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Hierarchical Bayesian modeling for Cambridge Bay Arctic Char, *Salvelinus alpinus* (L.), incorporated with precautionary reference points

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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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ABSTRACT

In response to growing concerns over fisheries sustainability and the vulnerability to climate changes, precautionary reference points have become central priorities for maintaining the healthy status of fish populations and fisheries. In the present study, we applied a hierarchical Bayesian state-space formulation of surplus production models to assessments of Arctic Char biomass dynamics in the Cambridge Bay area and to estimates of a set of precautionary reference points (PRPs) with uncertainties for evaluation processes. Four kinds of probability distribution functions (pdfs), uniform (UKR), lognormal (LNKR), half-Cauchy lognormal (HCLNKR), and random walk with lognormal (LNKRWQ), were structured to specify priors on model parameters, *K*, *r*, and *q* in a Markov chain Monte Carlo (MCMC) framework. We employed deviance information criterion (DIC) and multimodel inference (MMI) to evaluate model performance and model selection. The model considered the best fit has the smallest DIC value, leading to the recognition that the model LNKRWQ was identified as the best among the candidate models. Model UKR produced next lowest DIC value, with a substantial difference (5.18) from LNKRWQ. Models LNKR and HCLNKR did not substantially support the model averaging of MMI. Given two better model scenarios, the populations for all years under model LNKRWQ, 93% DIC weight, had experienced somewhat lower targeted exploitation rate (F_{MSY}=0.1761±0.1098 per year) and the population biomass remained in the healthy zone. Under model UKR, 7% DIC weight, the targeted exploitation rate seemed to be slightly higher (F_{MSY}=0.2390±0.1182 per year) but were never exceeded. The results from both models demonstrated that Cambridge Bay Arctic Char populations were in the Cautious Zone of the Precautionary Approach Framework at the start of the time series. Under the current exploitation strategy, the populations are in the Healthy Zone. With the data currently available it was not possible to estimate these reference points for individual stocks (i.e., waterbodies). This does not imply that there should be a change to the current management units or methods of the collection of fishery statistics. However, additional information, proportional contributions from river-based stocks and river-specific catch-per-unit-effort (CPUE), should be collected that would facilitate definition of individual stock reference points.

Modélisation bayesienne hiérarchique pour l'omble chevalier de la Cambridge Bay, *Salvelinus alpinus* (L.), incorporant des points de référence de précaution

RÉSUMÉ

En réponse aux préoccupations croissantes concernant la durabilité des pêches et la vulnérabilité aux changements climatiques, l'utilisation de points de référence de précaution est devenue une priorité centrale du maintien de l'état sain des populations de poissons et des pêches. Dans la présente étude, nous avons appliqué une formulation bayesienne hiérarchique état-espace des modèles de production excédentaire aux évaluations de la dynamique de la biomasse de l'omble chevalier dans la région de Cambridge Bay ainsi qu'aux estimations d'un ensemble de points de référence de précaution (PRP) avec certaines incertitudes pour les processus d'évaluation. Quatre types de fonctions de distributions de probabilités (FDP), soit uniforme (UKR), log-normale (LNKR), log-normale demi-Cauchy (HCLNKR) et marche aléatoire + log-normale (LNKRWQ) ont été structurées pour préciser a priori les distributions des paramètres du modèle, *K*, *r* et *q* dans un cadre de Monte Carlo par chaîne de Markov (MCMC). Nous avons utilisé le critère DIC (*deviance information criterion*) et l'interférence multimodèles (MMI) pour évaluer le rendement et la sélection des modèles. Le modèle jugé comme étant le mieux adapté a la valeur DIC la plus faible, ce qui nous a permis de reconnaître que le modèle LNKRWQ était le meilleur parmi les modèles envisagés. Le modèle UKR est arrivé au deuxième rang en termes de valeurs DIC les plus faibles, avec une différence substantielle par rapport au modèle LNKRWQ (5,18). Les modèles LNKR et HCLNKR n'ont pas soutenu de façon substantielle la combinaison de modèles de la MMI. Vu qu'il y avait deux meilleurs scénarios modèles, dans le modèle LNKRWQ, les espèces (pondération DIC 93 %) ont connu des taux d'exploitation ciblés plutôt faibles pour toutes les années (F_{RMS} = 0,1761 ± 0,1098 par année) et la biomasse de la population est restée dans la zone saine. Dans le modèle UKR (pondération DIC 7 %), le taux d'exploitation ciblé semblait être légèrement plus élevé (F_{RMS} = 0,2390 ± 0,1182 par année), mais n'a jamais été dépassé. Les résultats des deux modèles ont démontré que les populations d'omble chevalier de Cambridge Bay étaient dans la zone de prudence du cadre de l'approche de précaution au début de la série chronologique. Dans le cadre de la stratégie d'exploitation actuelle, les populations se trouvent dans la zone saine. Avec les données actuellement disponibles, il n'a pas été possible d'estimer ces points de référence pour des stocks individuels (c.-à-d. étendues d'eau). Cela ne signifie pas qu'il faille apporter des changements aux unités de gestion actuelles ou aux méthodes de collecte de statistiques sur les pêches. Toutefois, il faudrait recueillir des renseignements supplémentaires et apprendre les contributions proportionnelles de stocks fluviaux et les captures par unité d'effort (CPUE) propre aux rivières. Cela faciliterait la définition de points de référence pour les stocks individuels.

INTRODUCTION

Following the international guidelines for precautionary approaches to fisheries (FAO 1995a, b, c), Fisheries and Oceans Canada (DFO) has adopted a fishery decision-making framework and integrated fisheries management plans (IFMPs), which detail how the precautionary approach will be put into practice in Canadian waters (DFO 2006). The Arctic is both one of the places on Earth that is most vulnerable to climate change and a place where vulnerability is of urgent global relevance (WWF 2008). Also, fisheries in the Arctic, marked by critical differences in ecosystem structural and functional components, need to receive urgent consideration for sustainable applications. Currently, this vulnerable system is experiencing increasing human interests for gas, oil, mineral, and fisheries development, and conspicuous modifications from global climate changes over sub-Arctic and Arctic habitats (Reist *et al.* 2006). Arctic Char, *Salvelinus alpinus* (L.), is a highly migratory salmonid that is found throughout sub-Arctic and Arctic freshwater and coastal areas (Reist et al. 1995, Scott and Crossman 1998). Cambridge Bay Arctic Char are targeted in one of the largest char fisheries across Nunavut and the Northwest Territories (Yaremchuk et al. 1989, Day and de March 2004). In response to growing concerns over fisheries sustainability and the vulnerability of fishes to climate changes, precautionary reference points have become central priorities for maintaining the healthy status of fish populations and fisheries in the Arctic.

Within DFO's integrated fisheries management framework, fishery stock assessment has become a key toolbox to be used for assessing stock status, informing management advice, and defining uncertainties (Hilborn and Walters 1992). Two mainstream statistics are used to these ends. Classical statistics, that is frequentist statistics, is prominently based on maximum likelihood estimates and hypothesis tests of *p*-values; they give no direct advice on how to implement analytical outcomes in the face of a multitude of uncertain possibilities. The Bayesian approach to statistical inference and decision making, as an alternative, has experienced rapid growth over the last thirty years in environmental modeling, particularly fishery stock assessment (Punt and Hilborn 1997, Hilborn and Liermann 1998). Compared with classical statistics, Bayesian statistics provides theoretical concerns with applicable management options and probabilities as a measurement of uncertainty (or relative credibility) (Carlin and Louis 2009). Beginning exactly as traditional frequentist methods do, the Bayesian approach combines point estimates of classical statistics with probability densities and decision analyses, taking a further step to help choose the best decision from a list of candidates (Kinas and Andrade 2007).

Applying Bayesian statistics to fisheries stock assessments involves the integration of a knowledge base (likelihood), current stock status information (probability distribution functions, pdfs), and nowadays inference toolboxes of precautionary management options with uncertainties for evaluation processes. The Bayesian approach is becoming a natural choice since it provides tools to perform the following tasks:

i) display inferences in the form of *posterior* probability distributions;

ii) include all relevant information outside the data by way of a *prior* probability distribution; and

iii) use Bayesian decision theory to compare and choose among alternative management options.

In fact, fisheries resources are rife with some degree of uncertainty, especially through the processes of field observations and laboratory experimentation. In contrast to a single aquarium in which we know the exact number of fish, it is impossible to count all of the individuals in the standing abundance in a waterbody of closed lakes and open rivers and marine systems using a sampling gear. Instead, inference becomes an intellectual alternative to estimate the total number of individuals and biomass through index sampling by a selected gear under defined assumptions. During their complicated life cycles, Arctic fish undergo seasonal migrations for feeding, spawning, and overwintering purposes, which normally occur in separate habitats. This results in spatial separation during life histories and co-existence with other species, and sympatric and allopatric competition. The study of fish population dynamics primarily requires the collection of field observation to represent stock status across all habitats. In fact, survey results are often biased during data collection with a single gear or in particular locations. Nevertheless, observational uncertainties cannot be controlled, even with carefully designed sampling protocols. Especially for commercial and recreational fisheries, experimental data collection and harvest statistics include observational uncertainty sources (Francis and Shotton 1997). In addition, a number of uncertainties occur during model construction, implementation, and institutionalization, as was proposed by Rosenberg and Brault (1993) and O'Boyle (1993).

Despite increasing concerns regarding climate change impacts, especially for the sustainability of Arctic fisheries, there is still limited information available on the biological characteristics of Arctic Char, which impedes the creation of stock assessment and fisheries management frameworks. Guided by DFO's benchmark on precautionary approaches (PA) to fisheries management and IFMPs (DFO 2006), this study on Cambridge Bay Arctic Char, *Salvelinus alpinus* (L.), was conducted primarily towards the following objectives:

i) construct a baseline model of an Arctic Char surplus production model, based on the dataset from 1960-2008;

ii) determine kernel parameters of fisheries management interest;

iii) delineate stock status and precautionary reference points; and

iv) account for uncertainties in the risk assessment and decision advice.

MATERIALS AND METHODS

STUDY AREA

Situated on the southeast coast of Victoria Island (*Kitlineq*), in the Canadian Arctic Archipelago, between Dease Strait and Queen Maud Gulf, Cambridge Bay (69°6'N, 105°8'W) is a transportation and administrative center for the Kitikmeot Region (Figure 1). The traditional Inuinnaqtun name for the area is *Ikaluktuutiak* (old orthography) or *Iqaluktuttiaq* (new orthography), meaning "good fishing place". Historically, all river systems in the area were likely fished for subsistence (DFO 2004).

Climatic conditions in Cambridge Bay are largely influenced by the geographic position of Victoria Island and the cold currents of the Arctic Ocean. Monthly mean temperatures above 0°C occurred in June through August, when rainfall peaked at more than 30 mm. Monthly temperatures varied between -33.50 ± 0.40°C in February and 8.35 ± 0.20°C in July, with an annual average of -14.58 ± 0.17°C, during 1950-2010 (Figure 2). During the winter (December to March), air temperature was below -30°C while the daily average depth of snowfall was >5 cm. The overall amount of precipitation, rainfall and snow combined, showed a single period of seasonal variation that was positively related to the air temperature (r=0.5568, p<0.0001, Climate Weather Office). Average monthly precipitation was 10 mm between June and October. The general climate pattern was for wetter and warmer weather in summer and early fall, while drier and colder conditions prevailed during winter.

DATA SOURCES

Fisheries and biomass index

Collection of commercial fisheries statistics commenced in 1960 (Yaremchuk et al. 1989). Fishers sought sea-run migrants at the mouths of the Lauchlan, Halovik, and Paliryuak rivers, north of Wellington Bay, in mid-July (Figure 3), and sea-return migrants in mid-August and early September by means of gillnets and weirs in several rivers (Day and de March 2004). With the exception of the Lauchlan River in 1963, the fisheries for char from the mouths of the Lauchlan, Halovik and Paliryuak rivers were combined under the Ekalluk River during the 1960s (Table 1). Although gillnets of various mesh sizes were used, the minimum mesh size allowed was established as 140 mm knot-to-knot stretched mesh. In recent years there has been a change in fishing gear from gillnets to weirs for several of the Cambridge Bay river mouth fisheries. There is no minimum fish-size limit but mesh-size is constrained by fishing license regulations.

Within the time spans from 1960 to 2010 (Table 1), three temporal phases of commercial fishery development can be easily seen over the seven fishing locations: an early development phase of the commercial fisheries during 1960-1976; a fully developed phase during 1977-1990; and the restoration of dynamics during 1991-2010 following a five-year reduction in the Ekalluk fishery in the early 1990s (Figure 3). A river-specific quota system commenced in 1972, and the fishable quota peaked between 1978 and 1984 (Table 2). The combined harvests from the Ekalluk and Jayco rivers have accounted for >50% of the total quota since 1994. As is detailed in a complementary document (Zhu et al. 2014), two sets of population biomass-based catch-per-unit-effort (CPUE) indices are used in the analysis: an experimental sampling series from 1975-2006, and an estimated series derived from a correlation between CPUE and winter (March) Arctic oscillation index (AOI) with a five-year lag. This index was expressed as tonnes per unit of gillnet.

SURPLUS PRODUCTION MODEL

Biomass index

Weight-based CPUE is an index of biomass (B_t). It is described by a functional relationship between the fishing mortality rate and fishable biomass. The fishing mortality rate can be further expressed by the product of the invested fishing effort at time t, E_t, and its catchability coefficient, q,

$$C_t = qE_tB_t \quad (1)$$

$$I_t = qB_t \quad (2)$$

where C_t and I_t are the reported harvest and CPUE at time t, respectively. The catchability coefficient specifies the retained proportion of the species captured by one unit of gear-specific effort (Hilborn and Walters 1992, Quinn and Deriso 1999). In fact, CPUE is greatly subject to changes in gear type and configuration as well as changes in targeting practices, such as switching from a single species to a multi-species bycatch pursuit (Hilborn and Walters 1992).

