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# Evaluation of Methods for Identification of Early Detection Monitoring Sites Based on Habitat Suitability for Invasive European Green Crab in the Salish Sea, British Columbia

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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

The European Green Crab (EGC) is a high-risk global invader that can devastate coastal marine ecosystems by displacing native species, degrading and disturbing native habitats (including eelgrass), and altering food webs. EGC has recently been detected in the Canadian portion of the Salish Sea. As EGC continue to establish in the region, identifying locations on which to focus limited monitoring resources is an ongoing problem given the vast amount of coastal habitat that could be occupied by the species. A variety of methods can be used to identify highly suitable habitats for EGC at a range of spatial scales. However, none have been evaluated in the context of informing EGC management, nor for the Canadian portion of the Salish Sea. Here we evaluate five individual methods developed to assess habitat suitability for EGC (i.e., MaxEnt, stochastic gradient boosted linear and logistic regression models, a rapid site selection tool, and a qualitative site assessment and ranking tool) and five derived models generated by multiplying the outputs of these individual models. Each model relied on slightly different environmental and habitat input variables affecting EGC invasion success. Thus, rather than identifying a single preferred model, we used a multi-model ensemble approach to identify sites that are expected to be most suitable for the species. The ensemble approach likely increases predictive power by including both environmental and habitat characteristics when identifying priority sites for early detection/monitoring for EGC in the Canadian waters of the Salish Sea. Finally, we describe how the models evaluated here, alone or in combination, could be used to identify additional sites either within the Salish Sea or into new areas.

# 1. INTRODUCTION

The European Green Crab (EGC; *Carcinus maenas*) is a common shore crab native to Europe but invasive in parts of Africa, Asia, Australia, and both coasts of North America (Behrens-Yamada 2001, Therriault et al. 2008). This species was first introduced to the west coast of North America in San Francisco Bay around 1990 (Cohen et al. 1995). Due largely to its long pelagic larval phase coupled with a strong El Niño event in 1988-89 (Yamada et al. 2021), EGC subsequently spread north, reaching British Columbia (BC) by the late 1990s (Gillespie et al. 2007) Since then the species has continued its northward spread and was detected on the Central Coast of BC by the mid-2000s and Haida Gwaii in 2020 (Yamada et al. 2021). Although EGC expanded rapidly on the west coast of Vancouver Island after their arrival to BC, they did not appear in the Salish Sea for an extended period of time. Human-mediated movements are known to contribute to the spread of EGC elsewhere in their invaded range (Klassen and Locke 2007) and the first detection of EGC in the Salish Sea in the Sooke Basin in 2012 was believed to have occurred via human-mediated movements (unintentional hitchhikers on shellfish) rather than natural dispersal from EGC populations on the outer Pacific coast (Curtis et al. 2015). However, the long lag between their arrival in BC and their spread into the Salish Sea suggests that natural larval dispersal remains the primary mode of introduction of EGC to sites within the Salish Sea and elsewhere along the BC coast. Subsequent detections of EGC in the Salish Sea are thought to be a result of natural dispersal from both the outer Pacific coast and the Sooke population (Brasseale et al. 2019, Carolyn Tepolt, Woods Hole Oceanographic Institute, pers. comm.). The first detection of EGC in the Salish Sea outside of the Sooke Basin occurred in United States (US) waters in the fall of 2016, resulting in several subsequent detection events on both the US and Canadian sides of the Salish Sea the following year (Yamada et al. 2021). This long delay in EGC range expansion into and around the Salish Sea is due to the natural barrier to dispersal caused by the volume, direction and seasonality of estuarine outflow from the Fraser and Skagit Rivers into the Strait of Juan de Fuca (Thomson et al. 2007), rather than a lack of suitable habitat within the Salish Sea or human-mediated dispersal vectors. Periodic changes in oceanographic conditions, such as those seen during the 2015-16 El Niño event, weaken this barrier and allow EGC larvae to enter and disperse throughout the Salish Sea (Brasseale et al. 2019, Yamada et al. 2021). Once EGC arrive to a site, they require access to prey and must overcome any potential biotic resistance from native species such as Dungeness or Red Rock crabs (McDonald et al. 2001; Hunt and Yamada 2003), which may limit invasion success at the individual site level.

European Green Crabs can have significant negative impacts on native shore crab and bivalve populations (Grosholz et al. 2000) and eelgrass habitats (e.g., Matheson et al. 2016; Howard et al. 2019), often in areas where EGC abundance is especially high – a finding consistent with other invaders where larger populations generally result in greater impacts (Parker et al. 1999; Byers et al. 2002; Dick et al. 2017). For this reason, detecting and eradicating invasive species in new areas while their numbers are still low is recognized as a crucial step in effective invasive species management and is often informed by habitat suitability models (e.g., Blackburn et al. 2011; Barbet-Massin et al. 2018). This is because management efforts are typically spatially and fiscally constrained, making it preferable to target areas for control or eradication that are most suitable to the invader. However, predicting suitable habitat can be a challenge for species like EGC that have broad environmental tolerances that can differ with life history stage (see Klassen and Locke 2007). While habitat suitability models are most useful if they make predictions at the same scale as management (de Rivera et al. 2007; Epanchin-Niell et al. 2012), this can be challenging in spatially heterogeneous environments, as invasive populations establish non-uniformly, making them harder to detect and increasing the risk that large

populations (those sought by managers) will be overlooked and continue to supply the area with propagules (Crooks 2005; Melbourne et al. 2007; Epanchin-Niell et al. 2012).

Many considerations affect the development and selection of approaches to habitat suitability modeling for aquatic invasive species including data availability, complexity of the model, and spatial and temporal scales. Models developed to predict the occurrence of an invasive species in new environments are generally parameterized based solely on presence-only data because the true niche is unlikely to be realized until the invasion process has ended (Guisan and Thuiller 2005; Lyons et al. 2020). In invasion ecology, the absence of an invader at a site may represent an unsuitable environment (a true absence), an incomplete invasion (i.e., absence from suitable habitat), or a failure to detect the invader due to small population sizes. Further, aquatic invasive species rarely spread uniformly across sites or over time, in part because larvae often have their own tolerances, durations, and developmental strategies from adults (Byers et al. 2015). Both habitat quality and biotic interactions further affect site-level population growth rates of invaders (Hirzel and Le Lay 2008), creating variation in population densities among sites, which has important implications for both management and future rates of spread (Crooks 2005).

Multiple habitat suitability models and site selection tools have been developed to identify suitable habitat for EGC in coastal BC waters. For example, Lyons et al. (2020) produced a MaxEnt model using occurrence data and environmental data layers, while Fisheries and Oceans Canada (DFO) Science Pacific Region developed boosted regression tree (BRT) models using catch data available for EGC in the Region and site-level habitat characteristics. DFO Science also developed a novel rapid site selection tool based on presumed important habitat characteristics for EGC. However, neither of these have been reviewed previously for accuracy (see 2.2.3). Similarly, Washington Sea Grant's "Crab Team" has developed a rapid site characterization tool based on habitat characteristics to inform their early detection efforts in US waters of the Salish Sea. While some of these approaches, such as the "Crab Team" tool, focus on detecting populations early and others explicitly predict established populations (e.g., MaxEnt), each specifically characterizes the habitat suitability for *adult* EGC. Therefore, successful dispersal to that location (either via natural or human-mediated movement) is always implied.

EGC is listed as a Control Species under the Aquatic Invasive Species (AIS) Regulations of the *Fisheries Act* and early detection is essential to inform EGC management. Although the approaches described above, which we collectively refer to as the 'individual models' throughout this document, rely on different inputs and generate different response variables all can be used to identify suitable habitat for EGC, albeit at a range of spatial scales. Areas identified as highly suitable by each of these models could be used to inform the selection of priority sites for ongoing monitoring and control efforts. However, outputs from these models have not yet been evaluated in the context of site selection for EGC early detection nor for the Canadian portion of the Salish Sea where EGC have only recently been detected.

To better understand the incursion of EGC into the Salish Sea, DFO's Ecosystem Management Branch and DFO Science AIS programs worked with the Washington Department of Fish and Wildlife, Washington Sea Grant's Crab Team, and University of Washington to develop a Salish Sea Transboundary Action Plan for Invasive European Green Crab (Drinkwin et al. 2019). This plan lays out early detection (monitoring) recommendations but does not specify how to identify or prioritize intertidal sites for EGC monitoring. Additionally, DFO's AIS National Core Program (NCP) has been working to develop a monitoring program for the early detection of EGC throughout coastal BC, with a focus on the Salish Sea. Given the extreme spatial extent to be monitored, efforts must involve citizen science and Indigenous groups focusing on sites most likely to have EGC. Thus, prioritized monitoring sites for EGC in Canadian waters of the Salish

Sea are urgently needed and the approach could be extended to other coastal areas in the future. The assessment and advice arising from this Canadian Science Advisory Secretariat Regional Peer Review will be used to inform EGC management in the Salish Sea and contribute to DFO's international commitment related to the Bilateral EGC Action Plan. The specific objectives as outlined in the Terms of Reference of this review are to:

1. Evaluate the strengths/weaknesses associated with four different methods of assessing habitat suitability for EGC, for the purpose of identifying potential monitoring sites in Canadian waters of the Salish Sea. Specifically reviewing: 1) MaxEnt; 2) Stochastic gradient boosted regression models; 3) Washington Sea Grant's Crab Team's site assessment tool; and 4) DFO Science's rapid site selection tool.

2. Identify uncertainties in each of the models evaluated in Objective 1.

3. Identify sites for EGC monitoring in Canadian waters of the Salish Sea using the preferred method(s) evaluated in Objective 1.

4. Characterize the feasibility of using the preferred method(s) to identify potential monitoring sites throughout coastal BC in the future.

## 1.1. SCOPE

Five individual approaches for identifying highly suitable habitat for EGC (collectively referred to as models) were used as the main inputs for this analysis. Although each was developed independently and for different purposes, all have the capacity to inform EGC management with respect to early detection/monitoring site selection. Here we evaluate the functionality of these models, both individually and in combination, to identify possible early detection/monitoring sites in Canadian waters of the Salish Sea for EGC, specifically for managers looking to prioritize their early detection trapping efforts. While this document provides a list of recommended 'highest priority' sites in the Salish Sea, the list is not comprehensive. We therefore address the feasibility of applying these methods when assessing additional sites within the Salish Sea or beyond, with respect to technical expertise, time, and input data requirements (Objective 4).

Although each model was internally validated, the primary objective here was to compare predictions of suitable sites for EGC in Canadian waters of the Salish Sea (Objective 1). Because this invasion is new (only 23 known invaded sites in the Canadian portion of the Salish Sea, at the time of writing, with many located within Sooke Basin) there is no independent dataset with which to statistically assess each models' predictive accuracy. As such, it was necessary to focus on the amount of agreement among models to inform management decision making. We expect that all of the models used are able to capture some of the complexity of EGC biology and factors affecting invasion success in their predictions, but none are perfect, and their limitations are noted (Objective 2). Further, it is important to note that our analyses do not provide a risk assessment and none of the models is predicting the arrival of EGC. Our assumption is that EGC could reach any site in the Salish Sea but should be detected first at sites that are highly suitable. Effects of climate change/extreme events on future environmental habitat suitability are also not captured in our analyses. Although models like MaxEnt can make predictions that include climate change, the immediate need is to identify early detection sites based on current conditions, while recognizing these may change in the future.

## 2. METHODS

### 2.1. SITE DATABASE

While the spatial domain of some of the models used in this analysis include the entire Pacific coast of Canada (e.g., MaxEnt), other models require site-specific inputs. To facilitate model comparisons, we created a single database of 447 discrete sites at which we apply each model. We defined a site as a section of continuous intertidal habitat that is delineated on all sides by barriers to movement for adult green crabs on the Pacific coast of North America (see Hunt and Behrens-Yamada 2003; Jensen et al. 2007; Klassen and Locke 2007): the sub- and supratidal across shore, and rocky shorelines, artificial structures, or large freshwater channels (i.e., rivers) alongshore. This definition informed the creation of site polygons used in our analyses (Figure 1). Microhabitats within sites (e.g., marshy areas, tidal channels, etc.) are not captured in this definition, although may be included in the database as site-level characteristics (e.g., eelgrass presence). It is important to note that each site has a different spatial extent (size) and it was not necessary to standardize for this (as our goal was not to predict the invasibility of sites, just their suitability), but management may need to consider site size when planning specific trapping programs.

The site database includes all sites previously surveyed by DFO for EGC in the Salish Sea and unsurveyed sites, identified by randomly generating points along the whole coastline of BC in QGIS (Geographic Information System). There were 500 randomly generated sites which were curated to include only those that were not already surveyed and had a minimum beach width of 40 m. Random sites were added to dilute the inherent bias in previously surveyed sites, which would have been selected with some expectation of finding EGC.
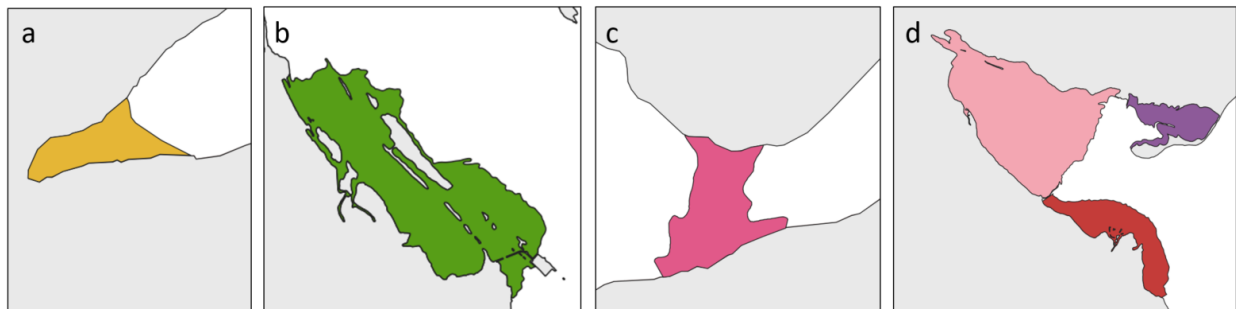


*Figure 1. Examples of sites as determined using a consistent set of rules based on green crab ecology where grey shading represents land and coloured shading represents intertidal sites. a) a 'simple' estuary (Roscoe Bay: 50.160, -124.770); b) a complex, continuous estuary (Chemainus River Estuary: 48.899, -123.662); c) a site between islands (Eveleigh Island: 50.140, -124.694); d) a complex, intermittent estuary containing three separate sites (Courtenay River Estuary: 49.674, -124.968).*

### 2.2. HABITAT SUITABUILITY ASSESSMENT METHODS

The following five methods of assessing habitat suitability for EGC, collectively referred to as the 'individual models' throughout, were developed to help understand the possible future distribution of EGC on the west coast of North America and support management decision making. The development and validation process for each, as well as a description of the original output and how the output was adapted for this analysis, are reviewed below and Table 1 provides an overview of the characteristics of each of these five individual models.

*Table 1. Overview of the five individual models used to generate predictions of suitable habitat for EGC in Canadian waters of the Salish Sea. Additional details on the MaxEnt EGC model can be found in Lyons et al. (2020). BRT = stochastic boosted regression tree models, WSG = Washington Sea Grant.*

| Model Traits | MaxEnt EGC Model | Linear BRT EGC Model | Logistic BRT EGC Model | Rapid Site Selection (RSS) Tool | Modified WSG Crab Team Method |
|---|---|---|---|---|---|
| General method and output | Species distribution model that predicts probability of presence (0-1) of an established EGC population. | Predictive linear regression model for relative abundance (catch-per-unit effort, $0 - \infty$) of EGC for individual sites. | Predictive logistic regression model for probability of presence (0-1) of EGC for individual sites. | Automated identification and ranking (ordinal score from 0-1) of coastal areas where important abiotic habitat variables for EGC are present. | Manual scoring system to identify and rank (ordinal score from 0-1) individual sites for early detection of EGC using aerial or satellite imagery. |
| Spatial scale | Original model coverage available for west coast of North America (Lyons et al. 2020). | Developed using data from the west coast of Vancouver Island. | Developed using data from the west coast of Vancouver Island. | Developed for the entire coast of BC. Implemented in the Canadian Salish Sea, Haida Gwaii, and North Coast. | Created for the Washington coast and US Salish Sea. Modified and implemented in the Canadian Salish Sea. |
| Temporal scale | Includes seasonal climatologies for salinity and sea surface temperature. | Uses data from ongoing trapping surveys for EGC. Otherwise all input variables temporally static. | Uses data from ongoing trapping surveys for EGC. Otherwise all input variables temporally static. | All input variables temporally static. | All input variables temporally static. |
| Abiotic inputs | Salinity (seasonal) Sea surface temperature (seasonal) | Intertidal area Edge length Beach isolation Beach width Fetch (max, min) Wave exposure (ShoreZone) Bottom type (substrate) Substrate type (ShoreZone) Sediment type (ShoreZone) Slope (ShoreZone) Width (ShoreZone) | Intertidal area Edge length Beach isolation Beach width Fetch (max, min) Wave exposure (ShoreZone) Bottom type (substrate) Substrate type (ShoreZone) Sediment type (ShoreZone) Slope (ShoreZone) Width (ShoreZone) | Beach width Freshwater input Substrate type (ShoreZone) | Beach isolation Beach width Freshwater input Shelter Wave energy Tidal channels |
| Biotic inputs | Species occurrence data (presence-only) | Eelgrass likelihood ShoreZone biobands EGC CPUE | Eelgrass likelihood ShoreZone biobands EGC presence/ absence | – | Presence/ absence of terrestrial vegetation |

### 2.2.1. MaxEnt

Lyons et al. (2020) compiled adult EGC occurrence data (latitude and longitude of each observation) primarily from DFO's AIS monitoring program, the Ocean Biogeographic Information System (OBIS 2018), as well as several other online databases and primary and gray literature publications. The model domain was 24°– 62°N and 111°– 155°W (i.e., Baja California to the Gulf of Alaska). Data from other parts of the world were excluded to ensure the model would reflect the environmental responses of the single genetic lineage that has invaded the study area (Tepolt et al. 2022, Brasseale et al. 2019). Prior to model fitting, the occurrence points were spatially rarified to a 10 km resolution using SDMtoolbox 2.0 for ArcGIS to reduce potential effects of spatial autocorrelation on the results (Brown et al. 2017).

