00	0.12	0.14	0.46	0.41	2.4	45.6	32.2	32.2	28.1	22.7
mlr76	0,0,0	5,1,5	mlr	3.1e-04	0.60	21	OISST23402; OSCAR213625; OISST23362	0.01	0.12	0.13	0.45	0.41	7.1	44.5	30.5	30.5	28.2	27.9
mlr58	0,0,0	5,1,5	mlr	2.1e-04	0.62	21	OISST23402; OSCAR213625; OISST23390	-0.00	0.12	0.14	0.46	0.41	3.6	45.3	32.3	32.3	28.4	27.6
mlr86	0,0,0	5,1,5	mlr	3.6e-04	0.59	21	OISST23402; OSCAR213625; OISST23346	0.01	0.12	0.14	0.46	0.40	5.5	44.1	32.0	32.0	28.4	28.5
mlr90	0,0,0	5,1,5	mlr	3.7e-04	0.59	21	OISST23402; OSCAR213625; OISST23358	0.00	0.12	0.14	0.46	0.40	4.0	43.3	33.1	33.1	28.4	29.7
mlr67	0,0,0	5,1,5	mlr	2.6e-04	0.61	21	OISST23402; OSCAR213625; OISST23400	-0.01	0.12	0.14	0.46	0.41	6.2	44.4	32.3	32.3	28.8	28.7
mlr75	0,0,0	5,1,6	mlr	3.1e-04	0.60	21	OISST23402; OSCAR213625; OISST23395	-0.00	0.13	0.14	0.47	0.41	2.2	46.7	34.2	34.2	29.3	23.4
mlr96	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23350	0.01	0.12	0.14	0.47	0.40	5.0	43.7	34.2	34.2	29.3	29.4

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr84	0,0,0	5,1,5	mlr	3.4e-04	0.59	21	OISST23402; OSCAR213625; OISST23354	0.01	0.12	0.14	0.46	0.41	8.6	45.8	32.4	32.4	29.8	27.8
mlr92	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23342	0.01	0.12	0.14	0.47	0.41	6.4	44.6	34.2	34.2	29.8	28.4
mlr93	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23383	0.00	0.13	0.14	0.47	0.41	0.2	46.6	36.2	36.2	29.8	27.1
mlr66	0,0,0	5,1,6	mlr	2.6e-04	0.61	21	OISST23402; OSCAR213625; OISST23374	-0.00	0.13	0.14	0.47	0.42	4.9	47.9	34.3	34.3	30.4	22.1
mlr100	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23343	0.01	0.12	0.14	0.47	0.41	5.5	44.9	35.7	35.7	30.5	27.9
mlr99	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23407	0.00	0.13	0.14	0.48	0.41	1.1	46.1	37.4	37.4	30.5	25.6
mlr101	0,0,0	5,1,5	mlr	3.9e-04	0.59	21	OISST23402; OSCAR213625; OISST23361	0.00	0.12	0.14	0.48	0.41	3.7	45.3	36.9	36.9	30.7	27.2
mlr89	0,0,0	5,1,5	mlr	3.7e-04	0.59	21	OISST23402; OSCAR213625; OISST23347	0.01	0.13	0.14	0.47	0.41	8.7	46.3	33.9	33.9	30.7	27.5
mlr83	0,0,0	5,1,6	mlr	3.3e-04	0.59	21	OISST23402; OSCAR213625; OISST23396	-0.00	0.13	0.14	0.47	0.42	2.1	48.6	36.2	36.2	30.8	23.7
mlr103	0,0,0	5,1,5	mlr	3.9e-04	0.59	21	OISST23402; OSCAR213625; OISST23371	0.00	0.13	0.14	0.48	0.41	2.4	46.1	37.7	37.7	31.0	26.2
mlr107	0,0,0	5,1,5	mlr	3.9e-04	0.59	21	OISST23402; OSCAR213625; OISST23389	0.00	0.13	0.14	0.48	0.41	1.5	46.7	38.0	38.0	31.0	25.5
mlr102	0,0,0	5,1,5	mlr	3.9e-04	0.59	21	OISST23402; OSCAR213625; OISST23352	0.00	0.13	0.14	0.48	0.41	4.7	46.1	37.1	37.1	31.3	26.6