BIOMASS DYNAMICS MODEL

When only harvest and relative abundance or biomass datasets are available, surplus production models simplistically integrate the quantities of growth, recruitment, and natural mortality into a comprehensive part of surplus production. Dynamic changes in instantaneous biomass can be balanced between surplus production and harvest removals, which is commonly represented by the Graham-Schaefer logistic surplus production model (LSPM) (Schaefer 1957, Hilborn and Walters 1992, McAllister and Kirkwood 1998),

$$\frac{dB}{dt} = rB\left(1 - \frac{B}{K}\right) - qEB \quad (3)$$

and generalized surplus production model (GSPM) (Pella and Tomlinson 1969; Fletcher 1978),

$$\frac{dB}{dt} = \frac{r}{z}B(1 - (\frac{B}{K})^z) - qEB \quad (4)$$

where, parameters r and K are the intrinsic population growth rate and virgin biomass or carrying capacity, respectively. An additional parameter, z, refers to a measure of production density dependence (Pella and Tomlinson 1969). When z=1, equation (4) is a logistic function (3) (Polacheck *et al.* 1993). Otherwise equation (4) is a skew-asymmetric function with a shape parameter z (Prager 2002, Barker and Sibly 2008).

To reduce parameter confounding, such as between B_t and K (Meyer and Millar 1999a, b, Millar and Meyer 2000), the GSPM was re-parameterized using relative biomass ($P_t=B_t/K$) to express annual biomass proportional to K,

$$P_{t+1} = P_t + rP_t(1 - P_t^z) - \frac{C_t}{K} \quad (5)$$

Then, a grid of alternative parameters for composing precautionary reference points can be derived, including maximum surplus production ($MSP=(B_{MSP})\times(F_{MSP})$), fishing mortality at maximum surplus production ($F_{MSP}=r/((z+1)^{(1/z)}$), biomass at maximum surplus production ($B_{MSP}=K/((z+1)^{(1/z)}$), the relative fishing mortality rate (F/F_{MSP}), and relative biomass (B/B_{MSP}) at sampling series (Quinn and Deriso 1999).

HIERARCHICAL BAYESIAN MODEL

A hierarchical Bayesian paradigm can explicitly account for a smooth ‘signal fit’ from noisy data and pursue a plausible representation of nonlinear covariates in both the population dynamics model and observations (Millar and Meyer 2000, Buckland et al. 2004). Combined with relevant uncertainties for errors with respect to parameter estimation, two interactive processes are involved in model performance: a state process of underlying stochasticity in population dynamics is an unobserved vector, representing Arctic Char population biomass; and a space process of data collection described by an observable vector, biomass-based CPUE from index surveys or covariate prediction, is a function of the unobserved state process (Francis and Shotton 1997, Meyer and Millar 1999a, Buckland et al. 2004, Thomas et al. 2005). Conceptually, the state process error also indicates uncertainty accounted for environmental noise or natural variability, assuming the observations are made without errors and all of the errors occur as a result of changes in population size (Polacheck et al. 1993, Bousquet et al. 2008). The observation process error estimator is made by assuming the population dynamics are deterministic and that all of the errors occur in the sampling procedures (Polacheck et al. 1993). In fact, these analytical errors may account for differences between expected and observed CPUE, and between model-derived and true biomass quantities.

As such, these stochastic forms for relative biomass (P_t) and CPUE (I_t) are obviously represented by a skewed and multiplicative lognormal distribution (Limpert et al. 2001) for t=1960,…2008,

$$logP_t = \log(\hat{P}_t) + \mu_t \quad (6)$$

$$LP_t = \frac{1}{\sqrt{2\pi\sigma P_t}}\exp(-\frac{\log(P_t)-\log(\hat{P}_t))^2}{2\sigma^2} \quad (7)$$

$$\log(I_t) = \log(\hat{I}_t) + v_t \quad (8)$$

$$LI_t = \frac{1}{\sqrt{2\pi\tau I_t}}\exp(-\frac{\log(I_t)-\log(\hat{I}_t))^2}{2\tau^2} \quad (9)$$

Where μ_t and v_t are independent and identically-distributed (iid) normal probabilities of $N(0,\sigma^2)$ and $N(0,\tau^2)$, respectively. LP_t and LI_t are likelihoods for P_t and I_t, given $\hat{P}_t$ and $\hat{I}_t$, respectively.

Priors and posterior probability distributions

As was indicated earlier, a Bayesian-based GSPM (eq. 4) is determined by the conditional state process posterior pdf (eq. 5), the state process pdf (eq. 6-7), the observation process pdf (eq. 8-9) with an unobservable parameter set, $\Theta=\{K, r, q, z, \sigma^2, \tau^2\}$, and relevant priors. Overall, there are six model parameters in Θ, 49 unknown and derived state time series of relative biomass P_t, and predicted CPUE (I_t) where t = 1960,…2008.

Prior to model implementation, two categories of prior pdfs need to be specified, assuming the parameters in Θ are independent *a priori* (Meyer and Millar 1999a, b, Millar and Meyer 2000): informative and non-informative. Informative priors are primarily determined by intensive assessment of the parameter choices and expert judgment using knowledge-based information (Walters and Ludwig 1994, Punt and Hilborn 1997, McAllister and Kirkwood 1998). Non-informative priors refer to prior probability distributions created without any information or without favoring one parameter value over another (Carlin and Louis 2009). The resulting inferences are completely objective. In this study, we applied both categories of priors when specifying prior pdfs for model parameters, especially for estimates of K and r.

To define non-informative uniform pdfs for K and r, because of the scarcity of sufficient documentation, we estimated the bound quantities for K used in the models, combined with spatially-specific harvest history. Since 1960, total harvested biomass in the commercial Arctic Char fisheries ranged from 5.77 metric tonnes in 1962 to 67.94 metric tonnes in 1978 (Table 1). The censored intervals for Arctic Char biomass, uniform pdf U(100, 1500), were subjectively selected by incorporating historical harvest records with an approximate factor of twenty times. Model parameter r is interchangeable with similar biological characteristics among species and stocks (Hilborn and Walters 1992, Sibly and Hone 2002). Accordingly, we described parameter r as a randomized variation of the uniform distribution probability U(0.01,1.05). For catchability coefficient q, a non-informative flat normal pdf was initiated with a bound of (10^{-6}, 1.0). Similarly, the shape parameter z was specified by a non-informative flat normal pdf prior with a bound of (0.1, 10).

$K \sim \text{uniform}(100{,}1500)$ or $K \sim \text{log-normal}(\mu_K, \tau_K)\text{I}(100{,}1500)$

$r \sim \text{uniform}(0.01{,}1.05)$ or $r \sim \text{log-normal}(\mu_r, \tau_r)\text{I}(0.01{,}1.05)$ (10)

$z \sim \text{normal}(0.0{,}10^{-6})\text{I}(0.1{,}15)$

$q \sim \text{normal}(0.0{,}10^{-6})\text{I}(10^{-6}, 1)$

where μ_K and μ_r are the prior means for parameters K and r, respectively, and τ_K and τ_r are the corresponding prior precisions for parameters K and r, which are known as hyper parameters (Harley and Myers 2001). To incorporate time-varying effects, lognormal pdfs were employed to express random walk q priors (Wilberg et al. 2010),

$$q_{t+1} = \sqrt{\frac{\tau_q}{2\pi}}\,\frac{1}{q}\exp\!\left(-\frac{\tau_q}{2}(log\ q - q_t\ )^2\right) \qquad (11)$$

Here, q_{t+1} and q_t were timely changes in q in year t+1 and t, and the precision term τ_q was specified by a non-informative prior as an inverse uniform pdf U(0.01,1.0).

To account for vague estimates for subsistence use, the following formula is used for total harvest, Total harvest=Commercial X (1+*HRR*) (12)

Here *HRR*, harvest report rate, is considered as the proportion of fisheries for subsistence use. Combined with a Nunavut Wildlife Harvest Study (Table 3; Priest and Usher 2004), an informative prior of 50% commercial harvest (Day and Harris 2013) was applied to the normal pdf prior with the bound of (0.01, 1.05),

$$HRR \sim normal(0.0,10^{-6})I(0.01,1.05) \quad (13)$$

In a scenario associated with a half-Cauchy hyper prior distribution, the estimation is obtained as the ratio of a normal and square root of a χ^2 distribution with one degree of freedom (Gelman 2006).

Process uncertainty variance, σ^2, was considered when modeling uncertainties of recruitment variability and environmental noise (Millar and Meyer 2000, Bousquet et al. 2008). Observation uncertainty variance, τ^2, was linked to uncertainties in data collection during sampling for the abundance index and fisheries statistics (Walters 1998; Meyer and Millar 1999b). Under the assumption of deterministic population dynamics, a reasonable range for observation error was 0.1 to 0.3 on the basis of a coefficient of variation (CV) on abundance-based CPUE (Hilborn and Liermann 1998, Walters 1998). A vague Gelman's prior, an inverse uniform pdf, U(0.01,100), was applied to σ^2 and τ^2 in the overall models (Carlin and Louis 2009). All notations of models are summarized in Table 4 with sequential calculations listed in Table 5.

Stochastic simulation and multimodel inference

Incorporated with a Markov Chain Monte Carlo (MCMC) simulation for a full range of uncertainties, Metropolis-Hastings within Gibbs sampling was employed for Bayesian nonlinear GSPM, defined in equations (3), (4), and (5). Under the computational framework of WinBUGS, we adopted three groups of model scenarios:

i) a general model pursuit using non-informative uniform pdfs for constants *K* and *r* (model UKR);

ii) comparative models by applying lognormal and half-Cauchy lognormal pdfs for constants *K* and *r* (LNKR and HCLNKR, respectively); and

iii) incorporation of time-varying effects on the catchability coefficient *q* (LNKRWQ).

For each model scenario, we used MCMC to run two-chains of Gibb's sampling with 3,250,000 iterations each. Following a burn-in period of 650,000 iterations, a total of 8,000 samples were obtained by sampling in a thin of the 325th iteration to avoid highly auto-correlated neighboring values (Spiegelhalter et al. 2002). Model convergence and stationarity were diagnosed using the R-based evaluation package CODA (Convergence Diagnosis and Output Analysis) for Gibbs sampling output, version 0.13-5 (Plummer et al. 2006, Ntzoufras 2009).

Deviance information criterion (DIC) with *a priori* parsimonious predictive Bayesian statistics was employed to measure the relative goodness of fit of the structural models, which profile the complexity and instability resulting from particular parameterization (Burnham and Anderson 1998, Spiegelhalter et al. 2002, Carlin and Louis 2009). Those models profile the complexity and instability resulting from a particular parameterization (Millar and Meyer 2000; Burnham and Anderson 2002; Spiegelhalter et al. 2002; Carlin and Louis 2009). The principle that the lowest DIC is the best model was applied for model selection among the plausible candidate models. As a generalization of the AIC, DIC can be expressed as,

$$D(\theta) = -2\log f(y|\theta) + 2\log h(y)$$

$$DIC = \overline{D} + pD \quad (14)$$

$$pd = \overline{D} - D$$

where f(y|θ) is the likelihood function for the observed data vector y given the parameter vector θ, and h(y) is a standardization function of the data alone (Carlin and Louis 2009). $\overline{D}$, D and pD are the posterior mean of the deviance as a measure of fit, the deviance of the posterior mean and the effective number of parameters as a measure of complexity in a Bayesian model, respectively (Lunn et al. 2009).

Multimodel inference (MMI) is one of information theoretic approaches to selection of the best model from a candidate model pool; the subsequent inference is conditional on that model (Burnham and Anderson 2002). For each fitted estimation model, the DIC weight (w_i) was calculated in terms of differences between the current (DIC_i) and minimum DIC_{min},

$$\Delta_i = \mathrm{DIC}_i - \mathrm{DIC}_{min} \quad (15)$$

$$w_i = \frac{\exp\left(-\frac{\Delta_i}{2}\right)}{\sum_{i=1}^{c} \exp\left(-\frac{\Delta_i}{2}\right)}$$

As a rule of thumb for MMI, Spiegelhalter et al. (2002) suggested that if models differ by only one or two DIC units then one cannot distinguish between the two models. If models differ by three to seven DIC units there is some support for the first model but the second model is clearly better. Essentially no support is found for two models whose DIC difference is greater than 10. So, a simple quantity, DIC, offers a straightforward means of comparing different models when using exactly the same observed data (Carlin and Louis 2009; King et al. 2010). The multi-model average model parameters, β_{MMI}, were estimated using w_i for the comparative model parameters

$$\beta_{\mathrm{MMI}} = \sum_{i}^{c} \beta_i w_i \quad (16)$$

where β_i is the appropriate parameter.