Surface water temperature and salinity, which are thought to influence the distribution of EGC (Compton et al. 2010) were selected as predictors for the model. Although different life stages or sexes have slightly different tolerances or may utilize the same habitat differently, MaxEnt is predicting the long-term occupancy of a site for adults in the population. Data for each predictor was averaged into seasonal climatology rasters, including winter (December to February) spring (March to May), summer (June to August), and fall (September to November). Salinity and temperature values were compiled from hindcasts from the University of British Columbia's Salish Sea Nucleus for European Modelling of the Ocean (NEMO) model (2014–2017 hind-cast, 0.006° resolution, Soontiens et al. 2016; Soontiens and Allen 2017), a Regional Ocean Modeling System (ROMS) model of the British Columbia shelf (BC ROMS 1981–2010 hindcast, 0.04° resolution, Peña et al. 2019), as well as the MARSPEC database (0.00833° resolution, Sbrocco and Barber 2013). The higher resolution data from the NEMO model and MARSPEC were resampled using bilinear interpolation to match the 0.04° resolution of the ROMS model data. Further, since EGC live primarily in intertidal and shallow subtidal areas close to the shore, model inputs and outputs were restricted to areas shallower than 100 m (see Lyons et al. 2020 for additional details).

The distribution of EGC was modeled using MaxEnt 3.4.1 (Phillips et al. 2017) with seasonal salinity and temperature as predictors. The default complementary log–log transform option was used to produce estimates of occurrence probability (Phillips et al. 2017). To choose the feature class (i.e., potential response curve complexity) and regularization parameter (i.e., penalty for model complexity) settings the *ENMeval* package (Muscarella et al. 2014) for R version 3.5.2 (R Development Core Team 2018) was used to evaluate a broad range of combinations. Model settings that resulted in the lowest corrected Akaike information criterion (AICc) were selected to fit the final model. This model was fit using the maximum possible number of background points and 30-fold random cross-validation to evaluate the model and estimate standard deviations for the model predictions.

#### 2.2.1.1. Internal validation and output

The average area under the receiver operating curve for the test data from the 30 cross-validation folds (AUC [area under the curve]: 0.92) and Continuous Boyce Index (0.91) suggest that model performance over the entire northeast Pacific range of EGC was very good. The sum of the permutation importance scores for the seasonal temperature and salinity variables indicated that, although both parameters were important in predicting the distribution of EGC, temperature (summed importance: 60.8) was a stronger predictor than salinity (summed importance: 39.1).

The MaxEnt model produced a continuous raster covering the entire Pacific coast from Mexico to Alaska (limited to 100 m depth) which was constrained to the Salish Sea for the purposes of this report. Values from the 4.5 km resolution raster were extracted and averaged for each site polygon using the "extract" function in R package *raster*. The MaxEnt raster covered 443 of 447

site polygons. Two of the sites without raster data were at the mouth of Indian Arm and two were in Howe Sound. No predictions were made for these locations due to a lack of environmental coverage, or because their depth did not fall between 0 and 100m in the 0.0042 degree-resolution bathymetry used to define the model domain. The range of MaxEnt values across all sites ranged from 0.03 to 0.85.

## 2.2.2. Gradient Boosted Regression Trees (BRTs)

Data on the occurrence and abundance of EGC from annual trapping surveys conducted or supported by DFO between 2009 and 2019 on the West Coast of Vancouver Island was used as the response variables for the BRT models. The trapping protocol employed by DFO Science in Pacific Region is consistent with respect to gear, bait, and deployment technique, with some variation in effort (i.e., number of traps deployed during a trapping event). A single trapping event represents a collection of traps set out in the intertidal and shallow subtidal zone of a site and allowed to soak for approximately 24 hours (one full tidal cycle). Additional details on the type and method of data collection can be found in Gillespie et al. (2007).

Raw catch-per-unit-effort (CPUE) was calculated for each trapping event as the number of EGC caught, divided by effort (i.e., the number of traps set multiplied by total average soak time of all the traps set during that event). Because catchability of EGC varies throughout the year as a consequence of water temperature (Duncombe and Therriault 2017), the analysis was initially limited to data collected between May and September and catches in the shoulder month adjusted using a correction factor. However, a second-order polynomial model fit to the average daily EGC CPUE (all years combined) over Julian day (JD) was significantly better than a linear model (Likelihood ratio test: $X2 = 1.12$, df = 1, p = 0.02), confirming that catch still tended to drop off in the shoulder months. The average peak trapping day for EGC across all years was determined from the polynomial model (July 21-22 or $JD_{peak}$ = 203.0) and CPUE was refit as a function of the absolute difference between $JD_{peak}$ and the actual trapping Julian day. The slope of this relationship was used to recalculate CPUE, adjusted for seasonal variation. No correction was made if CPUE was zero, as it cannot be assumed that these are failures to detect EGC due to catchability, rather than true absences. Biased resampling was then applied to the dataset because trapping events where EGC catches were very high were rare. Biased resampling is a common approach when modeling extreme or rare events (Oliveira et al. 2019). Because there were temporal and spatial patterns in the data, preferential up-sampling of events to favour those from more recent years and those that were more geographically distant from other clusters of sites was also used. Resampling was conducted using the R package *STResamplingDSAA* (Oliveira et al. 2019).

The predictor variables for the BRTs were all static habitat features that may influence local EGC survival and population size at the site level. The factors chosen were those that could affect larval propagule pressure, the availability of shelter or prey, and oceanographic characteristics such as freshwater outflow and exposure. Most of these data were derived from GIS data layers (Table A1) using QGIS (v.3.0).

Models were generated using two distributions of the catch data: logistic regression and linear regression. The logistic BRT modeled the probability of EGC site occupancy using a binomial (Bernoulli) loss function (n = 731 events, resampled). The linear regression model predicted the CPUE of EGC across all presence-only sites and trapping events (n = 591 events, resampled) using a Gaussian loss function. Modeling was done using the R package *gbm* in conjunction with the *caret* wrapper to produce gradient boosted trees (Elith and Leathwick 2011; Kuhn 2008). These models combine the predictions from many weak models, called trees, to optimize the predictive performance of a final, average model. Each successive tree minimizes the error of the preceding tree following the loss function (Elith et al. 2008). As a result, trees become

successively better at predicting the response variable while also minimizing error (De'ath 2007; Elith et al. 2008). This approach also allows for categorical and continuous predictor variables, which can interact in complex and non-linear ways, and has relaxed assumptions around data structure, units, interactive effects, and missing values (Elith et al. 2008).

### 2.2.2.1. Internal validation and output

Model performance was evaluated using 8-fold cross-validation. This method was preferable to creating a dedicated testing and training set, as it allowed the use of all available data in a relatively small dataset. Because sites occurred along a geographically complex north-south gradient and trapping locations tended to be clustered, there was potentially significant spatial non-independence in the dataset. To account for this, folds were not assigned randomly, but instead spatially blocked, which assumes that all sites within a fold would experience similar oceanographic and climatic conditions and similar propagule pressure from EGC larvae and are therefore non-independent. Block size and number were optimized using R package *blockCV* (Valavi et al. 2019). By spatially blocking the cross-validation folds, the models encounter 'new' clusters of sites during each iteration of the learning process. This both reduces overfitting and addresses the issue of spatial non-independence within the data (De'ath 2007; Roberts et al. 2017; Valavi et al. 2019).

The *caret* package was used to run all of the BRTs as this package makes it possible for the boosting algorithm to find the optimal combination of learning rate, interaction depth, and number of trees for each model (Kuhn 2008). Additionally, the *caret* package allowed further refinement of the dataset by centring and scaling the continuous predictors, removing any categorical variables with zero or near-zero variance, and weighing the observations by the total number of traps set. Finally, *caret* (via the *gbm* package) also addressed missing values in the dataset by surrogate splitting, which assigns observations with missing values to groups of observations that are otherwise similar.

The metric used to determine the best model across all runs depended on the model's response variable. The linear regression models were evaluated using root-mean-squared-error (RMSE) and the logistic regression models were evaluated using overall accuracy. The relative variable importance (RVI) was used to look at the top predictors within each of these models. RVI is calculated by averaging the relative influence of a variable across all trees generated by the boosting algorithm (Ridgeway 2020).

The best linear regression model had an RMSE of 0.59 ($R^2$ = 0.59). Across all trees run, the length of the high water line (km) was the top predictor (RVI = 12%), followed by inlet length, measured as the distance from the site to open water (in km) (RVI = 9.5%) (Figure 2). Increasing high water line length had a positive relationship with CPUE, suggesting that EGC abundance increases with more available upper intertidal habitat. Inlet length also had a positive relationship with CPUE, suggesting that once invaded, highly isolated sites are more likely to retain larvae over time leading to greater overall EGC abundance (DiBacco and Therriault 2015).

The best logistic model had an overall accuracy of 0.84, which represents the ratio of correct predictions made compared to the total number of predictions, irrespective of class (e.g., EGC present or absent) or the number of observations per class. The no-information-rate was 0.81 (p = 0.02), meaning the model performed significantly better than random, and the balanced accuracy was 0.67, which is calculated by averaging the predictive accuracy of the positive and negative classes (i.e., sensitivity and specificity). The logistic model was better at predicting true positives (sensitivity = 0.94) than true negatives (specificity = 0.40). Minimum fetch (km) was the most important predictor variable across all iterations of the model (RVI = 27%) (Figure 2). The probability of EGC being present at a site increases rapidly with increasing fetch distance,

before plateauing. As with the linear regression model, inlet length was the second most important variable (15% RVI) (Figure 2). The probability of EGC being present at a site decreased with increasing inlet length, suggesting these sites are harder for propagules to reach (but if they do they can support relatively large EGC populations – see above).
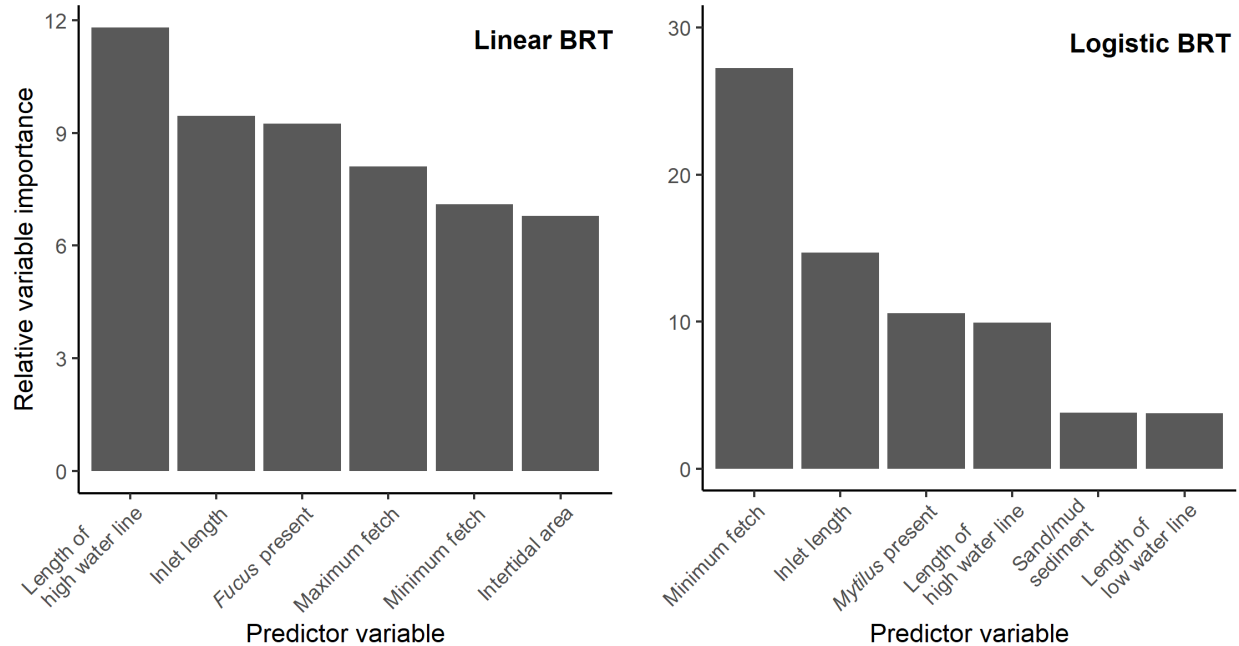


*Figure 2. Top six most important predictor variables, as determined by their relative importance across all iterations of the model, for the linear boosted regression tree model (left panel), which predicts the CPUE of EGC at a site, and the logistic boosted regression tree model (right panel), which predicts the probability of EGC being present at a site.*

The two BRT models were then used to predict into the Salish Sea. Equivalent site level data was collected for all the original predictor variables (Table 1) for each of the 447 sites in the Salish Sea. As with the training data, the Salish Sea dataset included missing values that were addressed by surrogate splitting. Two model outputs were generated: the linear BRT predicted EGC CPUE at each site (range: 0.01–3.07) and the logistic BRT predicted the probability (0–1) of EGC being present at a site.

## 2.2.3. Rapid Site Selection Tool (RSS)

The RSS tool was developed as an interim method for rapidly informing EGC early detection efforts in BC. Recognizing that one of the major drawbacks of complex statistical models like those produced by MaxEnt and BRT modeling was the amount of time required to curate the input data, this method was developed using a very small number of easily accessible spatial data layers with broad coverage (Table 1). Given the expressed need for advice to be at the site-level, a method to 'auto-detect' individual beaches was developed as the first step in the process. Automating beach identification makes it possible to assess large sections of coastline without having to manually delineate individual sites.

Automatic beach detection was done by first calculating the straight line distance between the high and low water lines, using a nearest neighbour algorithm in QGIS (v. 3.6.0), as a measure of intertidal beach width. The high water line was used as the 'origin' in this algorithm to better capture convex beach shapes (Figure 3). The water line input layers were generated by the

Canadian Hydrographic Service (CHS). Measurements of intertidal width were taken at 40 m intervals along the entire coastline. Wider, flatter areas more likely to support EGC were isolated by eliminating all sections of beach less than 50 m wide. Several threshold widths between 40 and 80 m wide were evaluated (e.g., Figure 3), but 50 m was determined to be optimal in that it eliminated all of the narrow, rocky coastline without missing too many smaller 'pocket beaches'. To confirm that autodetection could perform at least as well as a person identifying beaches from a map, we tested both approaches over a predefined area of coast (southeast coast of Vancouver Island and the Gulf Islands). Autodetection identified 1727 beaches compared to 1061 beaches identified manually, which took significantly longer and was more subjective. However, the autodetect method does not generate well-defined site-level polygons such as those shown in Figure 1. If required by the end-user (e.g., for mapping purposes), site polygons must still be generated manually.



*Figure 3. Sample visualization of nearest-neighbour analysis to measure distances between the high and low water lines, for a section of coastline (Kuleet Bay near Ladysmith, BC), with lines representing intertidal widths equal or greater than 60 m. Points along the high and low water lines are spaced 40 m apart.*

Once all the possible beaches were identified they were further refined based on a general understanding of habitat preferences for EGC in the region, which tend to be associated with beaches that have some freshwater input and softer sediment (Klassen and Locke 2007). While EGC are not a freshwater species they can tolerate lower salinity water and occasional freshwater pulses better than native crabs in BC and are therefore more likely to be detected in these refuge habitats, especially during the early stages of the invasion process (Barrios-O'Neill et al. 2015). Therefore, beaches with no freshwater input were eliminated by buffering the beach polygons to 50 m and only keeping those that intersected with a freshwater stream network base layer (Gray 2010). Fifty meters reliably captured nearby freshwater outflows without expanding too far inland to be unrealistic. The remaining beaches were then weighted by sediment type (Table 2). Beaches with no sediment (rock cliffs or banks) were given the lowest weight (0) and estuaries with fine sediment given the highest weight (1) because EGC on the Pacific coast of North America show a preference for soft sediment habitats (Klassen and Locke 2007). Sediment type at each site was determined using shared characteristics from the ShoreZone coastal classification system, available in the CHS High Water line metadata, i.e., all coastal classifications where the substrate was 'sediment only' were grouped together for the purposes of weighting (see Table 6 in Howes et al. 1995). The high water line was selected over the low water line layer as EGC, and especially newly settled individuals, are more commonly found in the upper intertidal zone (Klassen and Locke 2007). If multiple shore types occurred along a beach, it was assigned the highest weight.