mlr95	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23348	0.01	0.13	0.14	0.47	0.41	7.2	46.4	36.0	36.0	31.4	27.1
mlr106	0,0,0	5,1,5	mlr	3.9e-04	0.59	21	OISST23402; OSCAR213625; OISST23406	0.00	0.13	0.14	0.48	0.42	2.0	47.5	38.3	38.3	31.5	25.3
mlr105	0,0,0	5,1,5	mlr	3.9e-04	0.59	21	OISST23402; OSCAR213625; OISST23373	0.00	0.13	0.14	0.48	0.42	3.6	47.2	38.2	38.2	31.8	25.8
mlr87	0,0,0	5,1,5	mlr	3.6e-04	0.59	21	OISST23402; OSCAR213625; OISST23376	0.01	0.13	0.14	0.47	0.42	7.3	48.3	35.8	35.8	31.8	27.2
mlr73	0,0,0	5,1,6	mlr	2.9e-04	0.60	21	OISST23402; OSCAR213625; OISST23364	-0.01	0.13	0.14	0.47	0.42	6.1	49.3	36.1	36.1	31.9	22.2
mlr80	0,0,0	5,1,6	mlr	3.3e-04	0.60	21	OISST23402; OSCAR213625; OISST23386	-0.00	0.13	0.14	0.48	0.43	4.3	50.1	37.4	37.4	32.3	23.1
mlr104	0,0,0	5,1,5	mlr	3.9e-04	0.59	21	OISST23402; OSCAR213625; OISST23397	0.00	0.13	0.14	0.49	0.42	3.9	48.6	39.1	39.1	32.7	25.7
mlr57	0,0,0	5,1,6	mlr	2.0e-04	0.62	21	OISST23402; OSCAR213625; OISST23353	-0.01	0.13	0.14	0.47	0.42	12.0	49.1	34.9	34.9	32.7	19.8
mlr98	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23370	0.01	0.13	0.14	0.48	0.42	6.6	48.2	38.0	38.0	32.7	26.3
mlr91	0,0,0	5,1,5	mlr	3.7e-04	0.59	21	OISST23402; OSCAR213625; OISST23375	0.01	0.13	0.14	0.48	0.42	8.9	48.9	36.8	36.8	32.9	26.8
mlr61	0,0,0	5,1,6	mlr	2.3e-04	0.61	21	OISST23402; OSCAR213625; OISST23344	-0.01	0.13	0.14	0.47	0.42	14.0	49.0	35.7	35.7	33.6	19.9
mlr68	0,0,0	5,1,6	mlr	2.8e-04	0.60	21	OISST23402; OSCAR213625; OISST23356	-0.01	0.13	0.14	0.48	0.42	11.6	49.5	36.7	36.7	33.6	21.0
mlr78	0,0,0	5,1,6	mlr	3.2e-04	0.60	21	OISST23402; OSCAR213625; OISST23384	-0.01	0.13	0.14	0.48	0.43	8.0	50.2	38.4	38.4	33.7	22.5
mlr94	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23408	0.01	0.13	0.14	0.49	0.43	7.0	50.4	38.9	38.9	33.8	26.6
mlr97	0,0,0	5,1,5	mlr	3.8e-04	0.59	21	OISST23402; OSCAR213625; OISST23404	0.01	0.13	0.14	0.49	0.43	6.7	49.9	39.3	39.3	33.8	26.2
mlr79	0,0,0	5,1,5	mlr	3.3e-04	0.60	21	OISST23402; OSCAR213625; OISST23394	-0.01	0.13	0.15	0.50	0.42	5.2	48.2	41.9	41.9	34.3	25.8
mlr70	0,0,0	5,1,6	mlr	2.8e-04	0.60	21	OISST23402; OSCAR213625; OISST23369	-0.02	0.13	0.14	0.48	0.42	15.0	49.1	37.7	37.7	34.9	20.9
mlr62	0,0,0	5,1,6	mlr	2.4e-04	0.61	21	OISST23402; OSCAR213625; OISST23349	-0.02	0.13	0.14	0.48	0.42	19.2	48.5	36.4	36.4	35.1	19.3
mlr74	0,0,0	5,1,6	mlr	3.0e-04	0.60	21	OISST23402; OSCAR213625; OISST23398	-0.02	0.13	0.14	0.48	0.42	15.9	48.8	38.6	38.6	35.5	21.6