RESULTS

DIAGNOSTIC TESTS FOR CONVERGENCE AND MODEL SELECTION

In the R-based package CODA with MCMC iterations, there are four kinds of tests for model diagnosis for convergence and stationarity (Plummer et al. 2006). The Geweke diagnostic is used to check for convergence of the mean of each parameter separately from the sampled values of a single chain. The derived Z-score indicates convergence if $|Z| \leq 2$. Despite the appearance of possible outliers ($|z|>2$) for some parameters in all model scenarios, the range of Z-scores in a single chain was smallest in LNKRWQ and greatest in HCLNKR (Table 6). Overall, the percentages of outliers varied from zero in one chain to 27% in other chains of UKR, suggesting the model was sensitive to the initial value. In addition, the average outlier percentage over two chains was lowest in LNKR (2.32%), followed by LNKRWQ (3.51%), indicating fewer outliers appeared in both models. The Gelman-Rubin diagnostic involves checking the convergence of the chain using two or more samples generated in parallel. Values close to one indicate convergence, showing that all samples of the model parameters reached convergence. The Raftery-Lewis test by independence factor is used to evaluate the appropriateness of setting the values of the burn-in period, the thinning period, and the total length of the sample; we concluded that the length of the burn-in and the number of subsequent cycles for all model scenarios were sufficient for the results to form the basis for inference (the average independence factor varied between 326-331), except LNKRWQ (independence factor 414-418). The fourth index diagnostic, the Heidelberger-Welch test, is used for the analysis of sample convergence of single chains from univariate observations, expressed by *p*-values. Under the statistically critical level α=0.05, the derived results showed that all parameters passed the test in models UKR and HCLNKR, but one parameter, P1965, in LNKRWQ and nine parameters in LNKR did not.

The model considered to have the best fit has the smallest DIC value. LNKRWQ was identified as the best among the four candidate models (Table 7). Uniform pdfs for *K* and *r* (model UKR) produced the next lowest DIC value, although with a substantial difference (5.18) from LNKRWQ. Models LNKR and HCLNKR generated very similar DICs with the difference of <1 between the two, but a definitive difference >15.70 between them and the best model. For simplicity, some parts of our analyses will omit the results of LNKR and HCLNKR. Using MMI, DIC weight w_i was calculated as 93% and 7% for LNKRWQ and UKR, respectively (Table 7).

Posterior median trends for the biomass index (CPUE) and total harvest mimic the observed data during 1960-2008 under three model scenarios: UKR, LNKRWQ and MMI estimates (Figure 4). There was considerable scatter in CPUE around the fitted distributions, especially for models UKR and LNKRWQ (Figure 4a). All models looked similar from the onset of data collection through 1992, when harvest underwent gradual increases to full exploitation (Figure 4b). The posterior median biomass trends for these models are shown in Figure 4c. Three stages of Arctic Char population development can be seen within the time series:

i) prior to the first peaks in CPUE and biomass in 1972;

ii) during fully-developed fisheries with stable biomass during 1973-1990; and

iii) a period of biomass re-growth and dynamic changes in harvest after 1991.

Taking examples of parameter *P* and biomass in three representative years, 1960, 1978, and 2008, we can further examine temporal variations in two parameters. Relative biomass (*P*=Biomass/*K*) increased more than fourfold between 1960 and 1978, from 0.1620 in 1960 to 0.7480 in 1978 (Figure 5a). From 1978 to 2008, *P* increased by only 0.14%. Similarly, biomass increased from 131 tonnes in 1960 to 568 tonnes in 1978, and continued to increase to 663 tonnes in 2008 (Figure 5b). Comparing two-chain results for posterior local likelihood density estimates of *P* and *B*, agreement was found on the basis of a K-S test (*p*=0.99), suggesting that there was proportionality between model parameter *P* and biomass given constant *K*.

QUANTITIES OF MANAGEMENT INTEREST

Regardless of the model structures and prior selections, the posterior distributions of *K* and *r* are of great interest for both stock assessment and decision-making purposes, particularly when incorporated with uncertainties of stochastic and observational processes. Among four candidate models, the variations of median *K* showed two similar groups: models UKR and LNKRWQ versus models LNKR and HCLNKR (Table 8), with a difference of 34 tonnes between the two extremes. For parameter *r*, the highest estimate was obtained in UKR (0.4977) and similar values were produced among the remaining three models (0.3427-0.3473), which is similar to the pattern observed for parameter HRR. Assuming a priori value of 50% of the commercial fisheries catch was used for estimating subsistence consumption by means of an informative prior in the models, the actual quantities were 34%, 35%, and 34% in LNKR, HCLNKR, and LKNRWQ, respectively, while a value of 47% was obtained in the UKR model scenario. The posterior distributions of B_{MSP} and F_{MSP} did not differ substantially between LNKR and HCLNKR. Comparing the UKR, HCLNKR, and LNKRWQ model scenarios, the posterior median for B_{MSP} was 460, 490, and 522 tonnes, while F_{MSP} was 0.2390, 0.1619, and 0.1761 per year, respectively. As a result, the posterior medians of maximum surplus production were 110, 80, and 92 tonnes for the UKR, LNKR, and LNKRWQ models, respectively. With respect to time-varying catchability (q), a random walk exercise was included to account for variation in gear configuration, such as gear structure, mesh size, and set duration, without fixed time constraints. Compared with UKR, there were substantial differences when the population was very low, before 1970, which conflicts with the constant assumption in LNKRWQ and MMI estimates (Figure 6).

Over-exploitation can be ascribed when the biomass status is less one (<1) or when fishing mortality status is greater than one (>1). Throughout the time series from 1960 to 2008, Arctic Char fisheries in Cambridge Bay underwent exploitation below the critical lower biomass level (Figure 7a), while it was near the full-exploitation criterion (Figure 7b) during 1978-1990 because of higher fishing mortality from LNKRWQ and MMI analysis. Since 1990, posterior median biomass status was >1 and fishing mortality status was <0.50, which suggested that the Arctic Char stocks have been well within the Healthy Zone.

Two types of uncertainties are included in assessing the model performance: process and observational. Among the four candidate models, the catchability-embedded model (LNKRWQ) produced the smallest values for process and observation errors, but separated natural variation in catchability, 0.1399, more than process error (0.0952) for random walk effects (Figure 8). More than three times the observation errors occurred in all other models. Among the tools proposed by Patterson et al. (2001), the choice of tools used to assess uncertainties in fish stock assessment may depend on the underlying stock assessment models, the major concerns regarding model structure, and the approaches used to assess the quantities of uncertainties, such as Bayesian, frequentist, and likelihood analyses.

BIOLOGICAL REFERENCE POINTS AND THE PRECAUTIONARY APPROACH

The determination of biological reference points (BPRs) is intended to trigger the establishment of management objectives that adhere to the reference points (Caddy and Mahon 1995). A fishery harvest control rule, also known as a decision rule, a catch control law, or a feedback control rule, represents a consistent procedure used to decide upon total allowable catch (TAC) given a set of biomass estimates from stock assessment models. In Bayesian statistics cases, the quantities of interest are the probability distributions of certain outcomes given a range of catch limit options. The target of the rule is therefore to provide a pre-defined means of changing the TAC in response to changes in the condition of the stock. Combined with control rules for stock status and harvest, underlying reference points and control rules have been incorporated in the DFO precautionary approach strategies (DFO 2006), both in the national fishery decision-making framework and in integrated fisheries management plans. The primary components of the generalized framework of the precautionary approach define the decision rules and reference points as short-term objectives (Patterson et al. 2001) by recognizing three zones of stock status regarding abundance or biomass (Caddy and Mahon 1995, DFO 2006):

(1) **Critical zone** where fishery management actions must promote stock growth and removals from all sources must be kept to the lowest possible until the stock has cleared this zone. Harvest rate is kept to an absolute minimum. A conservation plan must be in place to ensure a high probability of the stock to be rebuilt within a reasonable timeframe;

(2) **Cautious zone** where socio-economic and biological factors will be balanced to reflect the stock trajectory and location in the zone. Harvest rate should progressively decrease from the established maximum and should promote the stock to grow into the healthy zone;

(3) **Healthy zone** where the removal rate should not exceed the maximum acceptable removal reference. Conservation measures should be consistent with sustainable use. Fishery management actions should be tolerant of normal stock fluctuations.

The delineation of the zones of stock status is mainly specified by a number of precautionary reference points that take into account the rational utilization of fisheries resources. The points are categorized into Target Reference Points (TRPs) and Limit Reference Points (LRPs). TRPs are considered indicators of desirable stock status for fisheries management after active monitoring and continuous re-adjustments of management measures on appropriate time-scales. LRPs are delineated by the boundaries of the critical and cautious zones; they largely indicate the states of fishing or resource use during exploitation, development, or rebuilding paradigms (Caddy and Mahon 1995, Prager et al. 2003, Schnute and Haigh 2006). In addition, an upper stock reference point (USP) was created at the boundary between the cautious and healthy zones, as well as removal references for each of the three zones, which provides sufficient opportunities for the management system to recognize declining stock status and sufficient time for management actions to be taken effect (DFO 2006).

For comparative purposes, the precautionary reference points are listed separately based on the UKR, LNKRWQ and MMI estimates:

(1) Critical zone specified by LRP
UKR: CPUE=0.0482 tonnes/gillnet, biomass=184 tonnes,
LNKRWQ : CPUE=0.0544 tonnes/gillnet, biomass=209 tonnes,
MMI: CPUE=0.0539 tonnes/gillnet, biomass=207 tonnes

(2) Cautious zone defined by USP
UKR: CPUE=0.0965 tonnes/gillnet, biomass=368 tonnes,
LNKRWQ : CPUE=0.1087 tonnes/gillnet, biomass=417 tonnes,
MMI: CPUE=0.1078 tonnes/gillnet, biomass=414 tonnes

(3) Healthy zone defined by TRP
UKR: CPUE=0.1206 tonnes/gillnet, biomass=460 tonnes,
LNKRWQ : CPUE=0.1359 tonnes/gillnet, biomass=522 tonnes,
MMI: CPUE=0.1348 tonnes/gillnet, biomass=517 tonnes

(4) The targets of fishing management would be considered,
UKR: B_{MSP} =459 tonnes, and F_{MSP} =0.2390,
LNKRWQ: B_{MSP} =522 tonnes and F_{MSP} =0.1761,
MMI: B_{MSP}=517 tonnes and F_{MSP}=0.1805

As is expected for the precautionary approach, the critical zone is entered if the mature biomass is less than or equal to 40% of B_{MSP}: biomass $\leq$40% B_{MSP}. Management strategies of closing fisheries and protecting areas would be ideal for ensuring the recovery of threatened species located in the critical stock status zone. The cautious zone is entered if the biomass is higher than 40% of B_{MSP} but less than 80% of B_{MSP}: 40% B_{MSP} $\leq$Biomass$\leq$80% B_{MSP}. This defines the upper stock point (USP). Direct reductions in exploitation should also be implemented when the exploited stock is in the cautious zone until the population biomass approaches the USP. The healthy zone is entered if the biomass or its index is higher than 80% of B_{MSP}: Biomass$\geq$80% B_{MSP}. In the healthy zone, the removal rate could be controlled on the basis of targets of maximum surplus production, but timely monitoring of stock status is required.

Given two model scenarios (Figure 9), under model UKR (upper panel) exploitation rates were somewhat lower than the target, and the population biomass remained in the healthy zone as compared to model LNKRWQ (lower panel). These results from both models also explicitly demonstrate that the population was located in the cautious zone in the very beginning of the time series. Under the current exploitation strategy, the population is in the healthy or sustainable zone. Combined the estimates from two selected models above, we produced a PA model for managing Cambridge Bay Arctic Char (Figure 10) in terms of MMI. The general pattern was quite similar to that of LNKRWQ in terms of the 93% DIC weight; the reference parameters (B_{MSY}=517 t, F_{MSY}=0.1805 per year, and MSY=93 t) were slightly different.

DISCUSSION

ADVANTAGES OF HIERARCHICAL BAYESIAN STATE-SPACE MODELS

In this study, we adopted hierarchical Bayesian state-space models to assemble a biomass index and fisheries series, focused on kernel model parameters of the population attributes of Cambridge Bay Arctic Char. Associated with the derived parameters, we developed precautionary reference points to diagnose stock status and outline management options for sustainability purposes. This exercise is our first attempt at quantitatively assessing Arctic Char population dynamics when confronted with a data-poor reality and rapid changes in an Arctic ecosystem (Tallman et al. 2014). During the modeling stages, we realized that there was a real challenge in knowing how sensitive the working models are to the initial value settings of parameter priors when the time-series index data was discontinuous (Zhu et al. 2014). Throughout the history of commercial Arctic Char fisheries, CPUE has only been observed for 12 years; additionally, nothing was recorded regarding fishing effort and incomplete data is available for subsistence fisheries. Fortunately, surplus production models and Bayesian inference provide us with extremely flexible solutions. Given the latent productivity of a population, it is of interest to determine what surplus is available for harvesting after the population is replenished through recruitment and growth and diminishment by natural mortality (Quinn and Deriso 1999).

The surplus production model is a standard model used for fish population assessments. Because of the simplicity of the model structure, topmost, and lower data requirement, it has been used for evaluations and management of a great number of animal populations (Meyer and Millar 1999, McAllister et al. 2001, Hammond and Trenkel 2005, Chaloupka and Balazs 2007). Moreover, combined with hierarchical Bayesian models, the distinct advantages of this approach allow for the use of incomplete and unbalanced data, heterogeneous variances, and errors-in-variables (Carlin and Louise 2009), as well as different sources of information (Ntzoufras 2009). This was of critical importance because the biomass index was estimated by applying a pair-wise correlation between winter AOI and observed CPUE (Zhu et al. 2014). The use of the exchangeability assumption played a central role in this approach. In addition, hierarchical models are mostly based on the stochastic process of biological production and related descriptive properties of model parameters. In contrast with traditional models of deterministic process, the stochastic process depends largely on the probability distribution function of the model prior and posterior components. The model priors were decomposed into two parts: structural information or assumptions concerning the model, and actual subjective information regarding model parameters. The evident advantage is that provides flexibility in parameter quantities in the varying prior pdfs for most model parameters. As a result, the hierarchical Bayesian models can better incorporate with some degree of uncertainties for future fisheries management risk analysis. Specifically, the uncertainty has been accounted for both within the model and during observational processes, despite the fact that there are a number of other kinds of uncertainties that can be accounted for during fisheries management (Francis and Shotton 1997). Knowing the sources and amplitudes of uncertainty can be appreciably helpful to advise the fisheries managers how to pinpoint the possible risks and its consequences when implementing specific sets of harvest control rules.