*Table 2. Description of sediment types following the ShoreZone classification system (Howes et al. 1995.). Each coastal class in the system is determined by a series of nested categorical characteristics: substrate, sediment, width, and slope. The first three of these were used to create five broad sediment types, which were weighted from least (0) to most (1) likely to support European Green Crabs. See Table 6 in Howes et al. (1995) for additional information.*

| RSS Sediment Type | RSS Weight | ShoreZone Substrate | ShoreZone Sediment | ShoreZone Width | ShoreZone Coastal Class |
|---|---|---|---|---|---|
| Estuaries | 1 | Sediment | Organics/fines | n/a | 31 |
| Sediment only beaches | 0.75 | Sediment | Gravel and/or sand and/or mud | Narrow or wide (> 30m) | 21-30 |
| Rock and sediment beaches (wide) | 0.5 | Rock and sediment | Gravel and/or sand | Wide (> 30m) | 6,7,11,12,16,17,18 |
| Rock and sediment beaches (narrow) | 0.25 | Rock and sediment | Gravel and/or sand or anthropogenic | Narrow | 8,9,10,13,14,15,19,20 and 32-33 (anthropogenic) |
| Rock only | 0 | Rock | n/a | n/a | 1-5 |

### 2.2.3.1. External validation and output

Unlike the MaxEnt and BRT models, which have internal model performance and validation metrics, the RSS tool required external validation to assess performance. Given that there is no independent validation dataset, as the Salish Sea is not fully invaded, a dataset from Barkley Sound on the West Coast of Vancouver Island where EGC have been established for more than two decades was used. Barkley Sound has been extensively surveyed for EGC since 2006 and the distribution of the species has remained largely consistent over that time, making the area a suitable proxy for an invasive species at equilibrium. A total of 63 sites have been surveyed in Barkley Sound, 42 of which have confirmed EGC presence.

The RSS method detected 580 discrete beaches in Barkley Sound, which was reduced to 61 sites once filtered for the presence of freshwater. This significant reduction in the number of sites demonstrates that the RSS method can effectively reduce the total number of possible early detection/monitoring sites to a manageable number based on important factors for the invader. To determine if the RSS method accurately predicts sites known to support EGC, we examined only the RSS beaches that aligned with past trapping sites (n = 63 sites possible). There were 21 overlapping sites, 15 of which had confirmed EGC presence (true positive rate = 0.71) (Table 3). Importantly, these 15 sites included all of the highest density sites in Barkley Sound (i.e., Pipestem Inlet, Effingham Inlet head, Hillier Island, Toquart Bay).

*Table 3. Comparison of RSS predictions against known sites trapped by DFO in Barkley Sound. Since 2006, DFO has trapped 63 beaches at least once, 42 of which had EGC present. The number of sites captured by the RSS method is shown for both the first and second RSS steps: beach autodetection and filtering by freshwater presence.*

| RSS Step | N Beaches Identified | N Previously Trapped (63 possible) | N with EGC (42 possible) | True Positive Rate |
|---|---|---|---|---|
| Step 1: autodetected beaches (unfiltered) | 580 | 53 | 37 | 0.70 |
| Step 2: filtered for freshwater presence | 61 | 21 | 15 | 0.71 |

When predicting for the Salish Sea, the RSS method initially identified 3779 beaches, which would normally then be reduced by filtering for freshwater presence, resulting in 852 possible beaches. However, to facilitate comparisons across the site selection models in this report, we only considered RSS beaches that aligned with the 447 predetermined Salish Sea sites. There were 547 RSS autodetected beaches that either matched or partially overlapped these predetermined sites. These were then filtered for freshwater presence, leaving 201 beaches. To maintain parity between the number of RSS beaches and the 447 Salish Sea sites, sites without a matching RSS beach were automatically scored as having the lowest probability of EGC presence (0), because the RSS method had excluded them for being unsuitable habitat, either on the basis of beach width or absence of freshwater. The remaining 195 beaches were then weighted based on sediment type (Table 2) generating 87 classified as an 'estuary' (weight = 1.0) and 98 sites classified as 'sediment-only' (weight = 0.75).

## 2.2.4. Modified Washington Sea Grant Site (WSG) Selection Tool

The Washington Sea Grant Crab Team method was developed to formalize their site selection and prioritization process for early detection monitoring. While the method is semi-quantitative, in that sites are assigned a score, scoring is a fully manual process that relies solely on satellite imagery of shoreline features that the WSG Team consistently found in association with EGC in California and the coastal estuaries of Washington, such as substrate, vegetation, and connectivity. Each of these features evaluated in this method is related to oceanographic or ecological processes that have the potential to drive green crab population growth, including connectivity/retention, abiotic conditions (e.g., temperature, salinity), and predation on juvenile EGC. These processes are most influential at the earliest stages of invasion, and thus together help identify sites where green crab survivorship is likely to be greatest, even when propagule pressure and population size is small.

To score a site, the user proceeds through a series of yes/no questions about the site and assigns scores accordingly. Although inter-assessor variability has not been formally tested for this method, we have observed that different assessors score sites differently but that site-level disagreement is usually low (i.e., differences of ±5 are more likely than differences of ±15). Regardless, a single assessor processed all 447 Salish Sea sites for consistency in the scoring rationale. The first question (Q1) addressed connectivity of the site and whether it might offer EGC refuge from predators. Ideal sites for EGC were thought to have *limited* connectivity to the open ocean -- enough that larvae can arrive and be retained by the habitat, but not so much that it would make the site favorable habitat or easily accessible, for larger, predatory native crabs such as Dungeness (Jensen et al. 2007) and Red Rock crabs (Hunt and Yamada 2003). Thus, relatively closed sites, like lagoons, are considered particularly suitable for EGC, as shallow depths and limited tidal exchange are factors typically correlated with increased water

temperatures and decreased water quality, generally reducing survivability for larger native predators. Conversely, factors contributing *against* isolation from predators are very narrow beaches or small intertidal areas adjacent to rocky intertidal or deep water channels, as both can funnel EGC predators towards the high intertidal where EGC tend to aggregate. The second question (Q2) addressed the structure and types of substrate available to EGC at a site. Sloughs, mudflats, marsh vegetation and impoundments were all counted as characteristics likely to be associated with EGC survival, either by virtue of providing protective structure for small crabs, or because they are habitats survivable for EGC while typically being inhospitable for their predators. The more of these types of substrates visible at a site, the higher the site was scored. Finally, the third question (Q3) penalized sites with high wave energy and/or extensive freshwater output (i.e., river mouths). While limited freshwater input can protect EGC from predators that prefer more saline waters, high flow river mouths, particularly those fed by glaciers or with large catchments, are not suitable for EGC for long periods. The original method then tallied the scores according to the formula shown in Figure 4 (top panel). We modified the method slightly, adding additional scoring options for Q2 and Q3, to help distinguish among sites scoring 15 or above (Figure 4, bottom panel). We also wrote more descriptive versions of the questions to better guide our scorer and converted the final habitat suitability score to a probability. Finally, because the original method was developed based on coastal geography more common in Washington than on the Canadian side of the Salish Sea, such as salt marshes, sloughs, coastal spits, and natural or artificial lagoons, we considered a broader range of shelter habitat types and types of intertidal 'standing water' (i.e., not only tidal sloughs and lagoons).
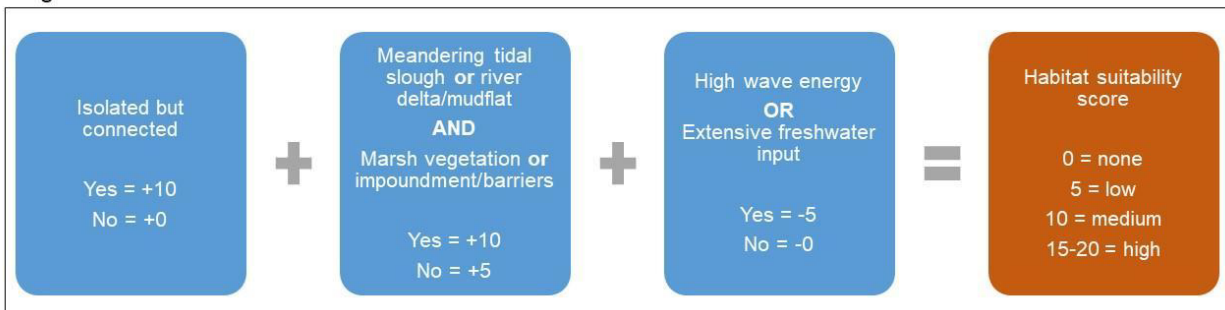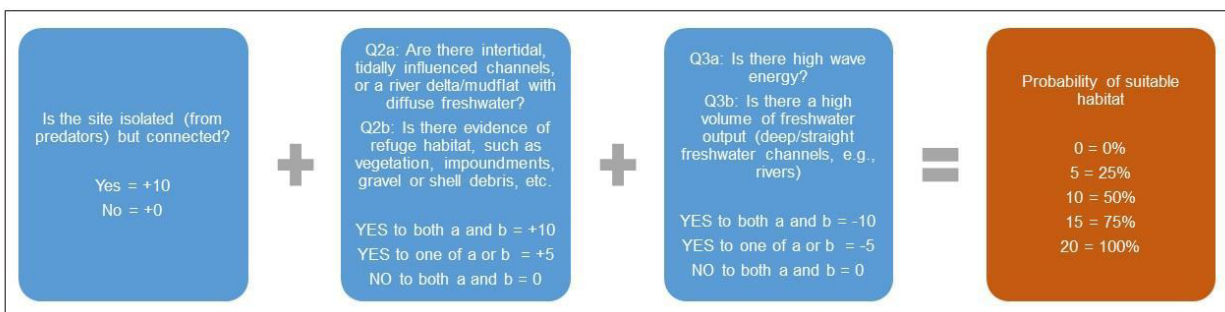


*Figure 4. Original WSG scoring method diagram (top panel) and DFO Science modified version (bottom panel).*

For this process, a single assessor was trained how to use the modified WSG method and asked to score sites accordingly. Scoring was done in the Spring of 2020 using imagery available in Google Earth Pro v. 7.3. The assessor first established the amount of connectivity the site had to the open ocean (Q1) and the extent to which this may or may not create a refuge from predators for EGC (Q2a). Particular attention was paid to whether channels remained flooded at low tide and whether those channels were shaped by freshwater outflow or tidal action. The rationale being that subtidal, saline channels could decrease isolation by allowing predatory crabs to remain at a site throughout the tidal cycle. The ability to view the site at various points in a tidal cycle using the Historical Imagery tool in Google Earth Pro was particularly helpful in establishing the amount of connectivity and isolation.

The assessor then identified visible substrate types that may facilitate EGC survival (Q2b). This mainly consisted of structurally complex substrates in the upper intertidal zone such as vegetation associated with euryhaline and low-flow conditions (e.g., *Salicornia*, *Zostera, Distichlis*), marshy areas and embankments, shore armouring such as riprap, woody debris such as old log dumps or derelict piers and pilings, and shell/cobble beaches.

Although sites with some amount of freshwater outflow and channelization were scored as being favourable habitat for EGC, they were also penalized for large volumes of freshwater, creating deep, fast outflows (Q3a). Similarly, while all sites required some connectivity, highly exposed sites were also penalized (Q3b).

### 2.2.4.1. External validation and output

As with the RSS method, there is no way to internally validate the modified WSG method, nor is there an independent validation dataset. However, because sites on the West Coast of Vancouver Island were also scored by the assessor, we again used the Barkley Sound dataset to assess the accuracy of the modified WSG method (see Section 2.2.3.1 for details on the Barkley Sound dataset).

The modified WSG method performed best in Barkley Sound when predicting sites with a high likelihood of supporting EGC (probability of EGC present ≳0.75), with accuracies between 0.71 and 0.75. The assessor using this method had no previous knowledge of the distribution or abundance of EGC in Barkley Sound, but was able to identify several known high density sites (e.g., Hillier Island, Toquart Bay, Effingham Inlet head). Interestingly, Pipestem Inlet was only given a 0.25 probability of EGC presence despite being a significant EGC "hotspot". This was due to the site's long, exposed, shoreline and minimal channelization, and possibly a mischaracterization of the available cover due to poor satellite imagery.

Of the 447 Salish Sea sites, 88 were classified as having the highest probability (1.0) of EGC being present, and 90 sites were classified as having the second highest probability (0.75). A total of 121 sites were given the lowest probability of EGC being present (0).

*Table 4. Predictive accuracy of modified WSG model based on previously trapped Barkley Sound sites. The modified WSG method ranks sites as a probability of EGC presence on an ordinal scale from 0-1. To calculate accuracy we treated sites ranked 0.5 or higher as a positive case (EGC present) and 0.25 or lower as the negative case (EGC not detected).*

| Modified WSG Rank | N WSG Sites | N Sites EGC Present | N Sites EGC Not Detected | True Positive Rate | True Negative Rate |
|---|---|---|---|---|---|
| 0 | 22 | 10 | 12 | – | 0.42 (12/22) |
| 0.25 | 10 | 8 | 2 | – | 0.20 (2/10) |
| 0.50 | 6 | 4 | 2 | 0.67 (4/6) | – |
| 0.75 | 8 | 6 | 2 | 0.75 (6/8) | – |
| 1.0 | 17 | 12 | 5 | 0.71 (12/17) | – |

## 2.2.5. Summary of the individual models

Each of the five individual models performs reasonably well on its own based on available internal or external validation metrics. However, they range widely in the types of data required and response variables (Table 1), and each has uncertainties related to predictions into the Salish Sea for EGC. We therefore considered ways to combine these models, thereby buffering uncertainty and maximizing the range of EGC ecology considered, by developing derived and ensemble models (see below).

## 2.3. DERIVED SPECIES DISTRIBUTION MODELS

One way to overcome potential limitations and uncertainty associated with individual models is to combine models mathematically by multiplying their outputs together. Highly suitable sites are those where the mathematically derived value represents agreement among the two component models (i.e., both being high produces a derived value that is high). In contrast, sites where component models differ will be low to moderately suitable. Low suitability sites will be those where the mathematically derived value is low due to agreement among component models (i.e., both being low produces a derived value that is even lower). We produced five derived models by multiplying the outputs of five model pairs. First, we combined the two BRT outputs: the continuous non-zero CPUE predictions ("CPUE" model) were multiplied by the probability of EGC presence ("PA" model) at each site, resulting in a conditional abundance model (CPUE*PA) that predicts the expected CPUE of EGC, if present at a site (e.g., Lynch et al. 2012; Dedman et al. 2015). A second derived conditional abundance model was produced using the MaxEnt model output, as this also predicts the probability of EGC presence (CPUE*MaxEnt).

Because the BRTs, RSS and modified WSG models all rely on static, site-specific habitat characteristics as their primary input variables, in contrast to the MaxEnt model which uses environmental conditions (i.e., temperature, salinity) and incorporates seasonality (Table 1), we also produced three derived models by multiplying the MaxEnt output with the remaining individual models. These derived models are annotated as: PA*MaxEnt (where PA is the logistic BRT output), RSS*MaxEnt, and WSG*MaxEnt. We hypothesized that, compared to the individual component models, the product of the MaxEnt output and the habitat-based outputs would be more likely to capture the full range of abiotic and biotic conditions influencing EGC occurrence at various sites in the Salish Sea. Unlike the conditional abundance models, these

three derived models do not have a direct biological interpretation, but a higher value does still indicate a site is more likely suitable for EGC in relative terms.

## 2.4. MODEL COMPARISON METHODS

### 2.4.1. Model standardization

One way to overcome potential limitations and uncertainty associated with individual models is to take a multi-model approach (e.g., ensemble models, hurdle models, etc.) when making predictions (Woodman et al. 2019; Waggitt et al. 2019). Such approaches are advantageous because while individual models can be informative, few can completely capture all the complexity of a species' biology. Each of the five individual models and five derived models represent different aspects of EGC ecology, with response values that are not directly comparable (e.g., probability of presence vs. predicted CPUE). To facilitate model comparisons and ensemble model predictions, we rank-transformed the output for each of the models, except RSS and WSG, into 20% percentiles (quantiles); i.e., percentile 1-20 = 1, percentile 21-40 = 2, percentile 41-60 = 3, percentile 61-80 = 4, and percentile 81-100 = 5. Transformation of the five derived models was done in the same way, after multiplying the respective individual model outputs. Quantile transformations were not carried out for the individual RSS and modified WSG models because their outputs are already ordinal categories of suitability, not continuous values. To keep all models on the same scale, the RSS and modified WSG outputs were converted as follows: 0 = 1, 0.25 = 2, 0.50 = 3, 0.75 = 4, 1.00 = 5. Figure 5 shows the distributions and quantile breaks for each of the models.