mlr56	0,0,0	5,1,6	mlr	2.0e-04	0.62	21	OISST23402; OSCAR213625; OISST23345	-0.02	0.13	0.14	0.47	0.42	22.5	48.4	35.9	35.9	35.7	18.0
mlr69	0,0,0	5,1,6	mlr	2.8e-04	0.60	21	OISST23402; OSCAR213625; OISST23410	-0.02	0.13	0.14	0.48	0.42	19.8	47.9	37.6	37.6	35.7	20.8
mlr64	0,0,0	5,1,6	mlr	2.5e-04	0.61	21	OISST23402; OSCAR213625; OISST23372	-0.02	0.13	0.14	0.48	0.42	22.1	48.3	37.2	37.2	36.2	19.6
mlr63	0,0,0	5,1,6	mlr	2.4e-04	0.61	21	OISST23402; OSCAR213625; OISST23391	-0.03	0.13	0.14	0.48	0.42	25.3	48.0	36.8	36.8	36.7	19.1
mlr60	0,0,0	5,1,6	mlr	2.2e-04	0.61	21	OISST23402; OSCAR213625; OISST23363	-0.03	0.13	0.14	0.48	0.42	26.6	48.2	36.4	36.4	36.9	18.4
mlr59	0,0,0	5,1,6	mlr	2.2e-04	0.62	21	OISST23402; OSCAR213625; OISST23399	-0.03	0.13	0.14	0.48	0.42	29.3	48.2	36.4	36.4	37.5	18.3
mlr55	0,0,0	5,1,6	mlr	1.9e-04	0.62	21	OISST23402; OSCAR213625; OISST23381	-0.03	0.13	0.14	0.48	0.42	31.0	48.6	36.3	36.3	38.1	17.5
nepstar9	-1,-1,0	7,1,3	mlr	7.1e-08	0.72	30	nepstar	0.02	0.12	0.16	0.53	0.40	20.9	43.9	49.3	49.3	40.9	16.2
OISST23400	0	5	lm	2.8e-06	0.51	32	truetemp	-0.04	0.14	0.15	0.52	0.47	44.8	62.4	46.7	46.7	50.1	35.5
OISST23405	0	6	lm	3.2e-06	0.50	32	truetemp	-0.03	0.14	0.16	0.55	0.47	30.0	61.5	55.6	55.6	50.7	32.1
OISST23403	0	5	lm	3.0e-06	0.51	32	truetemp	-0.03	0.15	0.16	0.55	0.50	30.1	68.9	53.8	53.8	51.6	37.5

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr17	0,0	5,6	mlr	1.3e-04	0.59	21	OISST23402; OISST23405	-0.07	0.12	0.16	0.53	0.41	67.3	44.5	49.1	49.1	52.5	35.0
OISST23380	0	5	lm	1.8e-06	0.52	32	truetemp	-0.05	0.15	0.16	0.54	0.49	45.2	67.0	51.1	51.1	53.6	36.0
OISST23390	0	5	lm	2.3e-06	0.51	32	truetemp	-0.06	0.14	0.15	0.52	0.46	61.9	60.0	47.7	47.7	54.3	35.0
OISST23385	0	5	lm	2.0e-06	0.52	32	truetemp	-0.03	0.16	0.17	0.57	0.52	32.5	73.6	58.4	58.4	55.7	37.5
mlr22	0,0	5,6	mlr	1.4e-04	0.58	21	OISST23402; OISST23395	-0.07	0.13	0.16	0.54	0.41	73.0	46.2	52.2	52.2	55.9	36.6
mlr16	0,0	5,6	mlr	1.3e-04	0.59	21	OISST23402; OISST23374	-0.07	0.13	0.16	0.54	0.42	72.8	47.3	52.1	52.1	56.1	34.8
OISST23395	0	6	lm	2.6e-06	0.51	32	truetemp	-0.05	0.14	0.17	0.56	0.47	47.1	61.1	58.1	58.1	56.1	34.9
OISST23374	0	6	lm	1.5e-06	0.53	32	truetemp	-0.05	0.14	0.17	0.57	0.48	47.2	62.7	58.3	58.3	56.6	32.3
mlr19	0,0	5,5	mlr	1.4e-04	0.59	21	OISST23402; OISST23400	-0.05	0.15	0.16	0.54	0.49	54.5	66.6	53.0	53.0	56.8	39.0
mlr6	0,0	5,6	mlr	1.2e-04	0.59	21	OISST23402; OISST23353	-0.07	0.13	0.16	0.54	0.42	73.6	49.5	53.0	53.0	57.3	32.6