POTENTIAL VIOLATIONS OF MODEL ASSUMPTIONS

A number of assumptions are made when applying surplus production models for fish stock assessment, including the following:

i) linear proportionality between the abundance index and the true abundance;

ii) a symmetric relationship between relative biomass and production;

iii) an instantaneous reaction of stock to exploitation;

iv) the stock is self-sustained and recruitment is stable;

v) no interspecific interactions;

vi) the environment is steady; and

vii) fishing catch is density-dependent.

Despite the extensive use of surplus production models for fish stock assessment, there are many arguments to challenge the underlying assumptions of the model framework. Harley *et al.* (2001) suggested that the power coefficients between CPUE and the abundance of a 30% surveyed stock were >1, i.e. hyperdepletion, and the rest were <1, i.e. hyperstability. Hilborn and Walter (1992) pointed out that equilibrium fitting methods are biased and unreliable. Also, there were some concerns about the lack of environmental considerations in the model (Quinn and Deriso 1999). Prager (2002) suggested that the generalized surplus production model (GSPM) is sensitive to data outliers.

In the Arctic Char population biomass models, we integrated winter AOI to extend the observed CPUE series, realizing that the population exhibited significant temporal variation with changing climatic scenarios (Zhu et al. 2014). When all interactions through meteorological, limnological, and biological processes are considered, changing climate conditions may impact Arctic Char population production, as was indicated by the time lag effect in this analysis. In fact, the fluctuations in the commercial fisheries can also demonstrate the existence of this interplay (Figure 3), combined with alterations in the targeting of stocks (Day and de March 2004). On the other hand, changes in fishing gear, either in the commercial harvest or during index sampling, were also responsible for biases in observation due to differences in catchability. ANOVA revealed that there were no significant differences from changes in sampling gears between gillnets and weirs (Zhu et al. 2014). With respect to those relevant assumptions, our model structure included a shape parameter to describe the symmetric and asymmetric relationship between relative biomass and production. It was assembled into the GSPM, indicating the applicability of asymmetric forms of biomass and production to Arctic Char populations.

In terms of the model convergence by CODA, model goodness-of-fit based on DIC, , and MMI, the best model, given 93% DIC weight (Table 7), was selected as the combination of lognormal *K* and *r* with time-varying catchability (LNKRWQ). Despite diverse model structures and underlying assumptions for priors, there were some degrees of similarities in derived model parameters when using the same datasets, such as LNKR and HCLNKR models. Compared with the model outputs, we found that one of the assumptions, constant catchability coefficient q, was substantially violated before 1970 when the population biomass was at a critical lower level (Figure 6). As the population grew, the constant *q* can only be approximated after 1970. In addition to the time-invariant q, the assumption that a linear proportionality exists between biomass or abundance and density (CPUE), is questionable for Arctic Char which may be considered as metapopulations (Gyselman 1994, Kristofferson and Berkes 2005). Though quite high natal fidelity, the summer fished stock units, composed of metapopulations or mixed stocks, are a complicated mosaic of discrete stocks with uniform annual variation in population parameters, as proposed by Day (2004). These stocks were believed mixed while overwintering and feeding over an extensive spatial scale. Current information collection for stock assessment is still insufficient to be able to distinguish stock-specific CPUE and harvest statistics. Instead, the discrete stock formulations will always be approximations irrespective of assumptions regarding density-dependence.

APPLICATION OF THE METHOD TO FISHERIES MANAGEMENT

The precautionary approach (PA) has been acknowledged as a central measure for managing fisheries and human participatory governance systems (DFO 2006, Punt 2006, Rice 2009). Implementation of the PA, integrated fisheries management plans (IFMP), and the ecosystem approach, such as ecosystem-based fisheries management (EBFM; Pikitch et al. 2004), requires a better understanding of the expected objectives for natural resources and indicator-based frameworks. Normally, the objectives are defined based on quantitative stock assessments of monitored fish stocks through short-, medium-, and long-term observation programs. Many working models for stock assessments can, thus, be adopted on the basis of distinct objectives, the availability of information, and a well-developed risk-and-decision system.

The analyses presented in this document provide evidence of the overall status of the Arctic Char populations in the Cambridge Bay area with respect to precautionary reference points. This information may be useful for managers tasked with setting quotas that are consistent with the PA. For fisheries that specifically target adults in particular rivers, attention should be given to interactions between the spawning stock and local environmental changes, as well as the spawner-recruitment relationship, because of reductions in fecundity and growth capacity of the exploited fish populations (Hilborn and Walters 1992). Preliminary reference points could be considered in concert with other indicators of population status, including abundance at recruitment, the sex ratio, fecundity, cohort strength, and feeding habits, among others. The development of decision control rules to guide fishing exploitation, which is an essential element in the application of the PA, depends on a sustainable balance between fishing capacity and resource availability. Socio-economic factors, such as the number of fishing licenses, the distribution of allocations among rivers, and local resource development, are also important considerations for exploitation decisions.

When formulating precautionary reference points, there are a number of scientific issues with CPUE observations, records of fishing effort for commercial and subsistence fisheries, general fish biology, and logistics. For example, the char fisheries have been primarily concentrated in traditional locations that are close to Wellington Bay (Ekalluk, Paliryuak, and Halovik rivers) and Coronation Gulf (Lauchlan River), as well as north of Cambridge Bay (Jayco River); samples from the Ellice and Perry rivers, close to Queen Maud Gulf, have been discontinuous since 2000. In the future, fisheries may occur in other locations.

Most historical CPUE series were sampled in one location each year (except two locations were sampled in 1975, 1980, and 1981), principally in the Ekalluk and Jayco rivers. The underlying assumption, that the CPUE from a single river system is representative of the entire waterbody, is somewhat subjective as a result of limited abundance index time series. To detect spatial variation in CPUE index among individual river systems, firstly, we need to extend the monitoring of stock status into multiple fishing river systems in a single year. Secondly, with respect to the quantitative assessment of stock status, a consistent sampling protocol should be established and maintained for the annual collection of CPUE observations by gillnets and weirs in at least two of the above locations during August and September. This should be done in conjunction with the collection of other biological observations including age-growth, recruitment, feeding habits, and density-dependent or density-independent fishing mortality.

Thirdly, although the CPUE series can be estimated by a predictive function linked to a large-scale climate covariant, wintertime AOI, future observations are needed for validation of the predictive model and timely adjustments. Fourthly, from a scientific perspective, we would also suggest a stock discrimination study to confirm the existence of one or multiple distinctly-delineated stock unit within each river.

Assessing fish stock dynamics and implementing harvest control rules within the framework of integrated fisheries management plans (IFMP) also depend on fishing effort information. For Arctic Char subsistence fisheries in the Canadian North these data are lacking. Despite the fact that minimum gear mesh size is fixed, it is still insufficient to get estimates of fishing mortality rate without fishing effort information, such as the number of nets used, the frequency at which the gear is checked, soaking time, and gear configuration. Additionally, no fishing effort information is available for local sport fisheries. A number of fishery-dependent data collection options could be initiated such as a pilot survey, a creel survey, interviews, and logbooks. It is not necessary to conduct these optional surveys every year, but it is valuable to measure the selectivity of particular fishing methods and estimate total fishing effort on the fish population dynamics.

Because of limited data availability, the analysis in this report is primarily based on the relationship between the stock index and commercial fisheries harvest, and can be treated as a starting point for defining precautionary reference points and harvest control rules for managing Arctic Char fisheries. Our analysis is rather preliminary but the outcomes of the model are promising, at least for modulating several useful references on exploitation and management as a whole. One of the important outputs of the model is the description of the trajectory variation in population biomass throughout forty-nine years of exploitation. Although the model inputs only included the biomass index and harvest, irrespective of divisions by life stages, such as recruits, juveniles and spawners, or any age structure, the descriptors were manifestly referred to the entire population. Biological fisheries data showed that more than 50% of Arctic Char (64% of female and 70% of male char) constituted the commercial harvests before 1990, and recent maturity assessments in the Halovik and Jayco rivers indicated that all of the harvested char were mature (Day and Harris 2013). Finally, to improve the capacity and effectiveness of the candidate working model, it is hopeful that we will have well-defined sampling protocols and consistent monitoring plans in the future. Without sufficient data support and plausible expert knowledge, models are dangerous because the outputs can be misleading and, ultimately, could lead to the extirpation of the exploited population.

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TABLES AND FIGURES

Table 1. Commercial fisheries harvest (tonnes) of Arctic Char from estuaries of rivers around Cambridge Bay, Nunavut during 1960-2010.

Year	Lauchlan	Halovik	Paliryuak	Ekalluk	Jayco	Ellice	Perry	Sum
1960	0.00	0.00	0.00	15.88	0.00	0.00	0.00	15.88
1961				10.82				10.82
1962	0.00	0.00	0.00	5.77	0.00	0.00	0.00	5.77
1963	2.27	0.00	0.00	13.88	0.00	0.00	0.00	16.15
1964	0.00	0.00	0.00	15.50	0.00	0.00	0.00	15.50
1965	0.00	0.00	0.00	20.87	0.00	0.00	0.00	20.87
1966	0.00	0.00	0.00	16.78	0.00	0.00	0.00	16.78
1967	0.00	0.00	0.00	27.70	0.00	0.00	0.00	27.70
1968	0.00	2.61	6.47	34.30	0.00	0.00	0.00	43.38
1969	0.00	25.86	0.00	22.70	0.00	0.00	0.00	48.56
1970	2.42	26.20	5.88	0.00	0.00	0.00	0.00	34.50
1971	19.05	10.43	0.00	0.00	0.00	12.82	0.00	42.30
1972	20.99	6.48	0.00	0.00	0.00	12.52	0.00	40.00
1973	9.66	1.92	0.00	9.63	0.00	7.24	0.00	28.44
1974	8.13	0.00	0.00	12.54	0.00	6.96	0.00	27.62
1975	0.00	0.00	0.00	12.26	8.23	10.36	0.00	30.85
1976	0.00	2.78	0.00	13.63	9.44	12.68	0.00	38.52
1977	1.52	4.62	3.26	15.90	7.56	20.80	13.65	67.31
1978	8.54	5.73	8.42	14.59	13.41	9.12	8.14	67.94
1979	10.85	7.32	11.82	15.81	12.24	7.18	1.74	66.93
1980	9.15	7.48	7.50	10.52	14.47	6.63	3.38	59.13
1981	8.72	7.01	8.64	14.28	13.32	5.74	2.84	60.55
1982	8.92	6.85	9.05	14.23	5.71	8.86	0.00	53.62
1983	9.11	6.83	8.83	14.84	12.97	9.05	0.00	61.61
1984	9.88	7.31	8.81	14.50	13.52	8.95	0.00	62.96
1985	9.06	6.45	9.29	14.52	11.58	5.60	0.00	56.50
1986	8.24	6.83	9.12	14.35	12.08	4.18	0.00	54.80
1987	9.55	6.88	8.67	14.66	13.69	4.53	0.00	57.97
1988	9.43	6.81	8.57	14.83	11.82	6.54	0.00	58.00
1989	9.18	6.86	9.18	13.57	10.29	5.97	0.00	55.05
1990	8.94	6.97	9.32	15.29	12.87	6.37	0.00	59.76
1991	8.81	6.35	8.95	0.00	2.23	7.97	0.60	34.91
1992	9.32	6.87	8.88	0.00	0.00	0.00	0.00	25.08
1993	9.31	5.94	6.58	1.48	15.41	8.02	0.00	46.73
1994	0.00	3.86	0.00	1.64	16.29	7.18	0.00	28.96
1995	1.44	4.27	0.00	4.67	12.56	7.54	0.00	30.47
1996	2.35	4.91	0.00	10.21	16.91	4.50	0.00	38.89
1997	0.90	5.00	0.00	14.33	10.59	0.00	0.00	30.81
1998	1.43	5.14	0.00	19.83	17.07	0.00	0.00	43.47
1999	2.74	5.12	5.68	14.58	17.09	4.50	0.00	49.71
2000	0.00	5.21	5.81	16.93	17.31	0.00	0.00	45.26
2001	0.44	5.43	5.77	16.55	16.37	0.00	0.00	44.55
2002	0.00	4.77	7.62	16.23	16.71	0.00	0.00	45.32
2003	1.52	5.48	0.00	15.84	17.17	0.00	0.00	40.01
2004	3.27	6.91	9.01	14.70	7.57	0.00	0.00	41.45
2005	2.91	6.62	8.83	13.72	2.61	0.00	0.00	34.69
2006	8.81	7.60	7.48	14.27	12.78	0.00	0.00	50.94
2007	8.68	6.80	8.75	10.61	8.65	0.00	0.00	43.50
2008	8.80	7.59	7.46	14.50	13.60	0.00	0.00	51.94
2009	0.00	5.22	8.66	12.67	6.51	0.00	0.00	33.06
2010	2.53	3.32	9.07	20.43	0.00	0.00	0.00	35.36

Table 2. River-based quotas (tonnes) for Cambridge Bay Arctic Char commercial fisheries during 1960-2010.