### 2.4.2. Analysis of model agreement

Since EGC have only recently been observed in the Salish Sea and this invasion is not yet considered established or complete, there is no independent dataset to evaluate model performance. We therefore assessed model agreement in two ways. First, by calculating correlation coeffects between quantile rankings (1 to 5) generated for the sites between pairs of methods. Second, we also assessed model agreement between the individual and derived methods by calculating the number of sites where the rank-transformed model values agreed, out of the total number of sites where both models had data (ranging from 444 - 447 sites).
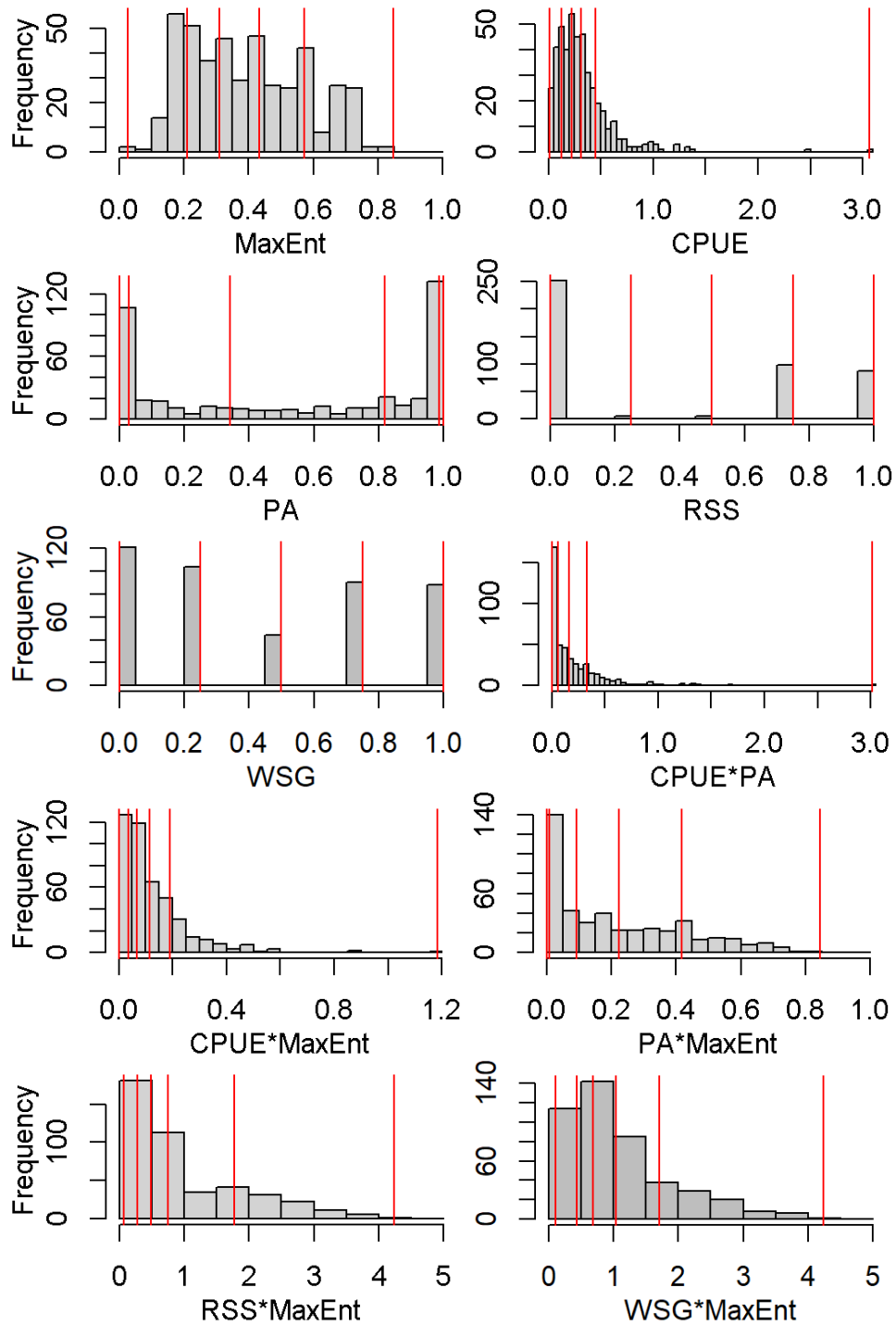
*Figure 5. Distribution of model values with 20% quantiles marked. Derived models (CPUE\*MaxEnt, CPUE\*PA, RSS\*MaxEnt, and WSG\*MaxEnt) were calculated by multiplying the values of their component models at each site.*

## 2.4.3. Using rank-transformed values for ensemble model predictions

To create the ensemble models we generated combinations of 3, 4, or all 5 of the original (individual) models only. Derived models were not considered in the ensembles as this would over-represent the MaxEnt model outputs in the ensemble predictions, as MaxEnt is a component of 4 of the 5 derived models. For each combination of individual models, we used the agreement among their standardized, rank-transformed values to determine site suitability for EGC. 'Suitability' was defined as any site with a rank-transformed value of 5 (i.e., outputs above the 80th percentile or a raw score of 1.0 for models with ordinal responses). To assess the effect using the 80th percentile when determining habitat suitability, we performed a sensitivity analysis using outputs above the 60th percentile (rank-transformed values of 4 or 5, or values of 0.75 for the RSS and WSG models). Using a lower threshold to indicate habitat suitability identifies a greater number of potential sites than using a higher threshold (see Results; Appendix Table A4).

We evaluated three types of agreement (mode, union, and intersect) in generating our ensemble model predictions; each with its own strengths and weaknesses (Figure 6). Intersect models have the most conservative definition of agreement, as a site would only be assigned a value of 5 (i.e., suitable for EGC) if *all* models in the combination had predicted a rank of 5 for that site (i.e., intersection = "AND"). Union models have the least conservative definition of agreement, as a site would be assigned a value of 5 if *any* model in the combination had predicted a rank of 5 for that site (i.e., union = "OR"). Finally, mode models assigned sites a value of 5 if it was the *most frequent* value across the combination of models. Sites with no model agreement (no most frequent prediction) have a mode of NA.
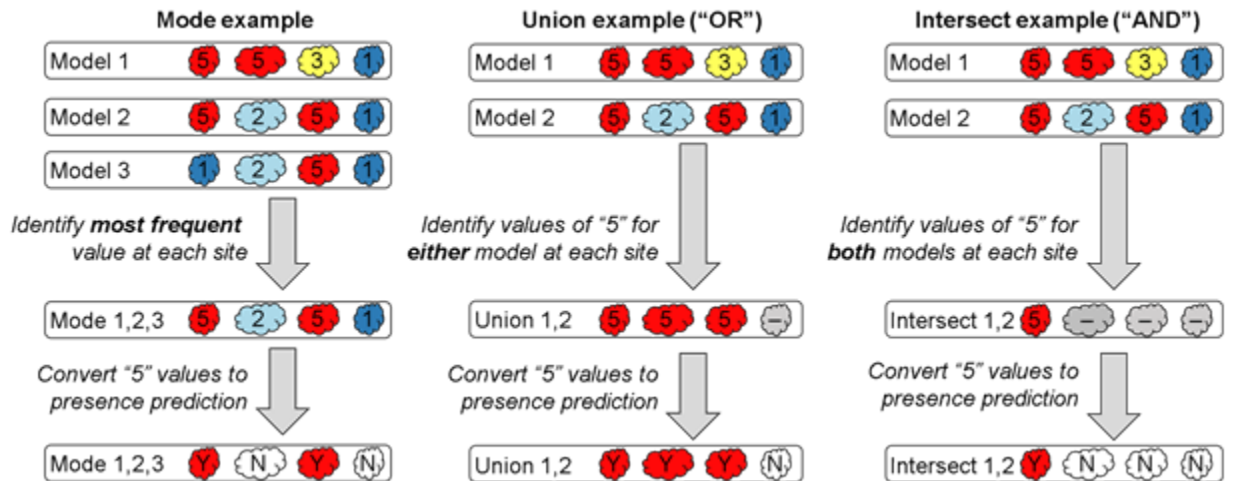


*Figure 6. A hypothetical example of calculating mode, union, and intersects from multiple models. Each colored shape represents a site, with the number indicating the rank-transformed value for each model at that site (1=1-20th percentile, 2=21-40th percentile, 5=81-100th percentile).*

# 3. RESULTS

## 3.1. RANK-TRANSFORMED PREDICTIONS FOR THE SALISH SEA

The site-level, rank-transformed predictions of the five individual habitat suitability models: MaxEnt, the linear boosted regression tree (CPUE), the logistic boosted regression tree (PA), the rapid site selection tool (RSS), and the modified Washington Sea Grant Crab Team site assessment (WSG) are shown in Figure 7–Figure 11. The site-level, rank-transformed predictions for the derived models, including two conditional abundance models, CPUE*PA and CPUE*MaxEnt, and thee models specifically incorporating the MaxEnt predictions: PA*MaxEnt, RSS*MaxEnt, and WSG*MaxEnt are shown in Figure 12–Figure 16. The list of sites where each model and model combination predicts highly suitable habitat for EGC are presented in Table A4 (individual models and 5-model modes, for rank-transformed values of 4 and 5), and in Table A5 (4- and 3- model modes, rank-transformed value of 5). Sites likely to support EGC are widely distributed across the Salish Sea irrespective of which model or method is used. Site-level predictions for Sooke Basin, Ladysmith Harbour, and Boundary Bay are shown in Appendix Figure A 1–3.
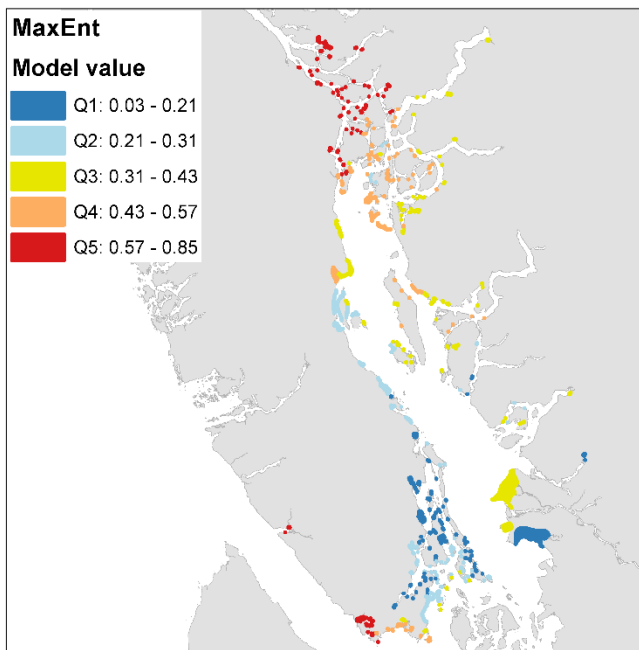


*Figure 7. Model outputs for the MaxEnt presence-only model. Site polygons are shaded based on rank-transformed quantiles (20th percentiles), where 5 is considered highly suitable EGC habitat. The range of raw predictions within each quantile is also given.*
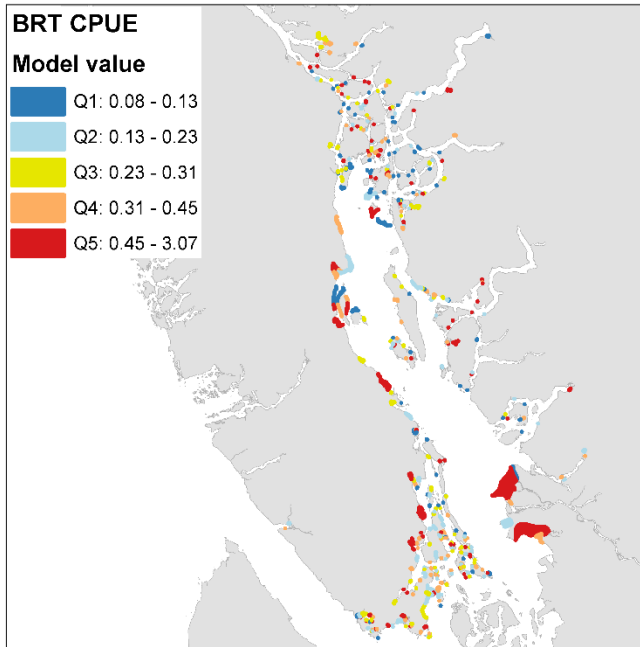
*Figure 8. Model outputs for the boosted regression tree catch per unit effort (BRT CPUE) model. Site polygons are shaded based on rank-transformed quantiles (20th percentiles), where 5 is considered highly suitable EGC habitat. The range of raw predictions within each quantile is also given.*
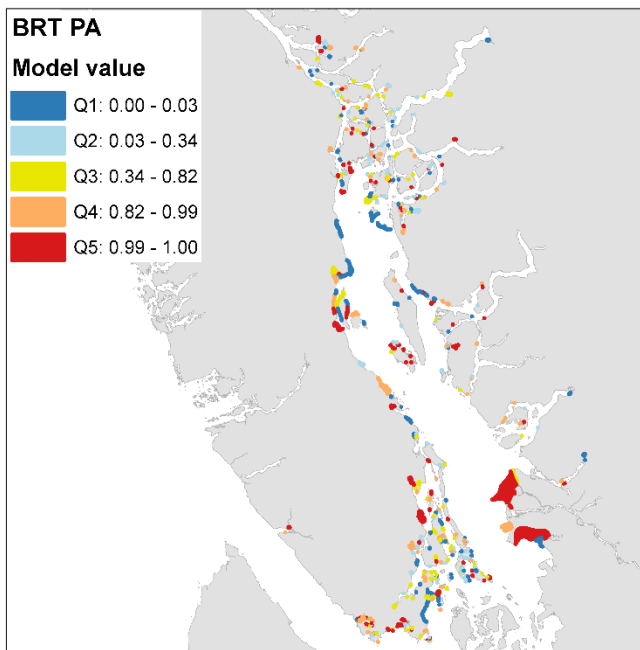


*Figure 9. Model outputs for the boosted regression tree presence-absence (BRT PA) model. Site polygons are shaded based on rank-transformed quantiles (20th percentiles), where 5 is considered highly suitable EGC habitat. The range of raw predictions within each quantile is also given.*
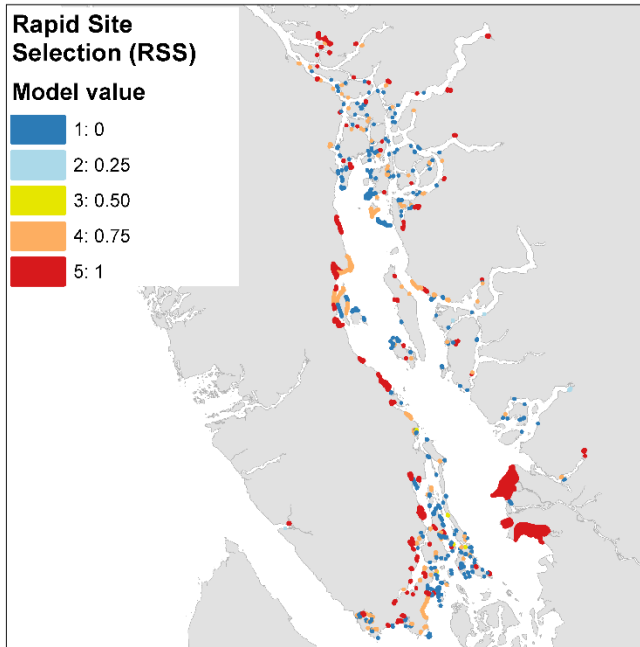
*Figure 10. Model outputs for the Rapid Site Selection (RSS) models. Site polygons are shaded based on rank-transformed values, where 5 is considered highly suitable EGC habitat. The original values for each rank-transformed value are also given.*
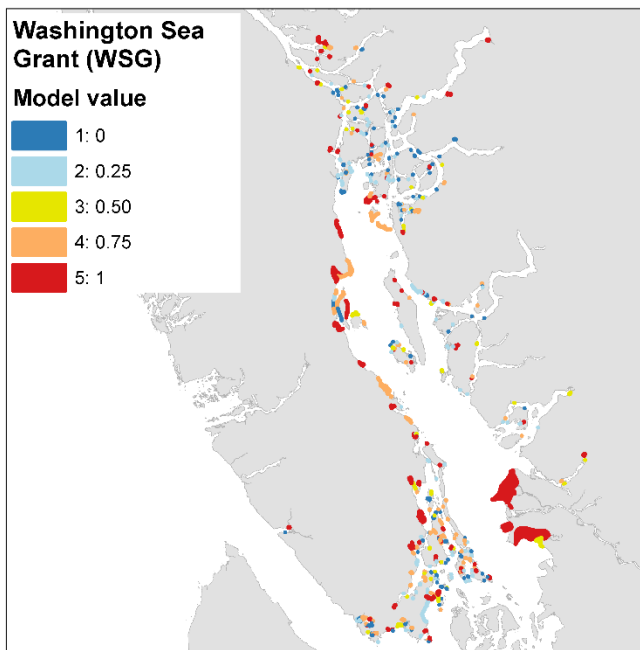