OISST23367	0	5	lm	1.4e-06	0.53	32	truetemp	-0.06	0.15	0.16	0.54	0.48	62.0	64.7	51.3	51.3	57.3	35.1
mlr28	0,0	5,5	mlr	1.5e-04	0.58	21	OISST23402; OISST23403	-0.05	0.15	0.16	0.55	0.50	51.8	68.0	54.8	54.8	57.4	39.3
mlr11	0,0	5,5	mlr	1.2e-04	0.59	21	OISST23402; OISST23390	-0.06	0.15	0.16	0.54	0.49	58.4	66.9	53.0	53.0	57.8	38.4
OISST23365	0	5	lm	1.3e-06	0.53	32	truetemp	-0.05	0.16	0.17	0.56	0.51	48.0	72.5	56.3	56.3	58.3	36.5
mlr27	0,0	5,5	mlr	1.5e-04	0.58	21	OISST23402; OISST23380	-0.05	0.15	0.16	0.55	0.50	52.6	70.0	55.6	55.6	58.4	39.0
OISST23402	0	5	lm	3.0e-06	0.51	32	truetemp	-0.07	0.14	0.16	0.54	0.45	72.1	56.9	52.4	52.4	58.4	37.1
OISST23353	0	6	lm	9.6e-07	0.54	32	truetemp	-0.05	0.15	0.17	0.57	0.49	47.2	66.9	60.3	60.3	58.7	29.8
mlr37	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23385	-0.05	0.15	0.17	0.56	0.51	51.0	70.8	57.2	57.2	59.0	38.9
mlr25	0,0	5,6	mlr	1.5e-04	0.58	21	OISST23402; OISST23396	-0.08	0.13	0.16	0.56	0.42	79.1	48.9	56.3	56.3	60.1	37.2
mlr18	0,0	5,6	mlr	1.3e-04	0.59	21	OISST23402; OISST23364	-0.08	0.13	0.16	0.56	0.42	79.1	49.5	56.2	56.2	60.2	35.3
mlr9	0,0	5,6	mlr	1.2e-04	0.59	21	OISST23402; OISST23344	-0.08	0.13	0.17	0.56	0.43	79.4	50.8	56.6	56.6	60.8	33.0
OISST23355	0	5	lm	9.9e-07	0.54	32	truetemp	-0.06	0.15	0.16	0.56	0.50	62.4	70.2	56.0	56.0	61.2	35.5
OISST23378	0	5	lm	1.8e-06	0.52	32	truetemp	-0.07	0.14	0.16	0.55	0.47	72.6	62.0	55.1	55.1	61.2	36.5
mlr34	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23365	-0.05	0.16	0.17	0.57	0.52	54.8	73.5	58.7	58.7	61.4	39.0
mlr24	0,0	5,5	mlr	1.4e-04	0.58	21	OISST23402; OISST23367	-0.06	0.16	0.17	0.57	0.52	56.6	73.1	58.2	58.2	61.5	38.8
mlr2	0,0	5,6	mlr	1.1e-04	0.60	21	OISST23402; OISST23345	-0.08	0.13	0.17	0.57	0.44	82.1	52.7	58.6	58.6	63.0	31.9
mlr23	0,0	5,6	mlr	1.4e-04	0.58	21	OISST23402; OISST23386	-0.08	0.13	0.17	0.57	0.43	82.8	50.8	59.5	59.5	63.1	36.1
OISST23364	0	6	lm	1.3e-06	0.53	32	truetemp	-0.06	0.15	0.17	0.59	0.48	61.3	63.8	63.7	63.7	63.1	34.3
mlr15	0,0	5,6	mlr	1.3e-04	0.59	21	OISST23402; OISST23356	-0.08	0.13	0.17	0.57	0.43	82.7	51.6	59.7	59.7	63.4	34.0
OISST23358	0	5	lm	1.1e-06	0.54	32	truetemp	-0.05	0.16	0.17	0.58	0.54	51.4	78.5	62.2	62.2	63.6	36.9
OISST23344	0	6	lm	8.0e-07	0.55	32	truetemp	-0.06	0.15	0.17	0.59	0.49	59.7	66.6	64.3	64.3	63.7	31.7
OISST23396	0	6	lm	2.7e-06	0.51	32	truetemp	-0.06	0.15	0.18	0.59	0.48	61.6	64.1	64.5	64.5	63.7	37.2
mlr8	0,0	5,6	mlr	1.2e-04	0.59	21	OISST23402; OISST23349	-0.08	0.13	0.17	0.58	0.44	84.6	52.7	60.9	60.9	64.8	33.0