Year	Lauchlan	Halovik	Paliryuak	Ekalluk	Jayco	Ellice	Perry	Sum
1960								
1961								
1962				18.16				18.16
1963				18.16				18.16
1964				18.16				18.16
1965				18.16				18.16
1966				18.16				18.16
1967								
1968								
1969								
1970								
1971						22.70		22.70
1972	18.16	9.10				11.35		38.61
1973	18.16	9.10		18.16		11.35		56.77
1974	11.35			11.35		11.35		34.05
1975				11.35	6.80	11.35		29.50
1976		9.10		11.35	6.80	13.60		40.85
1977	6.80	4.50	4.50	11.35	6.80	13.60	11.35	58.90
1978	6.80	4.50	6.80	11.35	11.35	13.60	11.35	65.75
1979	9.10	6.80	9.10	14.50	13.60	9.10	11.35	73.55
1980	9.10	6.80	9.10	14.50	13.60	9.10	11.35	73.55
1981	9.10	6.80	9.10	14.50	13.60	9.10	6.80	69.00
1982	9.10	6.80	9.10	14.50	13.60	9.10	6.80	69.00
1983	9.10	6.80	9.10	14.50	13.60	9.10	6.80	69.00
1984	9.10	6.80	9.10	14.50	13.60	9.10	6.80	69.00
1985	9.10	6.80	9.10	14.50	13.60	4.50	4.50	62.10
1986	9.10	6.80	9.10	14.50	13.60	4.50	4.50	62.10
1987	9.10	6.80	9.10	14.50	13.60	4.50	4.50	62.10
1988	9.10	6.80	9.10	14.50	13.60	6.00	4.50	63.60
1989	9.10	6.80	9.10	14.50	13.60	6.00	4.50	63.60
1990	9.10	6.80	9.10	14.50	13.60	6.00	4.50	63.60
1991	9.10	6.80	9.10	1.50	15.60	8.00	6.50	56.60
1992	9.10	6.80	9.10	7.50	15.60	8.00	6.50	62.60
1993	9.10	6.80	9.10	7.50	15.60	8.00	6.50	62.60
1994	9.10	5.00	0.00	20.00	17.00	8.00	6.50	65.60
1995	2.40	5.00	0.00	20.00	17.00	8.00	6.50	58.90
1996	2.40	5.00	0.00	20.00	17.00	8.00	6.50	58.90
1997	2.40	5.00	0.00	20.00	17.00	8.00	6.50	58.90
1998	2.40	5.00	0.00	20.00	17.00	8.00	6.50	58.90
1999	2.40	5.00	0.00	20.00	17.00	8.00	6.50	58.90
2000	2.40	5.00	0.00	20.00	17.00	8.00	6.50	58.90
2001	2.40	5.00	0.00	20.00	17.00	8.00	6.50	58.90
2002	2.40	5.00	0.00	20.00	17.00	8.00	6.50	58.90
2003	2.40	5.00	0.00	20.00	17.00	8.00	6.50	58.90
2004	9.10	6.80	9.10	14.50	13.60	8.00	6.50	67.60
2005	2.40	5.00	9.10	20.00	17.00	8.00	6.50	68.00
2006	2.40	5.00	9.10	20.00	17.00	8.00	6.50	68.00
2007	2.40	5.00	9.10	20.00	17.00	8.00	6.50	68.00
2008	2.40	5.00	9.10	20.00	17.00	8.00	6.50	68.00
2009	2.40	5.00	9.10	20.00	17.00	8.00	6.50	68.00
2010	2.40	5.00	9.10	20.00	17.00	8.00	6.50	68.00

Table 3. Harvest statistics for subsistence use of Arctic Char by the Aboriginal residents of Cambridge Bay, Nunavut. Data is from a Nunavut wildlife harvest study conducted during 1996-2001 (Priest and Usher 2004), showing the numbers of char harvested and fishers for char by month and year.

Year	Number	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Total
1996	Arctic Char	205	2,601	1,155	25	43	64	313					38	4,444
1997	Arctic Char	194	668	328	110	35		22					80	1,437
1998	Arctic Char	813	1,084	1,416	1,235	26	168				1		2	4,745
1999	Arctic Char	977	4,087	3,063	965	129	21							9,242
2000	Arctic Char	915	2,956	5,309	2,009	522	11	129				54	530	12,435
	Mean	621	2,279	2,254	869	151	66	155			1	54	163	6,461
1996	Hunter	6	14	9	1	2	1	1					3	23
1997	Hunter	12	14	11	5	1		1					5	33
1998	Hunter	27	14	14	14	3	4				1		2	40
1999	Hunter	17	26	36	10	5	1							50
2000	Hunter	22	29	37	20	10	1	2				2	8	55
	Mean	17	19	21	10	4	2	1			1	2	5	40

Table 4. Notation for hierarchical Bayesian state-space statistics for a generalized surplus production model of Cambridge Bay Arctic Char.

Symbol	Description
Indices and index ranges	
Y	Final year of modeled time
y	Year, where $1 \le y \le Y$ and y=1 corresponds to the first year
N	Number of non-missing observations for the index series
i	Index of non-missing biomass index observation i=1,…,n
Data	
C_y	Commercial harvest during year y
I_y	Survey relative biomass observation for year y
Model parameters	
K	Carrying capacity or virgin biomass
r	Intrinsic population growth rate
q	Catchability coefficient for relative biomass observations
B_0	Unfished or pre-exploitation population biomass
z	Shape parameter between relative biomass and harvest
State variable	
B_y	Biomass at the beginning of year y
Derived management quantities of interests	
MSP	Maximum surplus production
F_{MSP}	Fishing mortality at MSP
B_{MSP}	Biomass at MSP
C^*	Quota based on optimal exploitation rate
U_{MSP}	Optimal exploitation rate
Statistical uncertainty (error)	
σ^2	Process deviation squared coefficient of variation
τ^2	Observation deviation squared coefficient of variation
μ_k	Median for log-transformed K
μ_r	Median for log-transformed r
τ_k	Precision for prior K
τ_r	Precision for prior r
τ_q	Precision for prior q

Table 5. Generalized surplus production model used for management procedure simulation and stock assessment analyses. The table represents an error-in-variables formulation of the Pella-Tomlinson biomass dynamics stock assessment model for estimating biomass and management quantities each year.

Model parameters

$$C_t = qE_tB_t$$

$$I_t = q \times B_t$$

$$\frac{dB}{dt} = rB\left(1 - \frac{B}{K}\right) - qEB$$

$$\frac{dB}{dt} = \frac{r}{z}B(1 - (\frac{B}{K})^z) - qEB$$

$$P_{t+1} = P_t + rP_t(1 - P_t^z) - \frac{C_t}{K}$$

Conditional

$$logP_t = \log(\hat{P}_t) + \mu_t$$

$$LP_t = \frac{1}{\sqrt{2\pi\sigma P_t}}\exp(-\frac{\log(P_t) - \log(\hat{P}_t))^2}{2\sigma^2}$$

$$\log(I_t) = \log(\hat{I}_t) + v_t$$

$$LI_t = \frac{1}{\sqrt{2\pi\tau I_t}}\exp(-\frac{\log(I_t) - \log(\hat{I}_t))^2}{2\tau^2}$$

Prior specification

$$K \sim \text{uniform}(100,1500) \text{ or } K \sim \text{log-normal}(\mu_K, \tau_K)\text{I}(100,1500)$$

$$r \sim \text{uniform}(0.01,1.05) \text{ or } r \sim \text{log-normal}(\mu_r, \tau_r)\text{I}(0.01,1.05)$$

$$z \sim \text{normal}(0.0,10^{-6})\text{I}(0.1,15)$$

$$q \sim \text{normal}(0.0,10^{-6})\text{I}(10^{-6}, 1)$$

Random walk for catchability coefficient

$$q_{t+1} = \sqrt{\frac{\tau_q}{2\pi}}\,\frac{1}{q}\exp(-\frac{\tau_q}{2}(log\ q - q_t\ )^2\ )$$

Accounting for subsistence harvest portion

Total harvest=Commercial X (1+*HRR*)

HRR~normal(0.0,10^{-6})I(0.01,1.05)

Management quantities of interests

$$F_{MSP} = \frac{r}{(z+1)^{(1/z)}}$$

$$B_{MSY} = \frac{K}{(z+1)^{(1/z)}}$$

MSP=$F_{MSP} \times B_{MSP}$

Table 6. Convergence and stationarity tests by the R-based CODA package for each group of model scenarios: uniform priors for K and r (UKR), lognormal priors for K and r (LNKR), half-Cauchy priors for lognormal K and r (HCLNKR), lognormal priors for K and r with random walk q (LNKRWQ). The Geweke test |Z|>2 indicates non-convergence of the parameter. The Gelman-Rubin diagnostic test involves checking the convergence of the chain if the value is close to one. The Raftery-Lewis test is used to determine the appropriateness of the values of burn-in, thin, and total length of the sample. The Heidelberger-Welch diagnostic is used for the analysis of single chains by p-values.

Test	Summary	UKR		LNKR		HCLNKR		LNKRWQ	
		Chain 1	Chain 2	Chain 1	Chain 2	Chain 1	Chain 2	Chain 1	Chain 2
Geweke's Z-score	Min	-1.7237	-2.9961	-1.3908	-2.3755	-3.6584	-2.4353	-2.3680	-1.8405
	Max	1.2174	2.3789	3.0995	1.1350	3.0050	2.8030	1.7740	2.1143
	Range	2.9411	5.3750	4.4903	3.5106	6.6633	5.2383	4.1420	3.9547
	Mean	0.0260	-1.1207	0.7627	-0.3832	0.5571	0.0365	-0.1587	0.2288
	s	0.5452	1.1049	0.7441	0.5747	0.9902	1.1363	1.2172	0.7398
	<-2	0	28	0	1	1	2	10	0
	>2	0	1	4	0	11	5	0	1
	%	0.00	26.85	3.70	0.93	10.53	6.14	6.37	0.64
Gelman-Rubin	Potential scale reduction factor ($\hat{R}$)	1	1	1	1	1	1	1	1
Raftery-Lewis	Average independence factor	331	326	330	329	326	331	418	414
Heidelberger-Welch's p-value	Min	0.0902	0.0550	0.0248	0.0026	0.0636	0.0600	0.0135	0.0551
	Max	0.9996	0.9965	0.9994	0.9949	0.9945	0.9968	0.9998	0.9974
	Mean	0.6845	0.4158	0.3604	0.6340	0.4524	0.6594	0.3907	0.5728

Table 7. *Model selections using DIC values for kernel parameters of multiple model scenarios. Values of $\overline{D}$, D and pD were posterior mean deviance, the deviance at the posterior mean, and a measure of model complexity. Δ_i and w_i were DIC difference and weight.*

Parameter	Chain 1				Chain 2				Average						
	$\overline{D}$	D	pD	DIC	$\overline{D}$	D	pD	DIC	$\overline{D}$	D	pD	DIC	Δ_i	$e^{-\frac{1}{2}\Delta}$	w_i
Uniform priors for *K* and *r* (UKR)															
HRR	8.667	8.667	0.000	8.667	8.667	8.667	0.000	8.667	8.667	8.667	0.000	8.667			
I	-134.202	-133.919	-0.283	-134.485	-134.202	-133.915	-0.287	-134.489	-134.202	-133.917	-0.285	-134.487			
P	4.640	3.936	0.704	5.344	4.640	3.937	0.703	5.343	4.640	3.937	0.704	5.3435			
q	8.746	8.746	0.000	8.746	8.746	8.746	0.000	8.746	8.746	8.746	0.000	8.746			
Z	4.185	4.185	0.000	4.185	4.185	4.180	0.000	4.185	4.185	4.185	0.000	4.185			
Total	-107.964	-108.385	0.421	-107.543	-107.964	-108.380	0.416	-107.548	-107.964	-108.383	0.419	-107.546	5.180	0.075	0.070
Lognormal priors for *K* and *r* (LNKR)															
HRR	8.667	8.667	0.000	8.667	8.667	8.667	0.000	8.667	8.667	8.667	0.000	8.667			
I	-135.152	-133.452	-1.700	-136.852	-135.143	-133.444	-1.699	-136.843	-135.148	-133.448	-1.700	-136.847			
K	6.789	6.789	0.000	6.789	6.789	6.789	0.000	6.789	6.789	6.789	0.000	6.789			
P	4.675	3.592	1.083	5.759	4.676	3.595	1.081	5.757	4.676	3.594	1.082	5.7575			
q	8.746	8.746	0.000	8.746	8.746	8.746	0.000	8.746	8.746	8.746	0.000	8.746			
r	5.677	5.677	0.000	5.677	5.677	5.677	0.000	5.677	5.677	5.677	0.000	5.677			
z	4.185	4.185	0.000	4.185	4.185	4.185	0.000	4.185	4.185	4.185	0.000	4.185			
Total	-96.412	-95.795	-0.619	-97.029	-96.402	-95.784	-0.619	-97.021	-96.408	-95.791	-0.618	-97.026	15.700	0.000	0.000
Half-Cauchy priors for lognormal *K* and *r* (HCLNKR)															
HRR	8.667	8.667	0.000	8.667	8.667	8.667	0.000	8.667	8.667	8.667	0.000	8.667			
I	-135.159	-133.39	-1.769	-136.928	-135.158	-133.387	-1.771	-136.929	-135.159	-133.389	-1.770	-136.9285			
K	6.875	6.875	0.000	6.875	6.875	6.875	0.000	6.875	6.875	6.875	0.000	6.875			
P	4.68	3.607	1.073	5.753	4.68	3.607	1.073	5.753	4.680	3.607	1.073	5.753			
q	8.746	8.746	0.000	8.746	8.746	8.746	0.000	8.746	8.746	8.746	0.000	8.746			
r	5.774	8.774	0.000	5.774	5.774	5.774	0.000	5.774	5.774	5.774	0.000	5.774			
z	4.185	4.185	0.000	4.185	4.185	4.185	0.000	4.185	4.185	4.185	0.000	4.185			
Total	-96.232	-95.536	-0.696	-96.928	-96.231	-95.533	-0.698	-96.929	-96.232	-95.535	-0.697	-96.929	15.797	0.000	0.000
Lognormal priors for K and r with random walk q (LNKRWQ)															
HRR	8.667	8.667	0.000	8.667	8.667	8.667	0.000	8.667	8.667	8.667	0.000	8.667			
I	-139.221	-129.346	-9.875	-149.095	-138.810	-123.475	-15.334	-154.144	-139.016	-126.411	-12.605	-151.620			
K	6.789	6.789	0.000	6.789	6.789	6.789	0.000	6.789	6.789	6.789	0.000	6.789			
P	3.762	2.658	1.104	4.866	3.707	2.619	1.088	4.794	3.735	2.639	1.096	4.831			
RWQ	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000			
Qinit	8.746	8.746	0.000	8.746	8.746	8.746	0.000	8.746	8.746	8.746	0.000	8.746			
r	5.677	5.677	0.000	5.677	5.677	5.677	0.000	5.677	5.677	5.677	0.000	5.677			
Shape	4.185	4.185	0.000	4.185	4.185	4.185	0.000	4.185	4.185	4.185	0.000	4.185			
Total	-101.394	-92.623	-8.771	-110.165	-101.038	-86.791	-14.247	-115.285	-101.217	-89.708	-11.509	-112.725	0.000	1.000	0.930

Table 8. Summary of posterior means and percentiles for management parameters and model variables derived from four hierarchical Bayesian state-space scenarios for modeling Cambridge Bay Arctic Char.