*Figure 11. Model outputs for the Washington Sea Grant (WSG) model. Site polygons are shaded based on rank-transformed values, where 5 is considered highly suitable EGC habitat. The original values for each rank-transformed value are also given.*
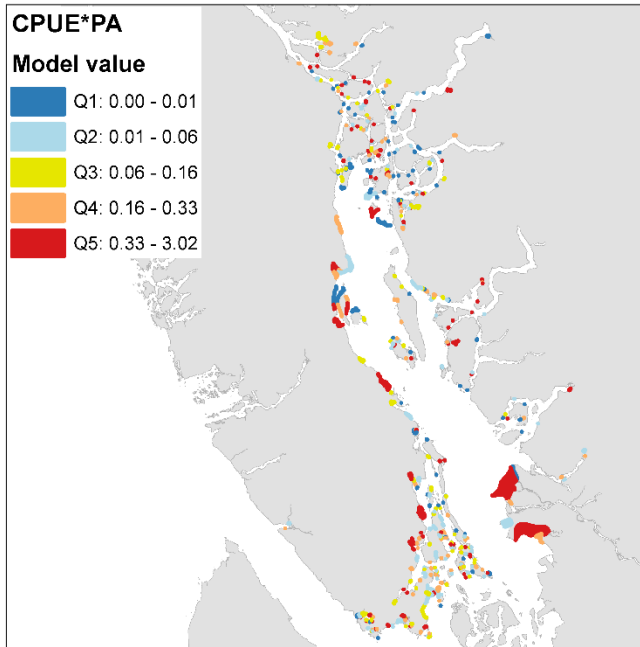
*Figure 12. Model outputs for product of the boosted regression tree catch per unit effort (CPUE) and presence-absence (PA) models. Individual component model values were multiplied together before transforming to quantiles. Site polygons are shaded based on rank-transformed quantiles (20th percentiles), where 5 is considered highly suitable EGC habitat. The range of raw predictions within each quantile is also given.*
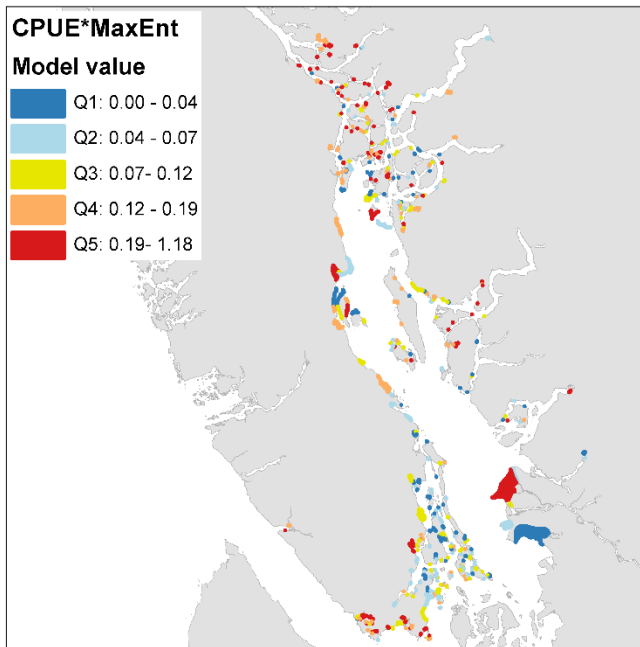


*Figure 13. Model outputs for product of the boosted regression tree catch per unit effort (CPUE) and MaxEnt models. Individual component model values were multiplied together before transforming to quantiles. Site polygons are shaded based on rank-transformed quantiles (20th percentiles where 5 is considered highly suitable EGC habitat. The range of raw predictions within each quantile is also given.*
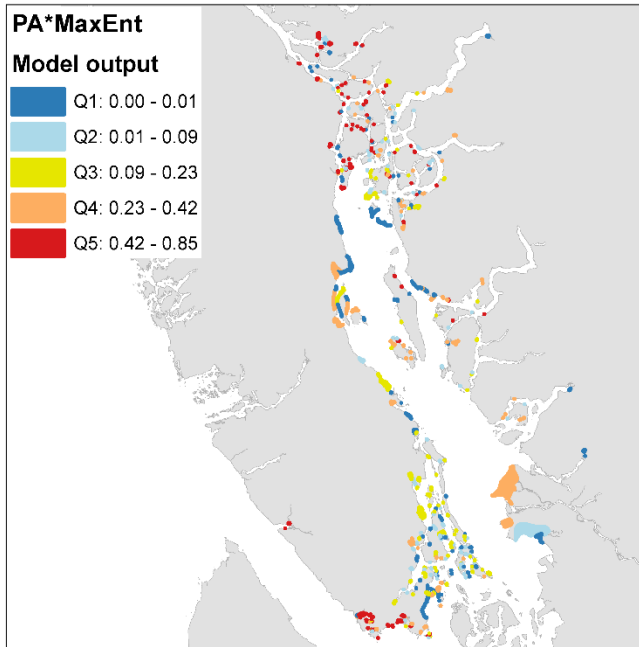
*Figure 14. Model outputs for product of the boosted regression tree presence-absence (PA) and MaxEnt models. Individual component model values were multiplied together before transforming to quantiles. Site polygons are shaded based on rank-transformed quantiles (20th percentiles), where 5 is considered highly suitable EGC habitat. The range of raw predictions within each quantile is also given.*
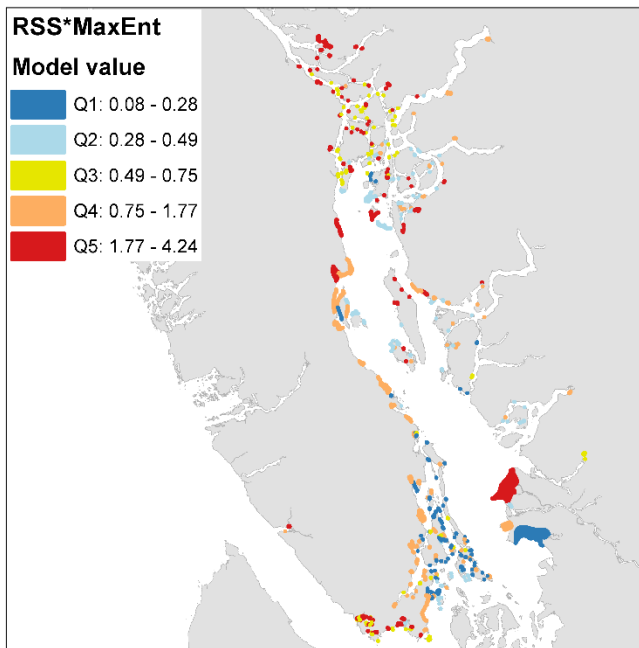


*Figure 15. Model outputs for the product of the Rapid Site Selection (RSS) and MaxEnt models. Individual component model values were multiplied together before transforming to quantiles. Site polygons are shaded based on rank-transformed quantiles (20th percentiles), where 5 is considered highly suitable EGC habitat. The range of raw predictions within each quantile is also given.*
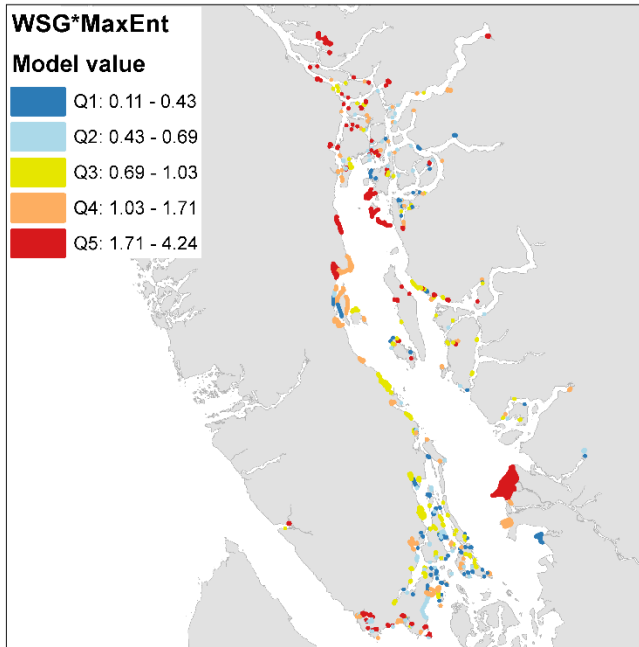
*Figure 16. Model outputs for product of the Washington Sea Grant (WSG) and MaxEnt models. Individual component model values were multiplied together before transforming to quantiles. Site polygons are shaded based on rank-transformed quantiles (20th percentiles), where 5 is considered highly suitable EGC habitat. The range of raw predictions within each quantile is also given.*

## 3.2. MODEL COMPARISON RESULTS

### 3.2.1. Model agreement

Rank-transformed values (quantiles) from the MaxEnt model had lowest agreement when compared to all other individual methods (19-20% of sites in agreement) (Table 5). This may be because the MaxEnt inputs are seasonal environmental conditions rather than habitat characteristics used in the other models. Not surprisingly, the RSS and modified WSG methods had the highest pairwise agreement (42%) (Table 5) as both use relatively simple scoring to classify sites and rely on similar habitat features believed important for EGC (Table 1). Pairwise agreement among just the derived methods was highest between CPUE*PA and PA*MaxEnt, with 51% of sites in agreement, while the other pairwise comparisons had 25-40% of sites in agreement. Agreement between the individual and derived models was highest in when comparing methods with shared inputs (e.g., PA and CPUE*PA, 54%; PA and PA*MaxEnt, 60%). If any one of the original or derived methods were singularly effective at capturing all aspects of EGC biology when determining habitat suitability, we would expect it to have reasonably high agreement with all other methods. However, on average only 30% of sites were shared among any two methods and no single approach stood out as the 'best', supporting our assumption that all of the methods capture some, but not all, aspects of EGC biology and therefore a multi-model (ensemble) approach is more appropriate.

*Table 5. Agreement between predictions made by individual models, based on the number of sites where the rank-transformed model values agree, out of the number of sites where both models have data (ranging from 444-447). Values above 50% are bolded.*

| Model | CPUE | PA | MaxEnt | RSS | WSG | CPUE* PA | CPUE* MaxEnt | PA* MaxEnt | RSS* MaxEnt | WSG* MaxEnt |
|---|---|---|---|---|---|---|---|---|---|---|
| CPUE | – | 25 | 20 | 27 | 25 | 33 | 44 | 23 | 23 | 23 |
| PA | – | – | 19 | 24 | 24 | **54** | 23 | **60** | 24 | 24 |
| MaxEnt | – | – | – | 20 | 19 | 22 | 37 | 28 | 28 | 33 |
| RSS | – | – | – | – | 42 | 25 | 24 | 22 | 41 | 28 |
| WSG | – | – | – | – | – | 23 | 22 | 19 | 27 | 37 |
| CPUE* PA | – | – | – | – | – | – | 36 | **51** | 25 | 30 |
| CPUE* MaxEnt | – | – | – | – | – | – | – | 27 | 30 | 32 |
| PA* MaxEnt | – | – | – | – | – | – | – | – | 31 | 36 |
| RSS* MaxEnt | – | – | – | – | – | – | – | – | – | 40 |

Agreement among the component models within each of the ensemble models depended on the approach used to create the ensemble. Intersection models identified the fewest number of sites for monitoring; as few as two sites when all five original models were included in the combination. This conservative approach increases the risk of overlooking otherwise suitable sites captured by some of the individual models, but not all. Union models had the least conservative definition of agreement and therefore usually identified the greatest number of sites for monitoring (up to a maximum of 141 sites for certain combinations). In addition to generating a potentially unreasonably large number sites to monitor, union models also a higher likelihood of Type 1 errors (i.e., unsuitable sites erroneously considered suitable). For these reasons, we prefer the mode models, as these balanced the need for agreement with the benefits of buffering the uncertainty in each of the individual models with a multi-model approach. Mode models identified an intermediate number of sites considered suitable for EGC, depending on the number and combination of models considered (range: 51 – 90 sites). Results for both 3 and 4-model combinations are presented in Appendix Table A5. However, we highlight the results of the mode model that included all five of the original models here, as this uses all available information for a total of 68 potential monitoring sites (Figure 17, Appendix Table A4).

## 3.3. IDENTIFYING POTENTIAL MONITORING SITES

Choosing which model(s) to use to determine potential early detection/monitoring sites for EGC is challenging, especially without an independent validation dataset to evaluate predictive performance. However, our analyses suggest that selecting sites with high ensemble model agreement is likely the most robust approach, as this approach reduced uncertainty by focussing on agreement among multiple lines of evidence. In particular, by defining agreement as the most frequent value (i.e., mode) the risk of either missing suitable sites or including many unsuitable ones is minimized (Figure 6). Here, we are able to use the rank-transformed outputs of all five of the original habitat suitability models to provide a list of 68 sites to be prioritized for early detection monitoring. If managers have the capacity to survey more sites, a longer, less

conservative site list can be generated either by moving to the union ensemble model, using all five individual models (113 sites), or lowering the threshold for suitability from the 80th percentile to the 60th percentile (151 sites for mode, 207 for union). Conversely, managers should use site-specific knowledge to exclude potential sites (e.g., if the information used to build the model does not reflect the actual conditions on the beach) or use independent datasets (e.g., presence of eelgrass beds, First Nation harvest sites) to further prioritize sites.

For identifying either more Salish Sea sites, beyond the 447 considered here, or predicting into new areas, an ensemble mode model is still recommended. However, complete data for all five methods may not always be available and thus will require managers to either generate new output or work with fewer models. It is important to note that the mode ensemble approach requires a minimum of three methods be available at any site of interest If this requirement is not met, managers can still use any of the existing methods, as all of them were reasonably good at identifying suitable habitat for EGC based on model validation using EGC data from outside the Salish Sea.
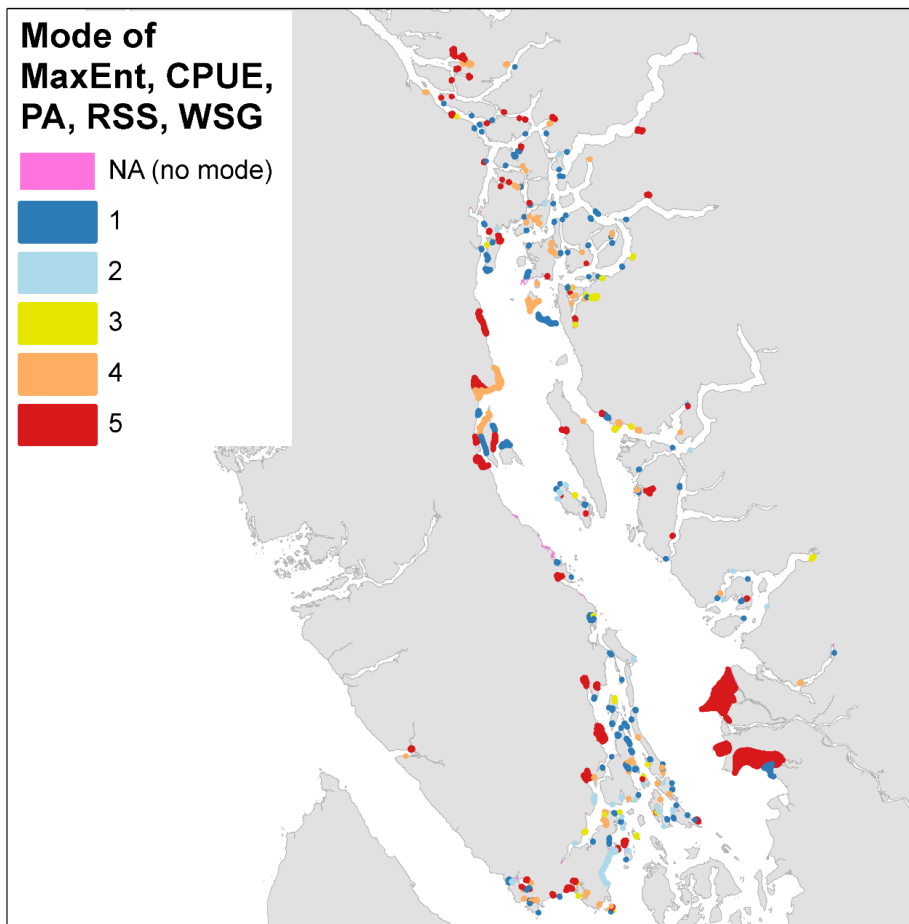


*Figure 17. Potential monitoring sites, based on model predictions from the mode of the five individual EGC habitat suitability models.*

# 4. UNCERTAINTIES AND MODEL LIMITATIONS

One of the most significant limitations to identifying a "preferred" model is the lack of a robust, independent validation dataset. Since EGC have only recently been observed in the Salish Sea and are not yet considered established in the region, there is no independent dataset to evaluate model performance. Only 23 confirmed reports of EGC have been made within the Salish Sea, with most of these spatially aggregated around Sooke Basin. It will not be possible to assess the accuracy of any of the individual models until the invasion cycle is fully complete in space and time (i.e., sites will either be persistently occupied or not). However, ongoing observations will be important to refine future predictions of habitat suitability for EGC in the Salish Sea and ultimately can be used retrospectively to evaluate model accuracy.

The choice of using the mode ensemble over either the union or intercept has important implications for EGC site identification. Intercept ensembles are the most restrictive for site identification as all models in the ensemble must rank a site high for it to be considered. In contrast the union ensembles are the least restrictive in that a site will be included if any model in the ensemble ranks a site high. We identified the mode as the preferred ensemble, since multiple models had to rank a site high but not all models had to. While we interpreted this as the most balanced approach, using more or less conservative methods (i.e., intercept or union ensembles) may be warranted depending on resources available and risk tolerance. Each of these ensemble modeling approaches represents a trade-off in model agreement that can substantially increase or decrease the number of potential early detection monitoring sites.