mlr43	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23358	-0.06	0.16	0.17	0.58	0.53	57.4	77.2	62.4	62.4	64.9	38.9
OISST23362	0	5	lm	1.2e-06	0.53	32	truetemp	-0.07	0.15	0.17	0.57	0.49	74.5	67.8	58.9	58.9	65.0	36.2
mlr21	0,0	5,6	mlr	1.4e-04	0.59	21	OISST23402; OISST23384	-0.08	0.13	0.17	0.58	0.43	84.4	51.3	62.3	62.3	65.1	35.1
mlr30	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23355	-0.06	0.16	0.17	0.58	0.53	58.9	77.5	62.7	62.7	65.5	39.0
mlr13	0,0	5,6	mlr	1.3e-04	0.59	21	OISST23402; OISST23369	-0.09	0.13	0.17	0.59	0.43	86.3	51.9	63.1	63.1	66.1	34.1
OISST23346	0	5	lm	8.4e-07	0.55	32	truetemp	-0.07	0.16	0.17	0.58	0.53	65.3	76.6	61.8	61.8	66.4	36.1
OISST23394	0	5	lm	2.6e-06	0.51	32	truetemp	-0.07	0.15	0.17	0.59	0.48	74.7	64.4	63.2	63.2	66.4	39.6
OISST23345	0	6	lm	8.3e-07	0.55	32	truetemp	-0.06	0.16	0.18	0.61	0.51	59.8	72.3	67.9	67.9	67.0	31.8
mlr3	0,0	5,6	mlr	1.1e-04	0.60	21	OISST23402; OISST23381	-0.09	0.14	0.17	0.59	0.45	88.3	55.4	63.1	63.1	67.5	32.2

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr4	0,0	5,6	mlr	1.1e-04	0.59	21	OISST23402; OISST23363	-0.09	0.14	0.17	0.59	0.44	88.6	54.7	63.6	63.6	67.6	32.7
mlr48	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23350	-0.06	0.16	0.18	0.59	0.54	61.6	79.5	64.7	64.7	67.6	38.6
OISST23356	0	6	lm	1.1e-06	0.54	32	truetemp	-0.07	0.15	0.18	0.61	0.49	65.6	67.6	69.2	69.2	67.9	34.4
mlr35	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23394	-0.08	0.15	0.17	0.59	0.48	78.4	65.2	64.2	64.2	68.0	41.2
OISST23350	0	5	lm	9.5e-07	0.54	32	truetemp	-0.06	0.17	0.18	0.60	0.55	55.8	83.2	66.7	66.7	68.1	36.8
mlr10	0,0	5,6	mlr	1.2e-04	0.59	21	OISST23402; OISST23372	-0.09	0.13	0.18	0.59	0.44	89.5	53.6	64.8	64.8	68.2	33.5
mlr14	0,0	5,6	mlr	1.3e-04	0.59	21	OISST23402; OISST23398	-0.09	0.13	0.18	0.60	0.43	90.3	51.2	65.7	65.7	68.2	34.6
OISST23386	0	6	lm	2.1e-06	0.52	32	truetemp	-0.07	0.15	0.18	0.61	0.49	67.8	66.7	69.8	69.8	68.5	36.9
mlr12	0,0	5,6	mlr	1.2e-04	0.59	21	OISST23402; OISST23410	-0.09	0.13	0.18	0.60	0.43	92.5	51.7	66.0	66.0	69.1	34.5
mlr7	0,0	5,6	mlr	1.2e-04	0.59	21	OISST23402; OISST23391	-0.09	0.13	0.18	0.60	0.44	91.6	54.2	65.6	65.6	69.2	33.6
mlr39	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23346	-0.06	0.17	0.18	0.60	0.55	64.3	81.1	66.4	66.4	69.6	39.2
mlr5	0,0	5,6	mlr	1.1e-04	0.59	21	OISST23402; OISST23399	-0.09	0.14	0.18	0.60	0.45	91.9	55.4	65.5	65.5	69.6	33.3
OISST23349	0	6	lm	9.3e-07	0.54	32	truetemp	-0.07	0.15	0.18	0.62	0.51	65.0	71.4	71.2	71.2	69.7	33.8