Parameter	Mean	S.D.	MC error	Percentiles 2.5%	median	97.5%
Uniform priors for K and r (UKR)						
K (tonnes)	904.50	323.70	2.5E+00	336.60	897.50	1466.00
r	0.4977	0.2738	2.2E-03	0.0830	0.4659	1.0120
q	3.0E-04	1.3E-04	1.0E-06	1.4E-04	2.6E-04	6.4E-04
HRR	0.4614	0.2940	2.2E-03	0.0278	0.4304	1.0110
Z	1.88	1.97	1.6E-02	0.23	1.13	8.10
B_{MSP} (tonnes)	479.90	191.10	1.5E+00	187.20	459.50	935.60
F_{MSP}	0.2483	0.1182	9.5E-04	0.0547	0.2390	0.4703
σ^2	0.1301	0.0385	3.0E-04	0.0674	0.1257	0.2166
τ^2	0.4442	0.0687	5.0E-04	0.3130	0.4419	0.5861
Lognormal priors for K and r (LNKR)						
K (tonnes)	881.60	337.80	2.6E+00	308.10	870.10	1463.00
r	0.3443	0.2536	2.1E-03	0.0253	0.2748	0.9562
q	3.2E-04	1.5E-04	1.1E-06	1.5E-04	2.8E-04	6.9E-04
HRR	0.4022	0.2882	2.3E-03	0.0225	0.3431	0.9936
Z	2.99	2.47	1.9E-02	0.33	2.12	9.14
B_{MSP} (tonnes)	523.30	229.20	1.8E+00	177.40	492.70	1021.00
F_{MSP}	0.1871	0.1200	9.5E-04	0.0170	0.1624	0.4588
σ^2	0.1331	0.0390	3.1E-04	0.0706	0.1286	0.2218
τ^2	0.4401	0.0698	5.1E-04	0.3057	0.4388	0.5820
Lognormal half-Cauchy priors for K and r (HCLNKRL)						
K (tonnes)	877.70	336.50	2.8E+00	310.00	863.00	1463.00
r	0.3427	0.2525	2.1E-03	0.0254	0.2735	0.9583
q	3.2E-04	1.5E-04	1.1E-06	1.5E-04	2.8E-04	7.0E-04
HRR	0.4058	0.2873	2.5E-03	0.0223	0.3514	0.9973
Shape (z)	3.04	2.50	2.1E-02	0.33	2.16	9.24
B_{MSP} (tonnes)	522.20	228.60	1.9E+00	180.00	490.30	1026.00
F_{MSP}	0.1868	0.1194	9.6E-04	0.0170	0.1619	0.4558
σ^2	0.1330	0.0387	3.0E-04	0.0695	0.1285	0.2199
τ^2	0.4411	0.0696	5.5E-04	0.3077	0.4389	0.5825
μ_K	0.5996	9.5250	7.2E-02	-17.9100	0.5727	19.2800
μ_r	-0.1782	9.5410	7.2E-02	-19.1100	-0.2262	18.7800
τ_K	0.4181	2.6260	2.1E-02	0.0000	0.0095	3.4760
τ_r	0.3645	2.1990	1.6E-02	0.0000	0.0098	2.9970
Lognormal priors for K and r with random walk q (LNKRWQ)						
K (tonnes)	898.30	332.10	4.4E+00	316.00	896.60	1464.00
r	0.3473	0.2292	2.1E-03	0.0423	0.2880	0.9269
HRR	0.4001	0.2871	2.3E-03	0.0231	0.3376	0.9949
z	3.31	2.53	2.0E-02	0.37	2.53	9.25
B_{MSP} (tonnes)	544.50	224.80	2.8E+00	187.50	521.60	1023.00
F_{MSP}	0.1963	0.1098	1.1E-03	0.0286	0.1761	0.4497
σ^2	0.0999	0.0424	4.4E-04	0.0321	0.0952	0.1950
τ^2	0.4230	0.0719	5.3E-04	0.2838	0.4218	0.5696
τ_q	0.1592	0.1104	1.1E-03	0.0152	0.1399	0.4235

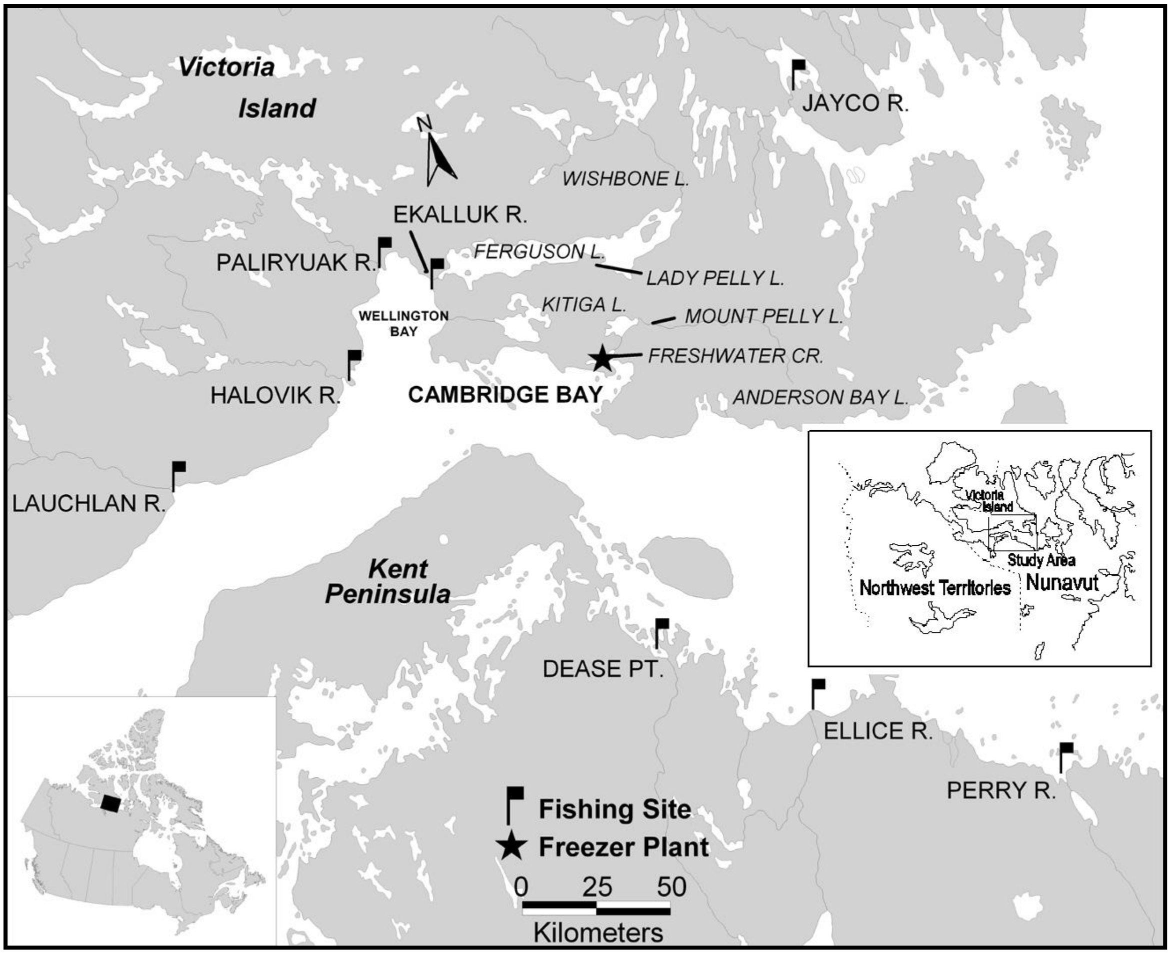

Figure 1. Map of Cambridge Bay, Nunavut, Canada, showing commercial fishing locations for commercial and subsistence uses of Arctic Char (after Kristofferson and Berkes 2005).

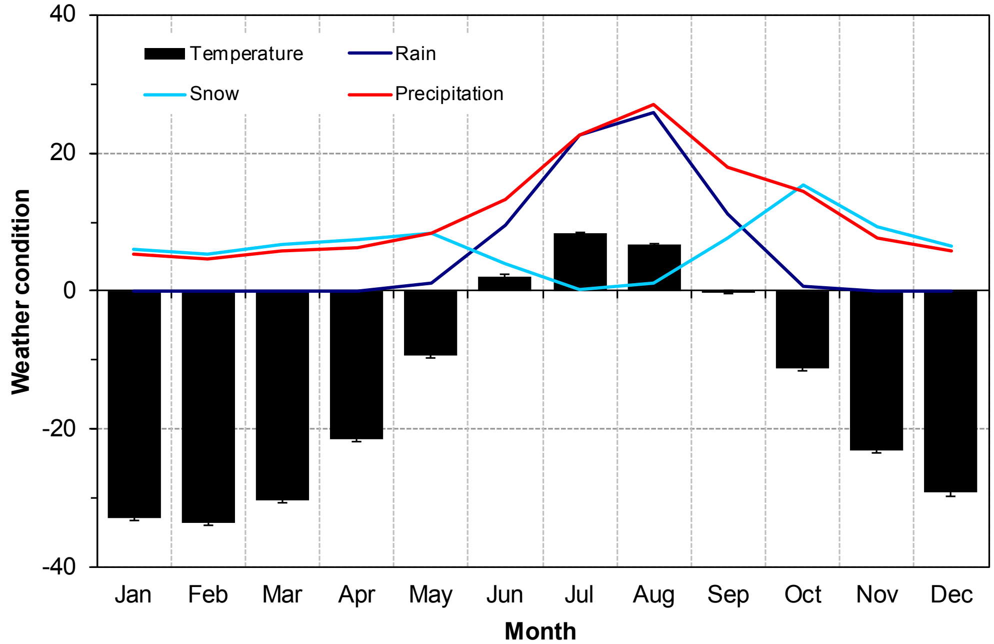

Figure 2. Monthly averages for air temperature (^{o}C), rain (mm), snow (cm), and total precipitation (mm) in Cambridge Bay, Nunavut, during 1950-2010. Data source: Climate ID: 2400600, WMO ID: 71925, TC ID: YCB.

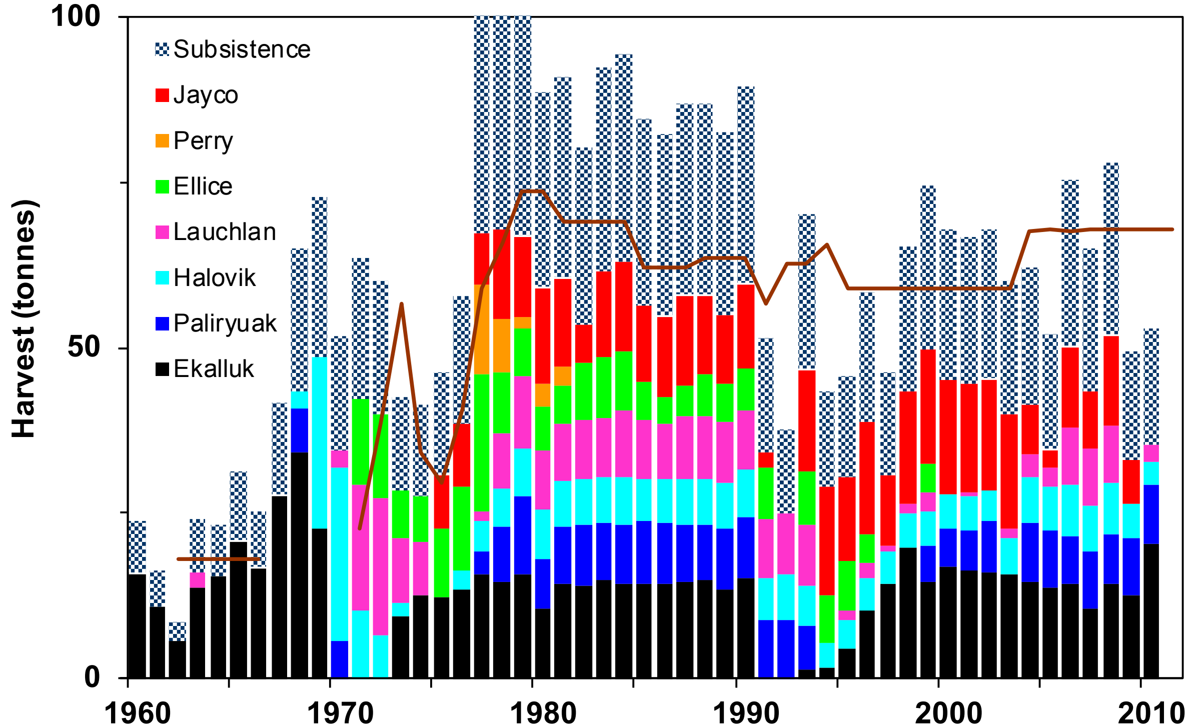

Figure 3. Changes in Arctic Char fisheries in Cambridge Bay during 1960-2010. Coloured bars indicate commercial fisheries in individual rivers and hatched bars show estimated subsistence fisheries. The brown line indicates the allowable quota.