The choice of thresholds used to delineate a site as 'suitable' for EGC also has important implications for the interpretation of outputs and site identification. Using a threshold of 5 (rank-transformed value, 80th quantile) to delineate suitability across the original five habitat suitability methods was intended to identify those sites that had the greatest probability of being suitable for EGC. However, it is important to note that this does not mean that sites not in this category are unsuitable for EGC and in fact we know sites that scored lower have EGC present. Additionally, only two of our individual models predict probability of occurrence as the output, for which this is most appropriate (the other models represent abundance or a habitat suitability score). Thus, we used the 80th quantile for all models as a consistent and repeatable method, noting that it is conservative in its application. We conducted a limited sensitivity analysis to address the rationale for this decision. The primary consequence of lowering the suitability threshold is that more sites are identified for monitoring. Thus, here too managers may opt for a less conservative approach if available resources allow.

The invasion process is complex and can be facilitated (or mediated) by a number of abiotic or biotic factors. Although the various individual habitat suitability methods attempt to capture different aspects related to EGC invasion dynamics there are others that are undoubtedly missed. For example, biotic resistance could be important when determining if a specific site will become invaded or not, but we lack both the mechanistic understanding and the raw data to fully include these in the current predictions. Such data is at least partially available for the west coast of Vancouver Island, as it was collected concurrent to annual EGC survey trapping, but a similar dataset does not exist for the Salish Sea (and energy devoted to collecting this would be more practically used to collect data on EGC directly). Also, none of the individual models explicitly capture micro-habitat suitability that might favour EGC. In the future, increased spatial and temporal resolution in the relevant biotic and abiotic predictor variables may make it possible to capture these more complex dynamics in future predictions of EGC distribution. Currently, the derived and ensemble models was our attempt to at least indirectly consider additional factors contributing to EGC invasion success and our results confirmed that including both environmental and habitat variables improved model performance.

Limitations on the accuracy and resolution of the input variables can also lead to uncertainties at the site level and may not be representative of conditions at a given beach. For example, MaxEnt input layers created from large-scale environmental variables are used to derive a continuous surface (rasters) that is then downscaled for an individual site (Table 1). However, individual sites may have specific characteristics that are either not adequately captured by the downscaling or might otherwise be considered completely unsuitable for EGC occupancy (e.g., exposed, rocky, deep). These sites are hard to identify *a priori* without a site visit so it is possible that some sites that were identified as priorities from the model predictions ultimately are de-prioritized for actual monitoring. Models that rely on CPUE to predict EGC abundance are prone to uncertainty due to variability in catch as a consequence of gear used, seasonality, etc. Similarly, occurrence records are also subject to uncertainty in the context of a new invasion. Absences may reflect truly unsuitable habitats, or a failure to detect a very small population of newly established individuals, or a site that simply has yet to be invaded. Presence records are more robust but do rely on the assumption that a single individual indicates the location is capable of sustaining an established population of the invader at equilibrium.

All of the individual models have the capacity to predict the suitability of new sites and/or new areas for EGC, and indeed some have already been used in other areas (i.e., MaxEnt, RSS). However, the availability and quality of the input data, the expertise of the user, and the spatial resolution required all potentially limit how readily these models can be applied for management purposes beyond the 447 sites considered here (see Table A1). Both the MaxEnt and BRT methods require a familiarity with ecological modelling and the technical expertise to assess and apply quality spatial layers correctly and access to those layers, which are not always readily available. The BRTs are further limited in that predictions can only be made for predetermined sites, due to the site-specific nature of the input variables (i.e., high water line length, isolation, etc.). Both the RSS and modified WSG methods are less demanding with respect to quality and type of input data and user expertise but, like the BRTs, the modified WSG requires sites of interest to be determined in advance. However, the BRTs, modified WSG, and RSS tool (to some extent) are better suited then MaxEnt when discreet sites are the preferred output for management. Ultimately, using as many of these models as possible in an ensemble approach will provide the most robust site identification.

Although beyond the scope of the initial request, AIS managers may opt to further prioritize sites in ways not discussed here. For example, sites could be prioritized based on important ecosystem components known to be degraded by EGC such as eelgrass meadows (e.g., Howard et al. 2019) or clam beds (e.g., Grosholtz et al. 2000), ease of access, or local volunteer capacity. Additionally, managers will need to apply their own expertise when determining trap placement within a site. Broadly speaking, the current best practice is to target features that may provide EGC with shelter, but what this looks like will vary widely among sites.

Our analyses focused on application of existing habitat suitability methods to identify potential monitoring sites for EGC. As such these models explicitly do not consider arrival probabilities for any sites as they assume propagules have the ability to reach each site which we know is not entirely true. Thus, future analyses could include measures of connectivity or propagule pressure to further refine sites for EGC early detection. One approach commonly used to model the movement of EGC larvae is particle tracking models and in fact Brasseale et al. (2019) have conducted such analyses with a focus on US waters of the Salish Sea but additional efforts would be needed to expand this approach to encompass all Canadian waters of the Salish Sea, especially the northern end. Additionally, EGC larvae have been introduced to new areas via human-mediated movements and future efforts could include information on potential pathways

for EGC movement including commercial shipping, recreational boating, aquaculture-related movements, etc.

Finally, we know that ecosystems are not static and that climate change and variability can influence the site-specific outcomes of an invasion, which in turn affects site identification for early detection monitoring programs. Of the habitat suitability methods used here, MaxEnt has the ability to predict distributions based on future conditions (assuming the relationships between environmental predictor variables and EGC ecology do not change) whereas the other models relied more on habitat features or characteristics that are less subject to change (e.g., substrate type, inlet length, etc.). Further, the more pressing issue for AIS managers is the identification of sites for early detection now rather than in the future. Similarly, the potential implications of climate change with respect to changing human-uses of the marine environment (and thus vectors and pathways) or environmental change is more likely to influence the persistence of EGC at any particular site which is beyond the scope of this analysis.

# 5. RECOMMENDATIONS

Although a single model for identifying habitat suitability from all factors important for EGC invasion success would be preferable, this is not possible with the current spatial/temporal coverage of abiotic and biotic variables and the lack of robust EGC-presence data in the Salish Sea. Every model we examined has limitations, especially for predicting suitable habitat for an invader like EGC that has broad environmental tolerances and can survive in a range of habitats (Klassen and Locke 2007; Therriault et al. 2008). However, by using information from an ensemble of five separate models, each using different predictor variables (see Table 1), it was possible to identify specific sites that are likely to be highly suitable for EGC and therefore worth consideration for early detection/monitoring plans in Canadian waters of the Salish Sea (Appendix Table A1). Although new in the context of aquatic invasive species management, the use of multi-models in resource decision-making has been used before (e.g., Woodman et al. 2019; Waggitt et al. 2019). Combining models, especially those derived from different aspects of a species' biology, increases the probability that suitable conditions (either environmental or habitat) are considered when making predictions into newly invaded areas, such as Canadian waters of the Salish Sea for EGC. Thus, we recommend using the mode of as many of the individual models as possible, provided at least three such individual models are available, when building new ensembles to identify additional monitoring sites in the Salish Sea or elsewhere in BC. However, while combining models this way should provide the greatest predictive power, any of the individual models or tools can be used on its own if necessary. Additional management considerations (e.g., sensitive areas, important species) can be used to further prioritize this list of sites (which is beyond the scope of the current analyses).

Methods that incorporated both environmental and habitat characteristics were the most informative in terms of identifying early detection/monitoring sites for EGC in the Salish Sea. Ideally habitat and environmental data would be available at a very high spatial and temporal resolution (on the order of meters) and in the intertidal zone, such that it could be used to generate a single model for EGC, but data limitations mean this is not currently possible. However, most (if not all) variables used here are available for the entire BC coastline such that it should be possible to generate similar predictions for other parts of BC beyond the Salish Sea. Future efforts to collect higher resolution data important for EGC and other intertidal invaders would improve future predictions. Finally, should EGC continue to expand their range in the Salish Sea or elsewhere in BC, all of the models we evaluated should be updated to better reflect potentially new suitable habitats for them.

# 6. ACKNOWLEDGEMENTS

# 7. ACRONYMS

**AIS**: Aquatic invasive species

**BC**: British Columbia

**BRT**: Boosted regression tree

**CHS**: Canadian Hydrographic Service

**CPUE*MaxEnt**: Derived model, product of linear BRT and MaxEnt models

**CPUE*PA**: Derived model, product of linear and logistic BRT models

**CPUE**: Catch-per-unit-effort (also refers to the linear BRT model)

**DFO**: Fisheries and Oceans Canada

**EGC**: European green crab (*Carcinus maenas*)

**JD**: Julian day

**NEMO**: Nucleus for European Modelling of the Ocean

**PA*MaxEnt**: Derived model, product of the logistic BRT and Maxent models

**PA**: Presence-absence (also refers to the logistic BRT model)

**RMSE**: Root-mean-squared-error

**ROMS**: Regional Ocean Modeling System

**RSS*MaxEnt**: Derived model, product of the RSS model (rescaled from 0-1 to 1-5) and MaxEnt model

**RSS**: Rapid site selection tool

**RVI**: Relative variable importance

**SDM**: Species distribution model

**WSG*MaxEnt**: Derived model, product of the WSG model (rescaled from 0-1 to 1-5) and MaxEnt model

**WSG**: Washington Sea Grant (also refers to the tool developed by WSG)

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# APPENDIX A. SITE AND MODEL INFORMATION

*Table A2. Usability of the five individual models highlighting the data processing requirements, technical expertise and feasibility of use for new sites or new areas. Additional details on the MaxEnt EGC model can be found in Lyons et al. (2020). BRT = stochastic boosted regression tree models, WSG = Washington Sea Grant.*

| Usability Traits | MaxEnt EGC Model | Linear BRT EGC Model | Logistic BRT EGC Model | Rapid Site Selection (RSS) Tool | Modified WSG Crab Team Method |
|---|---|---|---|---|---|
| Data required | A limited number of spatial data layers that cover the study area and presence-only records for EGC. | Many spatial data layers to extract site-specific information and catch data for EGC. | Many spatial data layers to extract site-specific information and either catch data or presence/absence data for EGC. | A limited number of spatial data layers that cover the study area. | No data requirements. High quality aerial and/or satellite imagery recommended. |
| Technical expertise | Statistics, coding, MaxEnt modelling techniques and GIS software. | Statistics, coding, and GIS software. | Statistics, coding, and GIS software. | GIS software. | None. |
| Resolution of output | Coast-wide, 0.04 degree resolution with values from multiple grid cells averaged for individual sites. | Individual, pre-defined sites of interest. | Individual, pre-defined sites of interest. | Coast-wide identification of possible sites. | Individual, pre-defined sites of interest. |
| Repeatability | High (mathematical model) | High (mathematical model) | High (mathematical model) | High (automated process) | Unknown, but possibly low due to subjectivity of method. |
| Update frequency | When new climatology data is available, or as new information on distribution of EGC is collected. | When new or improved spatial layers become available, or as new EGC trapping survey data is collected (from west coast Van. Isl.). | When new or improved spatial layers become available, or as new EGC trapping survey data is collected (from west coast Van. Isl.). | When new or improved spatial layers become available. | When new or improved aerial or satellite imagery becomes available for areas/sites of interest. |
| Applicability for new sites/areas | Can be applied rapidly, as coast-wide raster is already available. Only requires defining areas or sites of interest. | Requires significant data collection using GIS analysis for all new sites of interest, but model itself can be run quickly. | Requires significant data collection using GIS analysis for all new sites of interest, but model itself can be run quickly. | Can be applied rapidly (1-2 days) as process is automatic and does not require sites of interest to be identified in advance. | Can be applied instantly, provided sites of interest have already been identified. |

*Table A3. List of sites referenced in this paper, with coordinates of their centroids. Site names are arbitrary and may be unique to this document.*

| Site | Lat | Long | Site | Lat | Long | Site | Lat | Long |
|---|---|---|---|---|---|---|---|---|
| agamemnon | 49.71353 | -124.081 | cabbage | 48.797 | -123.085 | discovery2 | 48.42218 | -123.243 |
| albert | 48.3939 | -123.49 | cadboro | 48.45752 | -123.288 | dmountain | 50.31414 | -125.401 |
| allies | 50.20995 | -124.806 | cain | 48.87943 | -123.323 | donop1 | 50.14192 | -124.956 |
| amor | 50.53451 | -124.998 | cairns | 49.47048 | -123.833 | donop2 | 50.16312 | -124.968 |
| anderson1 | 48.35968 | -123.654 | camp | 48.74536 | -123.182 | drew | 50.10345 | -125.205 |
| anderson2 | 48.36 | -123.66 | campbell | 48.85826 | -123.272 | dudley | 50.20168 | -124.614 |
| annie | 49.38944 | -124.593 | capemudge | 49.99414 | -125.174 | edith | 50.37511 | -125.544 |
| april | 50.06135 | -125.236 | captain | 49.78264 | -123.994 | egerton | 50.48348 | -125.252 |
| arnette | 48.82315 | -123.38 | carlson | 49.53996 | -123.799 | ekins | 49.53021 | -123.39 |
| artaban | 49.476 | -123.348 | charles | 48.84044 | -123.381 | elagoon | 48.42636 | -123.463 |
| artificial | 50.38923 | -125.519 | chatham | 48.42978 | -123.25 | elford | 48.79726 | -123.131 |
| ashworth | 49.96596 | -124.918 | chisholm | 48.79221 | -123.6 | elizabeth1 | 50.31344 | -124.855 |
| asman | 50.40321 | -125.147 | chivers | 48.95438 | -123.572 | elizabeth2 | 50.31097 | -124.841 |
| attwood | 50.30986 | -124.661 | church | 48.80797 | -123.199 | elk | 50.28123 | -125.44 |
| aubyn | 50.32037 | -125.244 | clam | 48.82202 | -123.312 | erskine | 48.84911 | -123.57 |
| baker | 49.93095 | -124.039 | clamshell | 48.85221 | -123.441 | esquimalt1 | 48.44845 | -123.433 |
| bargain | 49.61179 | -124.037 | coal | 48.68053 | -123.379 | esquimalt2 | 48.45382 | -123.443 |
| barnes | 50.32704 | -125.267 | coghlan | 48.39123 | -123.485 | esquimalt3 | 48.4534 | -123.454 |
| bear | 50.36276 | -125.658 | coles | 48.62989 | -123.467 | esquimalt4 | 48.44207 | -123.432 |
| beaver | 48.76386 | -123.381 | columbine | 49.41808 | -123.321 | evans1 | 50.19792 | -125.063 |
| becher | 48.34237 | -123.589 | comet1 | 48.67002 | -123.3 | evans2 | 50.19918 | -125.094 |
| becher1 | 48.33827 | -123.602 | comet2 | 48.66448 | -123.294 | evans3 | 50.20948 | -125.085 |
| becher2 | 48.33833 | -123.599 | comox1 | 49.66375 | -124.945 | evans4 | 50.2218 | -125.069 |
| becher3 | 48.33667 | -123.627 | comox2 | 49.66705 | -124.918 | eveleigh2 | 50.13972 | -124.694 |
| becher4 | 48.33917 | -123.596 | connis | 50.30154 | -124.898 | evening | 48.98758 | -123.773 |
| bedwell | 49.31453 | -122.919 | conville | 50.1922 | -125.142 | false | 49.48942 | -124.355 |
| beecher1 | 48.33033 | -123.592 | coode1 | 50.02806 | -124.745 | fanny | 49.51445 | -124.826 |
| beecher2 | 48.333 | -123.591 | cooper | 50.30517 | -125.244 | fawn | 50.08191 | -125.216 |
| bennett | 48.84624 | -123.25 | copper | 50.11443 | -125.297 | fegen | 49.5216 | -124.386 |
| bessborough | 50.49278 | -125.771 | cordero | 50.4506 | -125.243 | ferguson | 48.60841 | -123.395 |
| bickley | 50.45128 | -125.393 | cordova2 | 48.50063 | -123.34 | fernwood | 48.91798 | -123.545 |
| billings | 49.69743 | -124.198 | cordova3 | 48.58997 | -123.372 | finnerty | 49.50353 | -124.389 |
| binnington | 50.34114 | -125.321 | cortes | 50.03286 | -124.976 | fleming | 48.42061 | -123.412 |
| bird | 50.20133 | -125.086 | cove | 49.31861 | -122.941 | forbes | 50.24296 | -124.59 |
| boatcove | 49.46728 | -124.243 | cowichan1 | 48.55847 | -123.365 | forrest1 | 48.66346 | -123.331 |
| boatswain | 48.71415 | -123.553 | cowichan2 | 48.7516 | -123.624 | forrest2 | 48.66241 | -123.337 |
| boot | 48.78895 | -123.2 | craig | 49.31448 | -124.263 | forward | 50.48935 | -125.701 |
| boothbay | 48.86702 | -123.55 | crescent | 49.05558 | -122.889 | frederick1 | 50.50439 | -125.258 |
| boscowitz | 49.01274 | -123.574 | cross | 50.05563 | -124.774 | fulford | 48.77037 | -123.461 |
| boundarybay | 49.07951 | -122.898 | cufra | 49.01343 | -123.685 | gabriola1 | 49.12959 | -123.72 |
| brem | 50.43242 | -124.654 | davie | 49.59977 | -124.386 | galley1 | 50.07157 | -124.778 |
| browning1 | 48.77912 | -123.274 | deceit | 50.24217 | -124.975 | galley2 | 50.07235 | -124.782 |
| browning2 | 48.77747 | -123.276 | deep | 48.68625 | -123.473 | galvani | 50.38197 | -125.845 |
| browning3 | 48.7778 | -123.267 | deepcove | 48.67984 | -123.476 | ganges | 48.85093 | -123.5 |
| buckley | 49.53122 | -124.853 | departure | 49.20292 | -123.97 | ganges1 | 48.8554 | -123.48 |
| bull | 49.47706 | -124.21 | depbay1 | 49.2101 | -123.959 | ganges2 | 48.84605 | -123.491 |
| bullock1 | 50.22541 | -125.004 | depbay2 | 49.20985 | -123.954 | ganges3 | 48.83525 | -123.471 |
| bullock2 | 50.22166 | -125.004 | dharbour | 50.04092 | -125.247 | gbay | 50.06718 | -124.787 |
| burdwood2 | 50.15948 | -125.103 | dinner | 48.83438 | -123.326 | genoa | 48.76717 | -123.599 |
| burgess | 49.44149 | -123.445 | dionisio | 49.01138 | -123.572 | gillies | 49.67966 | -124.509 |
| burgoyne | 48.78912 | -123.52 | discovery | 48.42778 | -123.241 | gloucester | 50.28635 | -124.857 |
| goldstream | 48.49105 | -123.553 | kar2 | 48.6706 | -123.373 | nanoosebay | 49.26447 | -124.18 |