OISST23354	0	5	lm	9.8e-07	0.54	32	truetemp	-0.08	0.16	0.17	0.59	0.52	77.0	74.4	64.0	64.0	69.9	36.2
OISST23383	0	5	lm	2.0e-06	0.52	32	truetemp	-0.08	0.15	0.18	0.60	0.51	78.5	70.8	67.1	67.1	70.9	39.0
mlr20	0,0	5,5	mlr	1.4e-04	0.59	21	OISST23402; OISST23378	-0.06	0.17	0.18	0.61	0.55	63.6	81.6	69.6	69.6	71.1	40.3
OISST23384	0	6	lm	2.0e-06	0.52	32	truetemp	-0.07	0.15	0.19	0.63	0.50	66.9	68.9	74.5	74.5	71.2	36.7
OISST23369	0	6	lm	1.5e-06	0.53	32	truetemp	-0.07	0.15	0.19	0.63	0.51	67.2	70.6	75.1	75.1	72.0	35.8
OISST23342	0	5	lm	7.8e-07	0.55	32	truetemp	-0.07	0.17	0.18	0.61	0.56	68.7	83.6	68.6	68.6	72.4	36.8
mlr46	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23342	-0.07	0.17	0.18	0.62	0.56	68.6	84.8	70.3	70.3	73.5	39.3
OISST23363	0	6	lm	1.3e-06	0.53	32	truetemp	-0.07	0.16	0.19	0.64	0.54	65.5	78.5	75.9	75.9	73.9	34.9
OISST23381	0	6	lm	1.8e-06	0.52	32	truetemp	-0.06	0.17	0.19	0.64	0.55	61.9	82.2	76.3	76.3	74.1	34.7
mlr26	0,0	5,5	mlr	1.5e-04	0.58	21	OISST23402; OISST23362	-0.07	0.17	0.18	0.62	0.56	69.7	83.8	72.0	72.0	74.4	39.9
OISST23372	0	6	lm	1.5e-06	0.53	32	truetemp	-0.07	0.16	0.19	0.65	0.53	68.1	75.9	77.6	77.6	74.8	36.1
OISST23347	0	5	lm	8.8e-07	0.54	32	truetemp	-0.08	0.17	0.18	0.61	0.55	79.8	81.5	70.0	70.0	75.3	36.7
OISST23398	0	6	lm	2.7e-06	0.51	32	truetemp	-0.07	0.16	0.19	0.66	0.51	69.3	72.5	80.1	80.1	75.5	38.0
mlr53	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23343	-0.07	0.17	0.18	0.62	0.57	72.9	86.3	72.0	72.0	75.8	39.3
OISST23376	0	5	lm	1.7e-06	0.52	32	truetemp	-0.08	0.16	0.18	0.62	0.53	83.2	77.9	72.3	72.3	76.4	38.4
OISST23391	0	6	lm	2.4e-06	0.51	32	truetemp	-0.07	0.16	0.19	0.65	0.54	67.9	79.9	79.7	79.7	76.8	37.4
OISST23410	0	6	lm	3.5e-06	0.50	32	truetemp	-0.07	0.16	0.19	0.66	0.53	70.2	75.7	80.8	80.8	76.9	38.9
mlr32	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23383	-0.08	0.16	0.19	0.63	0.53	82.0	77.0	74.5	74.5	77.0	42.6
mlr33	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23354	-0.07	0.17	0.19	0.63	0.56	74.7	86.1	74.3	74.3	77.3	40.0
OISST23343	0	5	lm	8.0e-07	0.55	32	truetemp	-0.07	0.18	0.19	0.63	0.58	71.7	89.4	74.1	74.1	77.3	37.3
mlr51	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23361	-0.08	0.17	0.19	0.63	0.57	77.7	86.5	73.0	73.0	77.5	39.6
OISST23399	0	6	lm	2.8e-06	0.51	32	truetemp	-0.07	0.17	0.19	0.66	0.55	66.4	83.5	80.0	80.0	77.5	37.4
mlr29	0,0	5,5	mlr	1.5e-04	0.58	21	OISST23402; OISST23408	-0.09	0.16	0.19	0.63	0.54	86.1	78.3	74.7	74.7	78.5	42.3