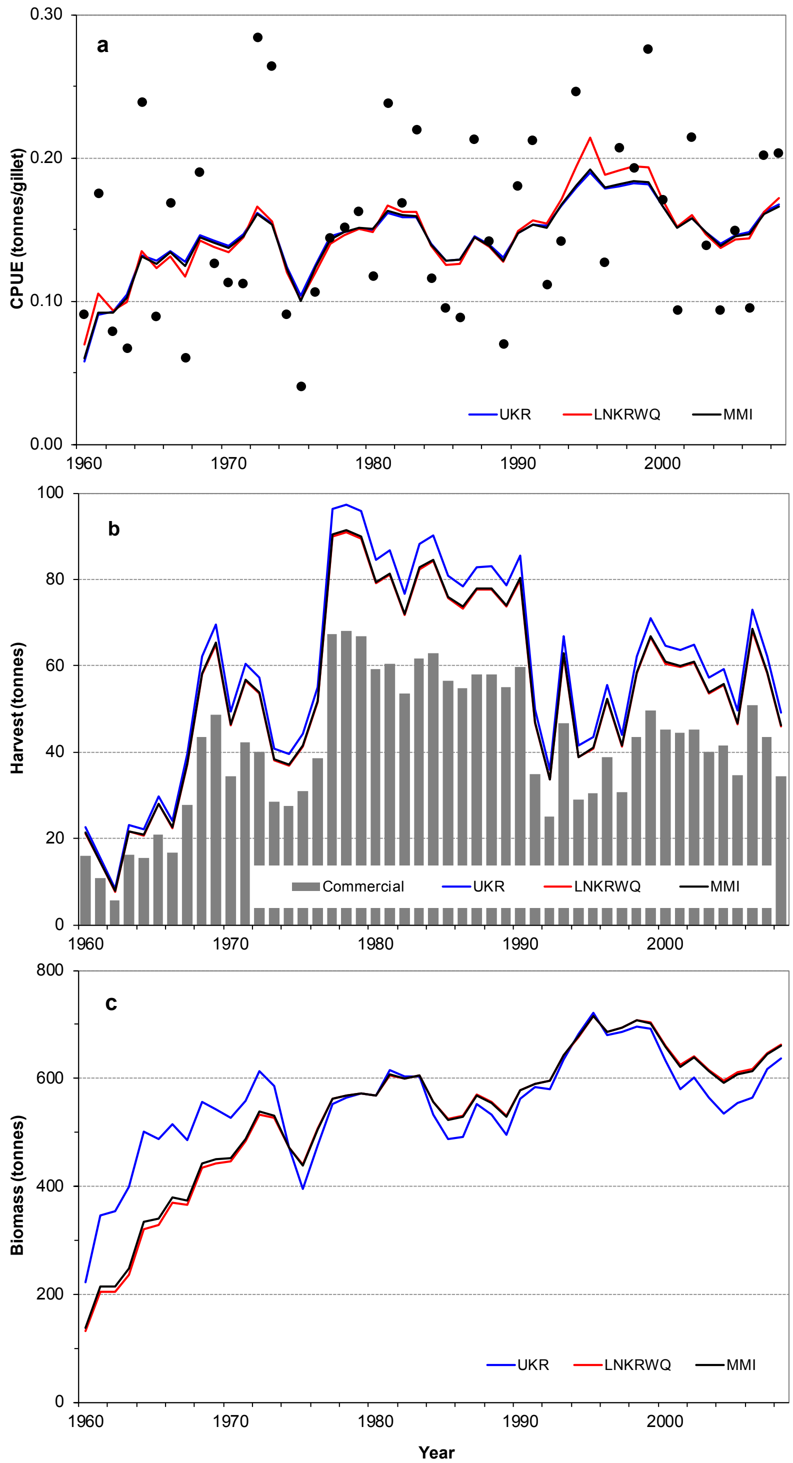

Figure 4. The posterior predictive medians of CPUE (upper panel), harvest (middle panel) and biomass (lower panel) of Cambridge Bay Arctic Char during 1960-2008, compared with the observed CPUE (black solid circles) and harvest statistics (grey bars). The predictions were made from hierarchical Bayesian state-space modeling by uniform (UKR), time-varying lognormal (LNKRWQ) K and r and MMI-based estimated values.

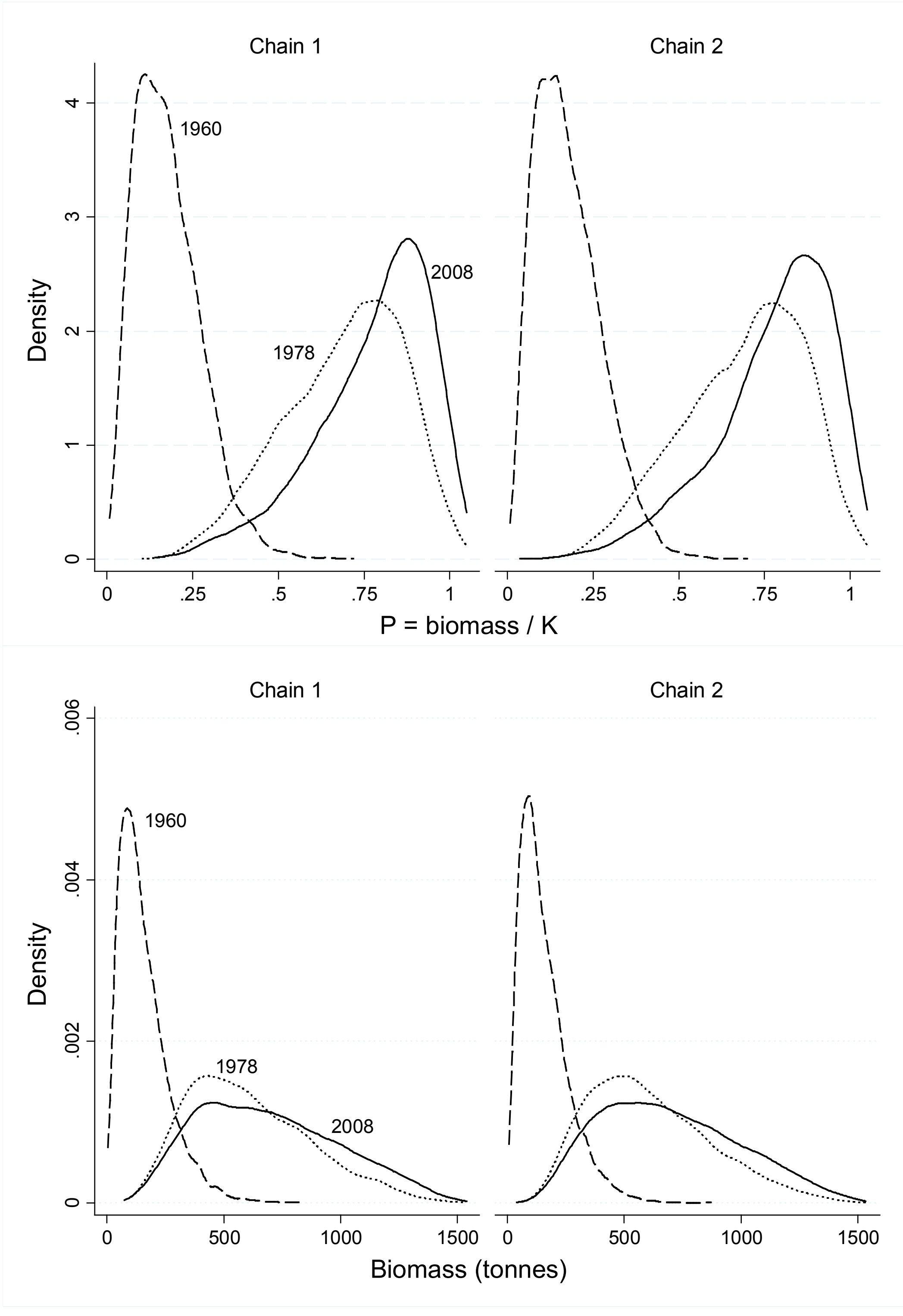

Figure 5. Graphical summary of LNKRWQ fitting for the hierarchical Bayesian state-space model, showing posterior local likelihood density estimates of relative biomass (upper panel) and biomass (lower panel) by lognormal K and r, and random walk q model.

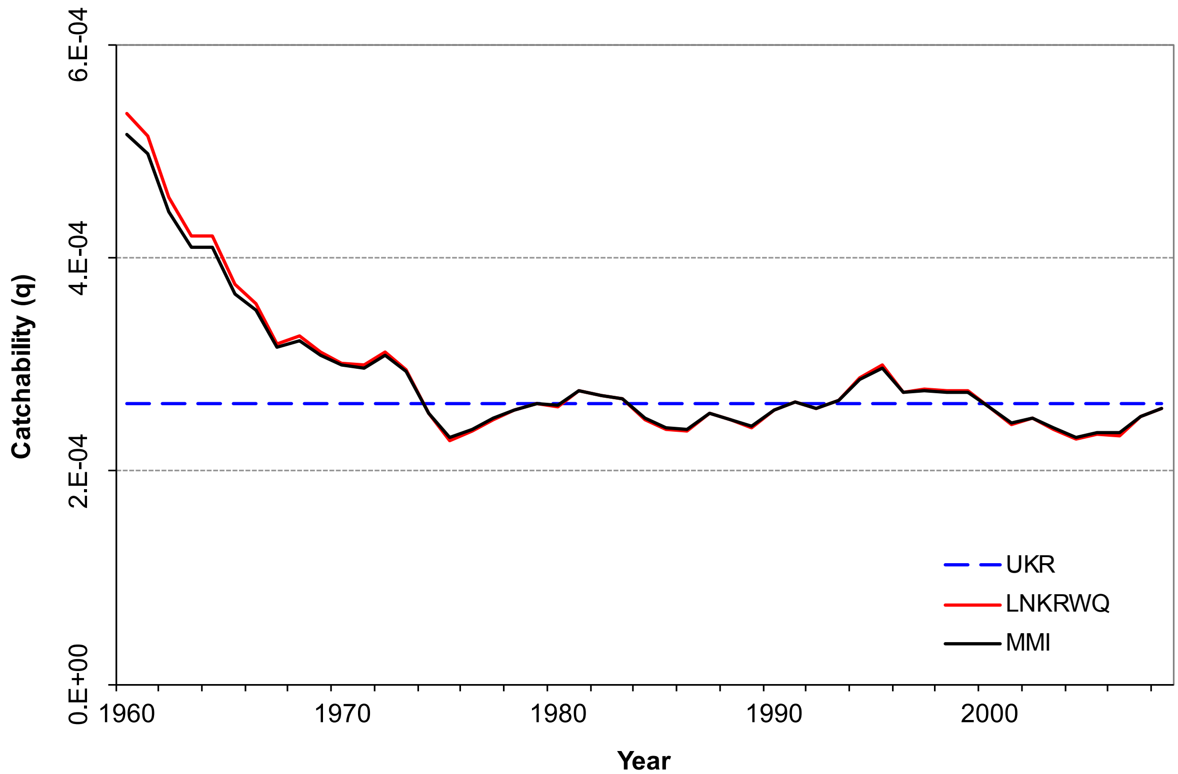

Figure 6. Posterior predictive medians of catchability (q) incorporated with UKR, LNKRWQ, and MMI estimates from hierarchical Bayesian state-space models of Cambridge Bay Arctic Char.