| Site | Lat | Long | Site | Lat | Long | Site | Lat | Long |
|------|-----|------|------|-----|------|------|-----|------|
| goose | 49.66013 | -124.925 | kents | 49.78105 | -124.216 | nares | 49.20291 | -123.943 |
| gossip | 48.89085 | -123.319 | keppel | 48.71959 | -123.465 | narvaez | 48.77417 | -123.1 |
| goudge1 | 48.68642 | -123.392 | killam | 49.80219 | -123.912 | needham | 50.38756 | -125.601 |
| goudge2 | 48.69588 | -123.399 | kilpahlas | 48.73842 | -123.605 | nodales | 50.36857 | -125.315 |
| gowlland | 50.10237 | -125.257 | kingfisher1 | 48.7593 | -123.412 | nodales1 | 50.36406 | -125.314 |
| grace1 | 50.04873 | -124.755 | kingfisher2 | 48.75957 | -123.41 | nsaanich | 48.67523 | -123.421 |
| grace2 | 50.05598 | -124.745 | knapp2 | 48.6995 | -123.401 | nsidney | 48.69787 | -123.436 |
| granite1 | 49.45023 | -122.862 | komas | 49.58048 | -124.799 | nwbay | 49.30055 | -124.224 |
| grazebrooke | 50.33613 | -124.706 | kulleet | 49.01753 | -123.778 | oak2 | 48.4291 | -123.305 |
| grouse | 48.75008 | -123.579 | ladysmith1 | 48.99652 | -123.793 | oaks | 49.50907 | -124 |
| hadley | 49.49786 | -124.353 | ladysmith2 | 49.00717 | -123.814 | octopus1 | 50.26807 | -125.227 |
| hagan | 48.59001 | -123.465 | ladysmith3 | 49.01933 | -123.841 | okeover1 | 50.01042 | -124.73 |
| hall1 | 50.4445 | -125.283 | lamalchi | 48.94243 | -123.641 | okeover2 | 49.97452 | -124.679 |
| hall2 | 48.86264 | -123.264 | lambert | 49.52695 | -124.751 | okeover3 | 49.96775 | -124.678 |
| hamilton | 48.77403 | -123.275 | lancelot | 50.0596 | -124.7 | orford | 50.59123 | -124.867 |
| hare | 50.06528 | -124.796 | langdale | 49.43384 | -123.474 | otter | 50.12641 | -124.73 |
| hay | 48.74258 | -123.225 | larsons | 49.9878 | -124.688 | paddy | 48.80733 | -123.587 |
| heath | 49.47784 | -124.361 | lawrence | 50.43275 | -125.112 | parker | 48.87703 | -123.402 |
| henrietta | 50.37262 | -125.105 | liddell | 48.80906 | -123.366 | parkin | 48.73091 | -123.313 |
| henry2 | 49.59137 | -124.838 | littlebay | 48.75544 | -123.203 | patricia | 48.65608 | -123.449 |
| heydon | 50.57816 | -125.572 | littledarcy | 48.57093 | -123.267 | pedder1 | 48.34873 | -123.577 |
| higgins | 49.49619 | -124.367 | long | 48.86665 | -123.475 | pedder2 | 48.35063 | -123.574 |
| hjorth1 | 50.18109 | -125.121 | loughborough1 | 50.58343 | -125.533 | pelorus | 48.72108 | -123.3 |
| hjorth2 | 50.17758 | -125.121 | loughborough2 | 50.58705 | -125.528 | pender1 | 49.63282 | -123.998 |
| hmpbck | 50.36147 | -125.689 | lyall | 48.7959 | -123.174 | pender2 | 49.62652 | -123.995 |
| hope2 | 48.80136 | -123.277 | mace | 49.95054 | -124.766 | pender3 | 49.62572 | -124.01 |
| horton1 | 48.82912 | -123.255 | madrone | 48.8595 | -123.489 | pender4 | 49.61613 | -124.048 |
| horton2 | 48.82388 | -123.243 | malaspina1 | 49.75017 | -124.279 | pendrell1 | 50.26863 | -124.729 |
| hotham1 | 49.83669 | -123.995 | malaspina2 | 49.76933 | -124.332 | pendrell2 | 50.2525 | -124.71 |
| hotham2 | 49.9204 | -124.024 | malaspina3 | 49.77425 | -124.352 | pendrell3 | 50.27317 | -124.728 |
| hotham3 | 49.91782 | -124.021 | malaspina4 | 49.77208 | -124.366 | pendrell4 | 50.2917 | -124.722 |
| hutchinson | 48.38887 | -123.635 | malaspina5 | 49.7726 | -124.379 | piers | 48.70955 | -123.418 |
| hyacinth | 50.30697 | -125.195 | malaspina6 | 49.72503 | -124.428 | piggot | 48.82451 | -123.274 |
| hyacinthe | 50.11964 | -125.229 | manzanita | 50.06685 | -124.908 | pim | 48.36388 | -123.662 |
| icarus | 49.24268 | -124.018 | maple | 48.81689 | -123.609 | piper | 49.55056 | -123.8 |
| idol | 48.91954 | -123.596 | maxwell | 48.85282 | -123.563 | plowden | 49.532 | -123.46 |
| iroquois | 48.68327 | -123.392 | mayes | 50.27477 | -125.077 | plunger | 50.12389 | -125.058 |
| ivanhoe | 50.37084 | -125.534 | mcken | 48.55467 | -123.505 | portsj1 | 48.55365 | -124.421 |
| jackson | 48.75157 | -123.442 | medecin | 48.76012 | -123.268 | portsj2 | 48.57933 | -124.413 |
| jackson1 | 50.52927 | -125.821 | medicine | 48.7613 | -123.264 | prevost | 48.84008 | -123.395 |
| jackson2 | 50.51467 | -125.757 | menzies | 50.13282 | -125.392 | prideaux1 | 50.14698 | -124.665 |
| james | 48.6171 | -123.377 | metcalf | 49.4948 | -124.761 | prideaux2 | 50.14185 | -124.669 |
| james1 | 48.60745 | -123.348 | millbay | 48.65593 | -123.557 | puget | 48.4352 | -123.248 |
| james2 | 48.5945 | -123.352 | miners | 48.85187 | -123.301 | quarry | 49.67632 | -124.084 |
| jelina | 49.51043 | -124.296 | mitchell | 49.461 | -123.367 | ramsay | 50.44574 | -125 |
| johns2 | 48.60376 | -123.521 | moh | 50.51661 | -125.038 | razor | 48.77138 | -123.25 |
| johnstone1 | 50.35681 | -125.085 | money | 48.84863 | -123.46 | read | 50.52987 | -125.78 |
| johnstone2 | 50.35925 | -125.072 | montague | 48.89743 | -123.407 | redonda | 50.25862 | -124.97 |
| joyce | 50.16099 | -124.877 | mortimer | 48.76678 | -123.256 | rendezvous2 | 50.27108 | -125.051 |
| junction | 50.14709 | -124.906 | mountwilliam | 50.2109 | -125.13 | retreat | 48.9416 | -123.501 |
| kanish | 50.25988 | -125.325 | mud | 49.46923 | -124.786 | ripple | 50.3563 | -125.556 |
| kanish1 | 50.24425 | -125.358 | mudge1 | 49.13107 | -123.803 | roche2 | 48.37037 | -123.624 |
| kanish2 | 50.24012 | -125.313 | mudge2 | 50.0325 | -125.21 | rock1 | 50.3525 | -125.488 |
| kanish3 | 50.26372 | -125.289 | murchinson | 48.88875 | -123.336 | rocky | 48.31752 | -123.54 |
| kar1 | 48.66953 | -123.373 | musqueam | 49.22504 | -123.204 | roscoe | 50.15859 | -124.774 |

| Site | Lat | Long | Site | Lat | Long | Site | Lat | Long |
|---|---|---|---|---|---|---|---|---|
| roy | 49.64952 | -124.941 | stella | 50.28677 | -125.434 | walkem1 | 50.35893 | -125.522 |
| ruckle | 48.78398 | -123.378 | steveston1 | 49.13027 | -123.21 | walkers | 48.89325 | -123.501 |
| rumbottle | 49.73517 | -124.499 | steveston2 | 49.1207 | -123.179 | walter | 48.84406 | -123.483 |
| ruxton | 49.07559 | -123.696 | stone1 | 48.91815 | -123.586 | walterinner | 48.84265 | -123.483 |
| saanichton | 48.59147 | -123.378 | stone2 | 48.9265 | -123.592 | welburg | 48.84955 | -123.449 |
| salamance | 48.90312 | -123.344 | stoney | 48.80539 | -123.583 | welbury | 48.84679 | -123.447 |
| sallas | 48.58818 | -123.291 | storey | 50.41905 | -125.331 | wellbore | 50.45332 | -125.769 |
| saltery1 | 49.78245 | -124.172 | stove | 50.10282 | -125.004 | whaler | 48.89207 | -123.341 |
| saltery2 | 49.77962 | -124.18 | stuart1 | 50.39366 | -125.103 | whaletown | 50.11048 | -125.056 |
| saltwater | 50.13945 | -125.337 | stuart2 | 50.41309 | -125.14 | whaling | 49.53325 | -124.619 |
| samuel | 48.81698 | -123.204 | sturt | 49.76275 | -124.572 | whiterock | 50.25695 | -125.088 |
| saratoga | 49.85786 | -125.106 | subtle | 50.11578 | -125.083 | wigwam | 49.46464 | -122.888 |
| sbasin1 | 48.36345 | -123.644 | suffolk | 50.3555 | -125.44 | williamsons | 49.44827 | -123.468 |
| sbasin2 | 48.36293 | -123.636 | tallac | 50.44489 | -125.471 | witty | 48.38617 | -123.513 |
| sbasin3 | 48.37285 | -123.631 | taylor | 49.19356 | -123.86 | yahoo | 49.4826 | -123.246 |
| sbasin4 | 48.37815 | -123.634 | teakerne | 50.18256 | -124.816 | young | 50.35182 | -125.365 |
| sbasin5 | 48.39418 | -123.655 | tenedos | 50.12529 | -124.705 | | | |
| sbasin6 | 48.38615 | -123.684 | theodocia1 | 50.07207 | -124.704 | | | |
| schooner | 49.28399 | -124.13 | theodocia2 | 50.0682 | -124.692 | | | |
| scottie | 49.51916 | -124.341 | theodocia3 | 50.07864 | -124.661 | | | |
| sechelt | 49.46958 | -123.775 | thetis1 | 48.97993 | -123.685 | | | |
| secretary | 48.96002 | -123.589 | thetis2 | 48.98347 | -123.675 | | | |
| selby | 48.83183 | -123.395 | thors | 50.05676 | -124.708 | | | |
| shaft | 49.19761 | -123.945 | thunder1 | 49.76126 | -124.269 | | | |
| shannon | 49.6744 | -123.163 | thunder2 | 49.7733 | -124.278 | | | |
| sharbour1 | 48.37187 | -123.706 | thurlow | 50.40565 | -125.504 | | | |
| sharbour2 | 48.36717 | -123.712 | thurston1 | 50.36236 | -125.323 | | | |
| sharbour3 | 48.36212 | -123.704 | thurston2 | 50.37688 | -125.316 | | | |
| sharbour4 | 48.3568 | -123.726 | tilly | 48.73242 | -123.206 | | | |
| sharbour6 | 48.36327 | -123.729 | tod | 48.55948 | -123.465 | | | |
| sharpe | 48.98248 | -123.77 | topaze | 50.52567 | -125.723 | | | |
| sheer | 50.19966 | -125.127 | tork | 50.13911 | -124.929 | | | |
| shields | 49.55127 | -124.682 | trueworthy | 48.76821 | -123.18 | | | |
| shoal | 48.89708 | -123.651 | tsawassen | 49.04857 | -123.113 | | | |
| shoalbay2 | 50.45765 | -125.368 | tugboat | 49.14879 | -123.69 | | | |
| shorter | 50.40918 | -125.731 | tumbo | 48.79498 | -123.091 | | | |
| sidney1 | 48.6149 | -123.301 | twin | 50.03173 | -124.935 | | | |
| sidney2 | 48.61073 | -123.313 | tyee | 50.04937 | -125.256 | | | |
| sidney3 | 48.63111 | -123.328 | uganda | 50.09607 | -125.038 | | | |
| skerry | 49.49912 | -124.237 | union | 49.56561 | -124.875 | | | |
| slab | 50.32064 | -125.443 | unionpoint | 49.5965 | -124.884 | | | |
| smelt | 50.03375 | -124.994 | vansittart | 50.37794 | -125.747 | | | |
| snarrows1 | 50.23428 | -125.145 | vantreight | 48.4391 | -123.253 | | | |
| snarrows2 | 50.23791 | -125.154 | venture | 50.30454 | -125.34 | | | |
| sooke1 | 48.37435 | -123.719 | vere | 50.39062 | -125.771 | | | |
| sooke2 | 48.38247 | -123.704 | vharbour | 48.43801 | -123.386 | | | |
| sooke3 | 48.38948 | -123.657 | victoria1 | 48.42865 | -123.385 | | | |
| sooke5 | 48.3642 | -123.712 | victoria2 | 48.43548 | -123.379 | | | |
| southey | 48.9412 | -123.592 | victoria3 | 48.44052 | -123.382 | | | |
| southgate | 50.88751 | -124.801 | village | 48.8424 | -123.323 | | | |
| spapiyus | 49.68429 | -123.876 | vondonop1 | 50.15233 | -124.949 | | | |
| spectacle | 48.55953 | -123.536 | vondonop2 | 50.13932 | -124.946 | | | |
| spotlight | 48.97867 | -123.567 | vondonop3 | 50.17513 | -124.972 | | | |
| spring | 49.52591 | -124.359 | waiatt1 | 50.26242 | -125.252 | | | |
| stag | 50.07838 | -125.218 | waiatt2 | 50.26224 | -125.241 | | | |

*Table A4. Components for numbered models. Mode models are considered to predict highly suitable habitat for EGC when two or more models have a rank-transformed value of 5. Union models are considered to predict highly suitable habitat when any of the component models have a rank-transformed value of 5. Model 6, in bold, is the recommended option for initial monitoring.*

| Model # | Type | Threshold Value | Component Model(s) | N Sites Identified as Suitable Habitat |
|---|---|---|---|---|
| 1 | Individual | 5 | MaxEnt | 88 |
| 2 | | | CPUE | 90 |
| 3 | | | PA | 90 |
| 4 | | | RSS | 87 |
| 5 | | | WSG | 78 |
| **6** | **Mode of 5 models** | | **MaxEnt, CPUE, PA, RSS, WSG** | **68** |
| 7 | Union of 5 models | | MaxEnt, CPUE, PA, RSS, WSG | 113 |
| 8 | Individual | 4 | MaxEnt | 130 |
| 9 | | | CPUE | 138 |
| 10 | | | PA | 141 |
| 11 | | | RSS | 146 |
| 12 | | | WSG | 136 |
| 13 | Mode of 5 models | | MaxEnt, CPUE, PA, RSS, WSG | 151 |
| 14 | Union of 5 models | | MaxEnt, CPUE, PA, RSS, WSG | 207 |
| 15 | Mode of 4 models | 5 | MaxEnt, CPUE, PA, RSS | 71 |
| 16 | | | MaxEnt, CPUE, PA, WSG | 75 |
| 17 | | | MaxEnt, CPUE, RSS, WSG | 71 |
| 18 | | | MaxEnt, PA, RSS, WSG | 64 |
| 19 | | | MaxEnt, RSS, WSG, CPUE*PA | 73 |
| 20 | | | CPUE, PA, RSS, WSG | 71 |
| 21 | | | CPUE, PA, RSS, WSG*MaxEnt | 75 |
| 22 | | | CPUE, PA, WSG, RSS*MaxEnt | 77 |
| 23 | | | CPUE, RSS, WSG, PA*MaxEnt | 67 |
| 24 | | | PA, RSS, WSG, CPUE*MaxEnt | 68 |
| 25 | Mode of 3 methods | 5 | CPUE, PA, RSS | 60 |
| 26 | | | CPUE, PA, RSS*MaxEnt | 60 |
| 27 | | | CPUE, PA, WSG | 62 |
| 28 | | | CPUE, PA, WSG*MaxEnt | 63 |
| 29 | | | CPUE, RSS, PA*MaxEnt | 57 |
| 30 | | | CPUE, RSS, WSG | 67 |
| 31 | | | CPUE, RSS, WSG*MaxEnt | 65 |
| 32 | | | CPUE, WSG, PA*MaxEnt | 57 |
| 33 | | | CPUE, WSG, RSS*MaxEnt | 64 |
| 34 | | | MaxEnt, CPUE, PA | 55 |
| 35 | | | MaxEnt, CPUE, RSS | 53 |
| 36 | | | MaxEnt, CPUE, WSG | 52 |
| 37 | | | MaxEnt, PA, RSS | 52 |
| 38 | | | MaxEnt, PA, WSG | 51 |
| 39 | | | MaxEnt, RSS, CPUE*PA | 60 |
| 40 | | | MaxEnt, RSS, WSG | 58 |
| 41 | | | MaxEnt, WSG, CPUE*PA | 60 |
| 42 | | | PA, RSS, CPUE*MaxEnt | 62 |
| 43 | | | PA, RSS, WSG | 65 |
| 44 | | | PA, RSS, WSG*MaxEnt | 64 |
| 45 | | | PA, WSG, CPUE*MaxEnt | 59 |
| 46 | | | PA, WSG, RSS*MaxEnt | 62 |
| 47 | | | RSS, CPUE*PA, WSG*MaxEnt | 69 |
| 48 | | | RSS, WSG, CPUE*MaxEnt | 68 |
| 49 | | | RSS, WSG, CPUE*PA | 72 |
| 50 | | | RSS, WSG, PA*MaxEnt | 65 |
| 51 | | | WSG, CPUE*PA, RSS*MaxEnt | 70 |