mlr41	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23347	-0.08	0.17	0.19	0.64	0.57	78.8	88.0	75.9	75.9	79.7	40.1
mlr31	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23376	-0.08	0.17	0.19	0.65	0.55	85.0	83.3	77.7	77.7	80.9	41.8
OISST23348	0	5	lm	8.9e-07	0.54	32	truetemp	-0.08	0.18	0.19	0.64	0.58	82.7	89.4	77.2	77.2	81.6	37.5
mlr49	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23348	-0.08	0.18	0.19	0.65	0.58	82.0	90.6	78.3	78.3	82.3	40.3
mlr40	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23407	-0.09	0.17	0.19	0.64	0.57	87.5	88.2	77.1	77.1	82.5	41.5
OISST23375	0	5	lm	1.5e-06	0.53	32	truetemp	-0.09	0.17	0.19	0.65	0.56	87.9	85.7	78.5	78.5	82.6	38.3

model num	year adjust	month val	model type	p val	rsq	n	data type2	mre	mae	rmse	ustat2	mase	mre rank	mae rank	rmse rank	ustat2 rank	jackk rank	jackk rank.1
mlr52	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23371	-0.09	0.18	0.19	0.65	0.58	86.0	90.0	77.9	77.9	82.9	40.5
mlr36	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23404	-0.09	0.17	0.19	0.65	0.56	90.1	84.3	78.9	78.9	83.0	42.3
mlr38	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23375	-0.09	0.17	0.19	0.65	0.57	88.1	86.6	78.9	78.9	83.2	41.4
mlr50	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23352	-0.08	0.18	0.19	0.65	0.58	84.5	91.1	78.8	78.8	83.3	40.3
OISST23361	0	5	lm	1.2e-06	0.54	32	truetemp	-0.08	0.18	0.19	0.66	0.60	75.1	96.4	80.8	80.8	83.3	38.7
mlr45	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23370	-0.09	0.18	0.20	0.66	0.58	90.2	90.0	81.2	81.2	85.6	41.3
mlr47	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23389	-0.09	0.18	0.19	0.66	0.58	91.8	90.8	80.5	80.5	85.9	41.5
mlr44	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23397	-0.09	0.17	0.20	0.66	0.57	93.2	88.3	81.4	81.4	86.1	42.2
OISST23352	0	5	lm	9.6e-07	0.54	32	truetemp	-0.08	0.18	0.20	0.67	0.60	84.6	95.9	82.8	82.8	86.5	38.5
mlr42	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23406	-0.09	0.18	0.20	0.66	0.58	94.2	89.6	81.3	81.3	86.6	42.3
mlr54	0,0	5,5	mlr	1.6e-04	0.58	21	OISST23402; OISST23373	-0.09	0.18	0.20	0.66	0.58	91.7	91.3	81.6	81.6	86.6	41.2
OISST23408	0	5	lm	3.5e-06	0.50	32	truetemp	-0.09	0.18	0.20	0.68	0.58	87.4	89.9	87.0	87.0	87.8	41.4
OISST23370	0	5	lm	1.5e-06	0.53	32	truetemp	-0.09	0.18	0.20	0.68	0.60	90.9	94.4	85.6	85.6	89.1	39.2
OISST23371	0	5	lm	1.5e-06	0.53	32	truetemp	-0.09	0.19	0.20	0.69	0.63	85.4	102.7	88.5	88.5	91.3	40.6
OISST23373	0	5	lm	1.5e-06	0.53	32	truetemp	-0.09	0.19	0.21	0.70	0.62	92.6	101.3	90.9	90.9	93.9	40.4