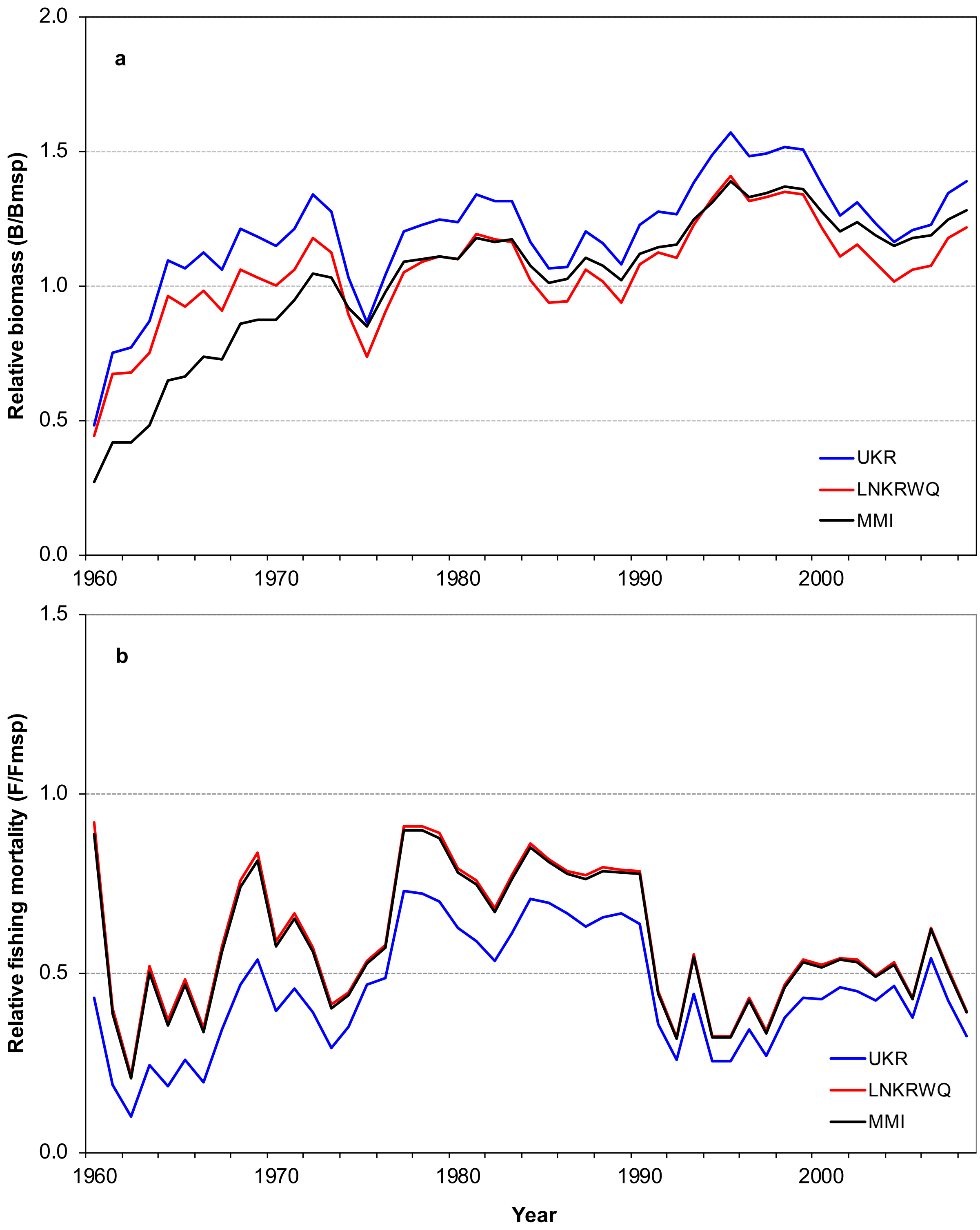

Figure 7. Graphical summary of posterior median time-trajectories for (a) biomass status (B/B_{MSP}) and (b) fishing mortality status (F/F_{MSP}) derived from UKR, LNKRWQ, and MMI estimates for Cambridge Bay Arctic Char during 1960-2008. The exploitation benchmarks were biomass status <1 and fishing mortality status >1, indicating a history of over-exploitation.

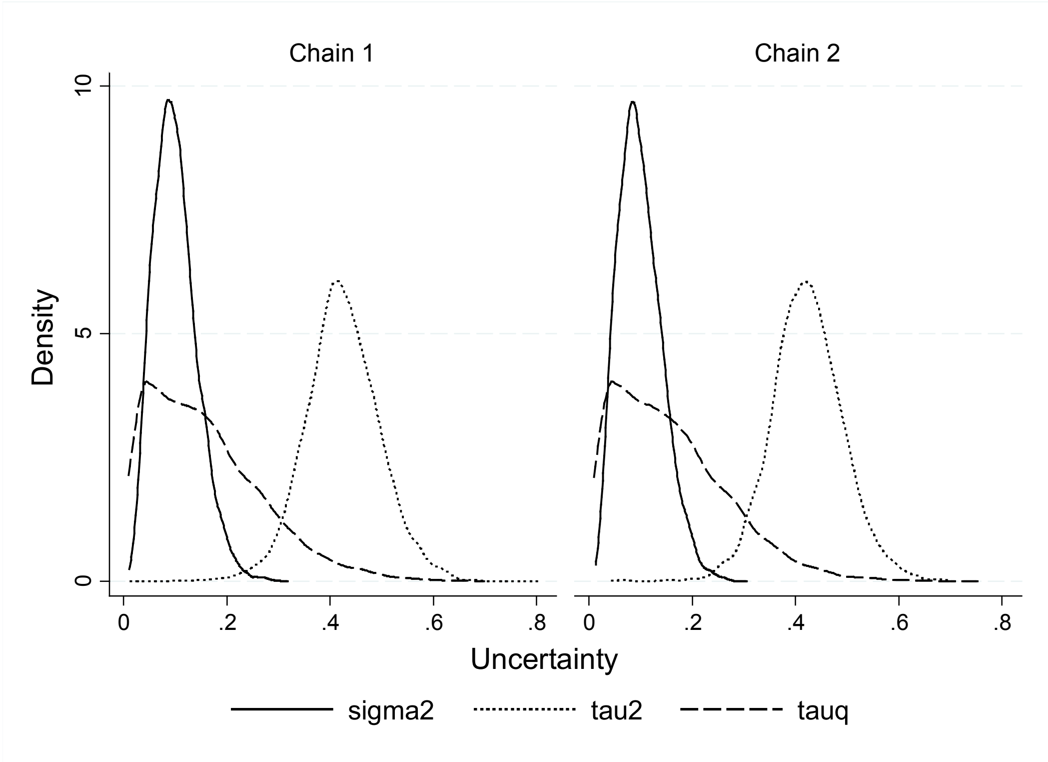

Figure 8. Uncertainties of model process (sigma2), observation (tau2), and time-varying catchability (tauq) in the LNKRWQ hierarchical Bayesian state-space model of Cambridge Bay Arctic Char.

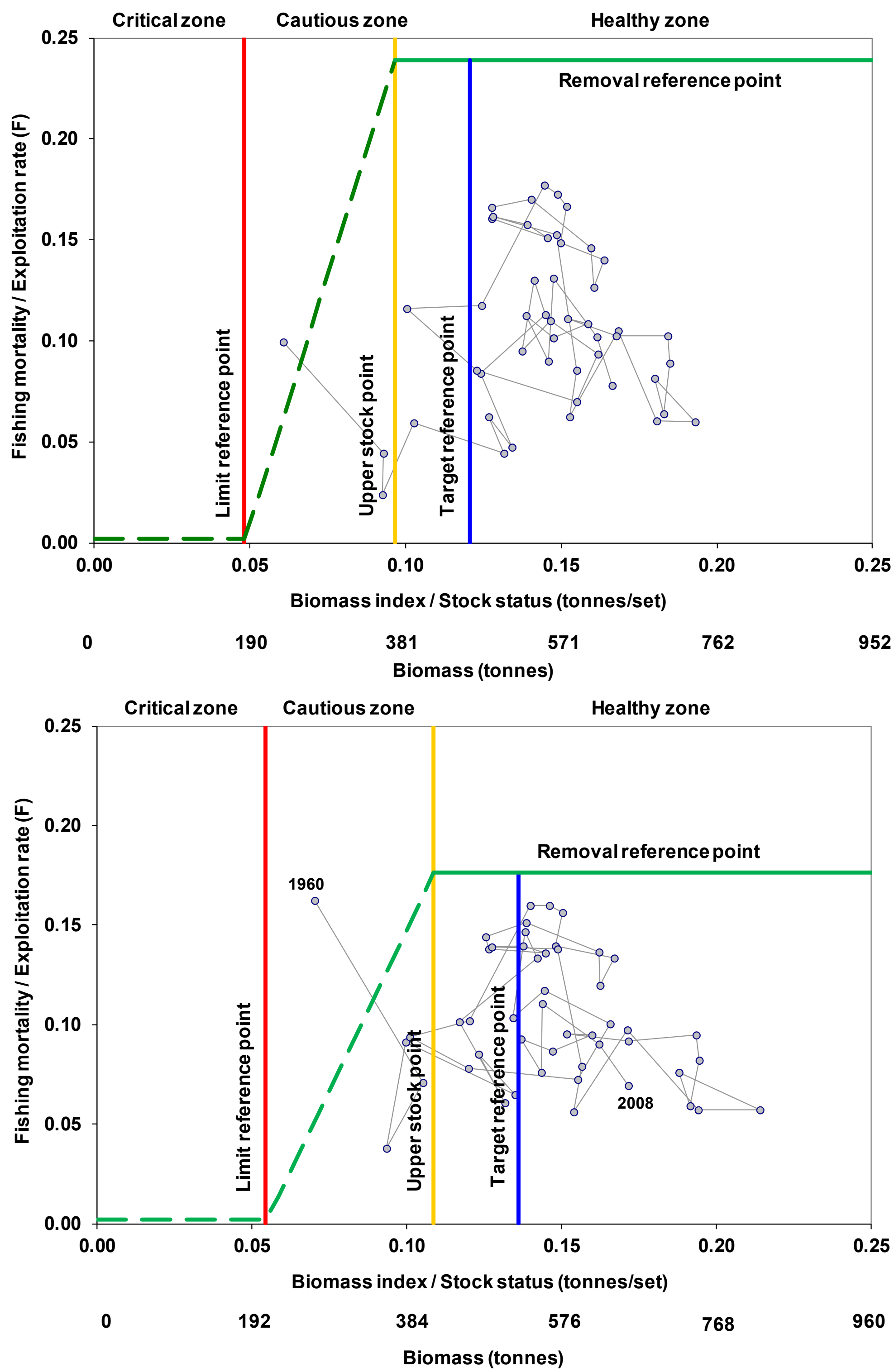

Figure 9. Precautionary approach models for managing Cambridge Bay Arctic Char fisheries based on the outcomes of uniform K and r priors (UKR) (upper panel) and lognormal K and r priors combined with random walk q (LNKRWQ) (lower panel). Reference zones are shown in green, indicating different harvest strategies depending on actual status of the stock.

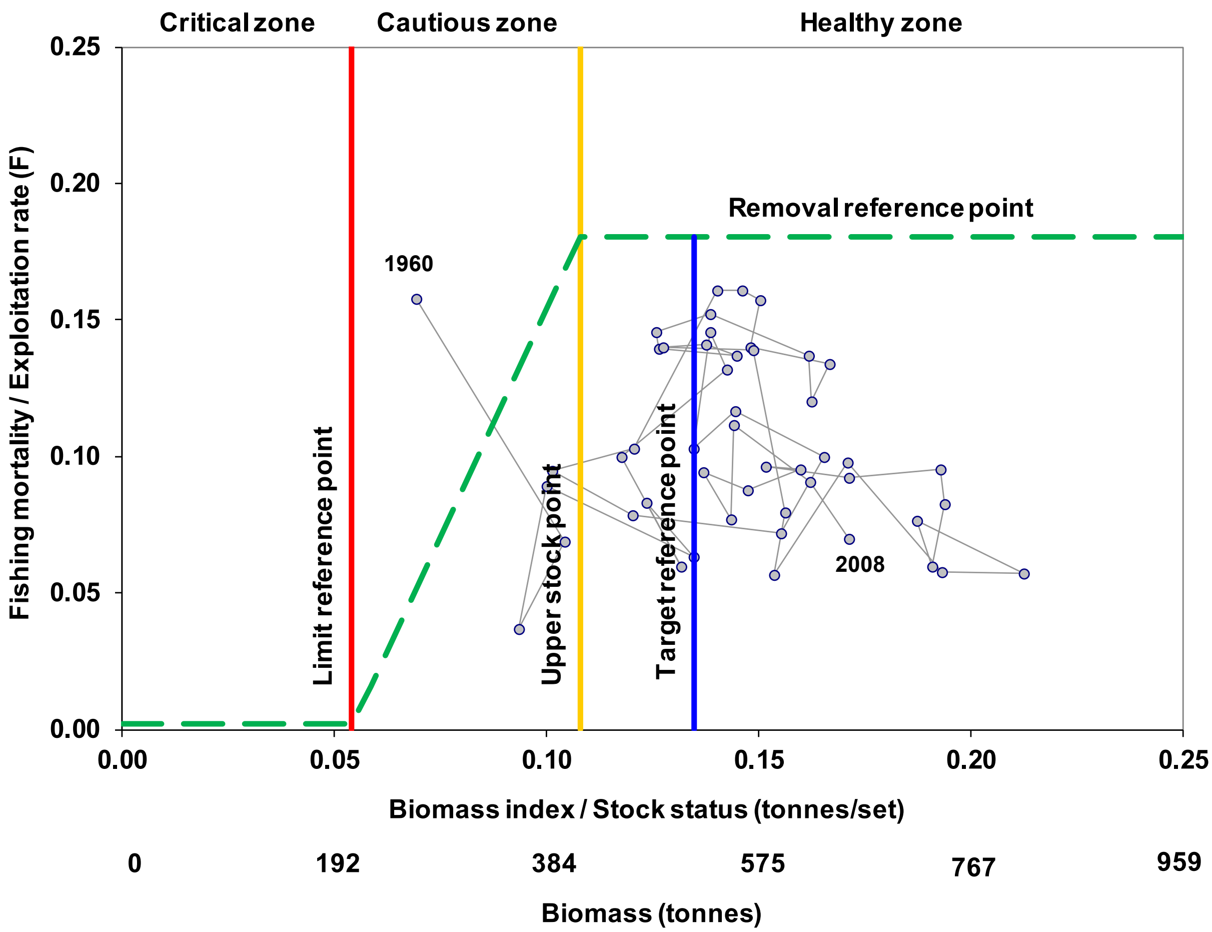

Figure 10. Precautionary approach models for managing Cambridge Bay Arctic Char fisheries based on the outcomes of MMI. Reference zones are shown in green, indicating different harvest strategies depending on actual status of the stock.