OISST23404	0	5	lm	3.1e-06	0.51	32	truetemp	-0.09	0.19	0.21	0.71	0.61	92.2	98.3	93.3	93.3	94.3	41.8
OISST23407	0	5	lm	3.4e-06	0.50	32	truetemp	-0.09	0.20	0.21	0.72	0.66	86.5	110.3	95.6	95.6	97.0	43.9
OISST23389	0	5	lm	2.2e-06	0.52	32	truetemp	-0.09	0.20	0.21	0.72	0.65	92.6	107.9	95.7	95.7	98.0	42.5
OISST23397	0	5	lm	2.7e-06	0.51	32	truetemp	-0.10	0.19	0.22	0.73	0.64	95.1	105.0	97.6	97.6	98.8	42.5
OISST23406	0	5	lm	3.2e-06	0.50	32	truetemp	-0.10	0.20	0.22	0.74	0.66	96.3	111.4	101.2	101.2	102.5	44.1
median4	0	0	median4	NA			0	0.02	0.28	0.32	1.07	0.92	24.1	180.0	180.0	180.0	141.0	101.9
median.all	0	0	median.all	NA			0	-0.15	0.25	0.28	0.94	0.82	151.3	152.3	148.3	148.3	150.1	184.0
median8	0	0	median8	NA			0	0.18	0.26	0.31	1.05	0.87	180.0	164.9	176.8	176.8	174.6	96.8

APPENDIX D: DEPENDENT DATA

Table 21. The dependent data used in forecasting models. Median return timing date of Early Stuart and Chilko; and northern diversion rate.

Year	Early Stuart	Chilko	ND
1951		27-Jul	
1952		25-Jul	
1953	04-Jul	23-Jul	0.09
1954	01-Jul	26-Jul	0.02
1955	30-Jun	30-Jul	0.09
1956		31-Jul	0.10
1957	05-Jul	03-Aug	0.20
1958	12-Jul	09-Aug	0.35
1959	04-Jul	04-Aug	0.15
1960		04-Aug	0.19
1961	02-Jul	28-Jul	0.16
1962	30-Jun	29-Jul	0.12
1963	29-Jun	22-Jul	0.11
1964		01-Aug	0.10
1965	30-Jun	27-Jul	0.10
1966	30-Jun	29-Jul	0.24
1967	08-Jul	29-Jul	0.25
1968		29-Jul	0.18
1969	01-Jul	23-Jul	0.15
1970	27-Jun	03-Aug	0.24
1971	02-Jul	29-Jul	0.12
1972		04-Aug	0.34
1973	02-Jul	01-Aug	0.09
1974	30-Jun	02-Aug	0.22
1975	29-Jun	25-Jul	0.12
1976		01-Aug	0.21
1977	30-Jun		0.18
1978	28-Jun	03-Aug	0.53
1979	02-Jul	03-Aug	0.26
1980	03-Jul	09-Aug	0.69
1981	03-Jul		0.67
1982	04-Jul	07-Aug	0.22
1983	01-Jul		0.80
1984	01-Jul	04-Aug	0.33
1985	05-Jul		0.32
1986	01-Jul	04-Aug	0.22
1987	05-Jul	10-Aug	0.37
1988	02-Jul	26-Jul	0.15
1989	03-Jul	09-Aug	0.43
1990	04-Jul	17-Aug	0.29
1991	08-Jul	14-Aug	0.40
1992	07-Jul	11-Aug	0.70
1993	10-Jul	15-Aug	0.75
1994	05-Jul	09-Aug	0.80
1995	01-Jul	06-Aug	0.55
1996	06-Jul	06-Aug	0.35
1997	11-Jul		0.77
1998	03-Jul	09-Aug	0.70
1999	03-Jul	08-Aug	0.45
2000	28-Jun	06-Aug	0.35
2001	29-Jun		0.20
2002	04-Jul		0.51
2003	06-Jul	08-Aug	0.69
2004	07-Jul	02-Aug	0.64
2005	17-Jul	23-Aug	0.74
2006	07-Jul	12-Aug	0.65
2007	01-Jul	06-Aug	0.44
2008	29-Jun	30-Jul	0.10
2009	29-Jun	04-Aug	0.47
2010	05-Jul	15-Aug	0.73
2011	04-Jul	11-Aug	0.62
2012	04-Jul	06-Aug	0.18
2013	02-Jul	10-Aug	0.71
2014	09-Jul	19-Aug	0.96