Table A5. Predictions of highly suitable habitat for EGC (√) at all sites for individual models and for 5-model mode and union models, using threshold values of 5 (i.e., 80th percentile) and 4 (i.e., 60th percentile). Sites are not shown if none of the models identify it as suitable, at a given threshold. Site coordinates are shown in Table A2 and model numbers (along top row) can be looked up in Table A2. Sites predicted by the mode of all five models, with a threshold of 5 (model 6) are highlighted and marked with an asterisk as the recommended option for initial monitoring.

| Site | Threshold = 5 (80th percentile) | | | | | | | Threshold = 4 (60th percentile) | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1: MaxEnt | 2: CPUE | 3: PA | 4: RSS | 5: WSG | 6: Mode | 7: Union | 8: MaxEnt | 9: CPUE | 10: PA | 11: RSS | 12: WSG | 13: Mode | 14: Union |
| agamemnon | − | √ | √ | − | − | − | √ | √ | √ | √ | − | − | √ | √ |
| albert | − | − | − | − | √ | − | − | √ | − | − | − | √ | √ | √ |
| anderson1 | √ | − | − | − | √ | − | √ | √ | √ | √ | √ | √ | √ | √ |
| anderson2 | √ | √ | − | − | − | − | √ | √ | √ | √ | − | − | √ | √ |
| annie | − | − | − | √ | √ | − | √ | − | − | − | √ | √ | − | √ |
| april | √ | − | − | − | − | − | − | √ | − | − | − | − | − | − |
| arnette | − | − | − | √ | − | − | − | − | − | √ | √ | − | − | √ |
| artaban* | − | − | √ | − | √ | √ | √ | − | √ | √ | − | √ | √ | √ |
| artificial* | √ | √ | √ | − | − | √ | √ | √ | √ | √ | √ | − | √ | √ |
| ashworth | − | √ | − | − | − | − | − | √ | √ | − | √ | √ | √ | √ |
| asman | √ | √ | − | − | − | − | √ | √ | √ | − | − | − | − | √ |
| attwood | − | √ | √ | − | − | − | √ | − | √ | √ | √ | − | √ | √ |
| baker | − | √ | − | √ | − | − | √ | − | √ | √ | √ | √ | √ | √ |
| bargain | − | √ | − | − | − | − | − | − | √ | − | − | − | − | − |
| bear | √ | − | − | − | − | − | − | √ | − | − | √ | − | − | √ |
| becher* | √ | − | √ | − | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ |
| becher1 | √ | − | − | − | − | − | − | √ | − | − | − | − | − | − |
| becher2 | √ | − | − | − | − | − | − | √ | − | − | − | − | − | − |
| becher3 | √ | − | − | − | − | − | − | √ | − | √ | √ | − | √ | √ |
| becher4 | √ | − | − | − | − | − | − | √ | √ | √ | √ | √ | √ | √ |
| bedwell | − | − | √ | − | − | − | − | N/A | − | √ | − | − | √ | √ |
| beecher1 | √ | − | − | − | − | − | − | √ | − | − | − | − | − | − |
| beecher2 | √ | − | − | − | − | − | − | √ | − | − | − | − | − | − |
| bessborough* | √ | − | √ | √ | √ | √ | √ | √ | − | √ | √ | √ | √ | √ |
| bickley* | √ | √ | − | − | − | √ | √ | √ | √ | − | − | − | √ | √ |
| binnington | √ | − | − | − | − | − | − | √ | − | − | − | − | − | − |
| boatcove | − | − | √ | √ | − | − | √ | − | √ | √ | √ | √ | √ | √ |
| boatswain | − | − | − | √ | − | − | − | − | − | − | √ | − | − | − |
| boot | − | − | √ | − | − | − | − | − | − | √ | − | − | − | − |
| boothbay | − | − | − | √ | − | − | − | − | − | − | √ | √ | √ | √ |
| boundarybay* | − | √ | √ | √ | √ | √ | √ | − | √ | √ | √ | √ | √ | √ |
| brem* | − | − | √ | √ | − | √ | √ | − | √ | √ | √ | − | √ | √ |
| bull* | − | √ | √ | − | √ | √ | √ | − | √ | √ | √ | √ | √ | √ |
| burgess | − | √ | − | − | − | − | − | − | √ | − | − | − | − | − |

| Site | Threshold = 5 (80th percentile) | | | | | | | Threshold = 4 (60th percentile) | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1: MaxEnt | 2: CPUE | 3: PA | 4: RSS | 5: WSG | 6: Mode | 7: Union | 8: MaxEnt | 9: CPUE | 10: PA | 11: RSS | 12: WSG | 13: Mode | 14: Union |
| burgoyne | – | – | – | √ | – | – | – | – | – | – | √ | – | – | – |
| cabbage* | – | – | √ | √ | √ | √ | √ | – | – | √ | √ | √ | √ | √ |
| cadboro | – | √ | – | – | √ | – | √ | – | √ | √ | √ | √ | √ | √ |
| capemudge | – | – | √ | – | – | – | – | √ | – | √ | – | – | – | √ |
| captain | – | √ | – | – | – | – | – | √ | √ | – | – | – | – | √ |
| carlson* | – | √ | – | √ | √ | √ | √ | – | √ | √ | √ | √ | √ | √ |
| charles | – | √ | – | – | – | – | – | – | √ | – | – | – | – | – |
| chatham | – | – | √ | – | – | – | – | √ | – | √ | – | √ | √ | √ |
| chisholm | – | – | √ | – | √ | – | √ | – | √ | √ | √ | √ | √ | √ |
| coghlan | – | – | √ | – | – | – | – | √ | – | √ | – | – | – | √ |
| comox1* | – | √ | – | √ | √ | √ | √ | √ | √ | – | √ | √ | √ | √ |
| comox2* | – | – | √ | √ | √ | √ | √ | – | √ | √ | √ | √ | √ | √ |
| conville | – | √ | – | – | – | – | – | √ | √ | – | – | – | – | √ |
| copper | √ | – | – | – | – | – | – | √ | – | – | – | – | – | – |
| cordero | √ | – | – | – | – | – | – | √ | – | – | – | – | – | – |
| cortes | – | – | – | – | √ | – | – | √ | – | – | – | √ | √ | √ |
| cowichan2* | – | √ | – | √ | √ | √ | √ | – | √ | √ | √ | √ | √ | √ |
| craig | – | √ | – | √ | – | – | √ | – | √ | √ | √ | √ | √ | √ |
| crescent | – | – | – | √ | – | – | – | – | √ | – | √ | – | – | √ |
| cross* | – | √ | √ | – | – | √ | √ | – | √ | √ | √ | – | √ | √ |
| cufra | – | – | √ | – | – | – | – | – | – | √ | √ | – | – | √ |
| departure | – | – | – | – | √ | – | – | – | – | – | √ | √ | – | √ |
| depbay2 | – | √ | – | – | – | – | – | – | √ | – | – | – | – | – |
| discovery | – | – | – | – | √ | – | – | √ | – | – | – | √ | – | √ |
| dmountain | √ | – | – | – | – | – | – | √ | – | – | √ | – | √ | √ |
| donop1 | – | √ | – | – | √ | – | √ | √ | √ | √ | √ | √ | √ | √ |
| drew* | – | – | √ | √ | – | √ | √ | √ | – | √ | √ | – | √ | √ |
| edith | √ | – | – | – | – | – | – | √ | – | – | – | – | – | – |
| egerton | √ | – | – | – | – | – | – | √ | √ | √ | √ | √ | √ | √ |
| elagoon* | – | – | √ | √ | – | √ | √ | √ | – | √ | √ | – | √ | √ |
| elk* | √ | – | – | √ | √ | √ | √ | √ | – | – | √ | √ | √ | √ |
| esquimalt1 | – | √ | √ | – | – | – | √ | – | √ | √ | – | – | – | √ |
| esquimalt2 | – | – | √ | – | – | – | – | – | – | √ | – | – | – | – |
| esquimalt3* | – | √ | √ | √ | – | √ | √ | – | √ | √ | √ | √ | √ | √ |
| evans1 | – | √ | – | – | – | – | – | √ | √ | √ | √ | √ | √ | √ |
| evans2 | – | – | √ | – | – | – | – | √ | √ | √ | – | √ | √ | √ |
| evans4 | – | √ | – | √ | – | – | √ | – | √ | √ | √ | √ | √ | √ |
| false* | – | √ | – | – | √ | √ | √ | – | √ | – | – | √ | √ | √ |
| fanny* | – | √ | √ | √ | – | √ | √ | – | √ | √ | √ | √ | √ | √ |

| Site | Threshold = 5 (80th percentile) | | | | | | | Threshold = 4 (60th percentile) | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1: MaxEnt | 2: CPUE | 3: PA | 4: RSS | 5: WSG | 6: Mode | 7: Union | 8: MaxEnt | 9: CPUE | 10: PA | 11: RSS | 12: WSG | 13: Mode | 14: Union |
| fawn | √ | − | − | − | − | − | − | √ | − | √ | − | √ | √ | √ |
| finnerty | − | − | √ | − | − | − | − | − | − | √ | − | − | − | − |
| forbes | − | − | − | √ | − | − | − | − | − | − | √ | √ | − | √ |
| forward* | √ | − | − | √ | √ | √ | √ | √ | √ | − | √ | √ | √ | √ |
| frederick1* | √ | − | − | √ | √ | √ | √ | √ | − | − | √ | √ | √ | √ |
| fulford | − | − | − | − | √ | − | − | − | − | − | √ | √ | √ | √ |
| gabriola1 | − | √ | − | − | √ | − | √ | − | √ | − | √ | √ | √ | √ |
| galvani | √ | − | − | − | − | − | − | √ | √ | √ | √ | − | √ | √ |
| ganges | − | − | − | − | √ | − | − | − | √ | √ | √ | √ | √ | √ |
| ganges1 | − | − | − | √ | − | − | − | − | √ | − | √ | √ | √ | √ |
| gillies* | − | − | − | √ | √ | √ | √ | − | √ | − | √ | √ | √ | √ |
| goldstream | − | − | − | √ | √ | − | √ | − | − | − | √ | √ | − | √ |
| gowlland* | √ | √ | √ | √ | − | √ | √ | √ | √ | √ | √ | − | √ | √ |
| grace1 | − | − | √ | − | − | − | − | − | √ | √ | √ | − | √ | √ |
| granite1 | − | − | − | √ | − | − | − | − | √ | − | √ | − | − | √ |
| hadley | − | √ | √ | − | − | − | √ | − | √ | √ | √ | √ | √ | √ |
| hagan | − | − | − | √ | − | − | − | − | − | − | √ | − | − | − |
| hall1 | √ | − | − | − | − | − | − | √ | − | − | − | − | − | − |
| hamilton | − | − | − | − | √ | − | − | − | − | − | − | √ | − | − |
| hay | − | √ | − | − | − | − | − | − | √ | − | − | − | − | − |
| heydon | √ | − | − | √ | − | − | √ | √ | √ | √ | √ | √ | √ | √ |
| higgins | − | − | √ | − | − | − | − | − | − | √ | − | − | − | − |
| hjorth1 | − | √ | − | − | − | − | − | √ | √ | − | − | √ | √ | √ |
| hmpbck* | √ | − | − | √ | √ | √ | √ | √ | − | − | √ | √ | √ | √ |
| hope2 | − | − | √ | − | − | − | − | − | − | √ | √ | √ | √ | √ |
| horton1 | − | √ | − | − | − | − | − | − | √ | − | √ | √ | √ | √ |
| horton2 | − | √ | − | − | − | − | − | − | √ | √ | − | √ | √ | √ |
| hotham1 | − | √ | − | − | − | − | − | − | √ | − | √ | √ | √ | √ |
| hotham2 | − | − | √ | − | − | − | − | − | √ | √ | − | − | − | √ |
| hotham3* | − | √ | √ | − | − | √ | √ | − | √ | √ | √ | − | √ | √ |
| hutchinson | √ | − | − | − | − | − | − | √ | √ | √ | √ | √ | √ | √ |
| hyacinth | − | √ | √ | − | − | − | √ | √ | √ | √ | − | − | √ | √ |
| hyacinthe | − | − | √ | − | − | − | − | − | − | √ | − | − | − | − |
| ivanhoe | √ | − | − | − | − | − | − | √ | − | − | − | − | − | − |
| jackson | − | − | √ | − | − | − | − | − | − | √ | − | − | − | − |
| jackson1* | √ | − | √ | √ | √ | √ | √ | √ | − | √ | √ | √ | √ | √ |
| jackson2 | √ | − | − | − | − | − | − | √ | √ | − | √ | − | √ | √ |
| james1* | − | √ | − | √ | √ | √ | √ | − | √ | − | √ | √ | √ | √ |
| james2 | − | − | − | − | √ | − | − | − | − | √ | − | √ | − | √ |

43

| Site | Threshold = 5 (80th percentile) | | | | | | | Threshold = 4 (60th percentile) | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1: MaxEnt | 2: CPUE | 3: PA | 4: RSS | 5: WSG | 6: Mode | 7: Union | 8: MaxEnt | 9: CPUE | 10: PA | 11: RSS | 12: WSG | 13: Mode | 14: Union |
| jelina | – | – | √ | √ | – | – | √ | – | – | √ | √ | – | – | √ |
| johns2 | – | – | – | √ | – | – | – | – | – | – | √ | √ | – | √ |
| kanish* | √ | – | √ | – | – | √ | √ | √ | – | √ | – | – | √ | √ |
| kanish1 | √ | – | – | √ | – | – | √ | √ | √ | √ | √ | – | √ | √ |
| kanish2* | √ | √ | √ | – | – | √ | √ | √ | √ | √ | √ | √ | √ | √ |
| kanish3* | √ | √ | – | √ | √ | √ | √ | √ | √ | – | √ | √ | √ | √ |
| killam | – | – | √ | – | – | – | – | √ | – | √ | – | – | – | √ |
| kilpahlas | – | √ | – | √ | – | – | √ | – | √ | – | √ | √ | √ | √ |
| kingfisher1 | – | – | – | – | √ | – | – | – | – | √ | – | √ | – | √ |
| komas | – | – | – | – | √ | – | – | – | √ | – | – | √ | – | √ |
| kulleet* | – | – | – | √ | √ | √ | √ | – | – | – | √ | √ | √ | √ |
| ladysmith2 | – | – | √ | – | – | – | – | – | – | √ | – | – | – | – |
| ladysmith3* | – | √ | √ | √ | √ | √ | √ | – | √ | √ | √ | √ | √ | √ |
| lamalchi | – | – | √ | – | – | – | – | – | – | √ | – | √ | – | √ |
| lambert* | – | √ | √ | – | √ | √ | √ | – | √ | √ | √ | √ | √ | √ |
| lancelot | – | √ | – | – | – | – | – | – | √ | √ | – | √ | √ | √ |
| larsons* | – | √ | √ | √ | – | √ | √ | √ | √ | √ | √ | – | √ | √ |
| long | – | – | – | √ | – | – | – | – | √ | √ | √ | √ | √ | √ |
| loughborough1 | √ | – | – | – | – | – | – | √ | – | – | √ | – | – | √ |
| loughborough2 | √ | – | – | – | – | – | – | √ | – | √ | √ | – | √ | √ |
| lyall | – | – | – | √ | √ | – | √ | – | √ | – | √ | √ | √ | √ |
| madrone | – | √ | – | – | – | – | – | – | √ | √ | √ | √ | √ | √ |
| malaspina1 | – | – | √ | – | – | – | – | – | – | √ | – | – | – | – |
| malaspina2 | – | – | – | √ | – | – | – | – | √ | – | √ | – | – | √ |
| malaspina3 | – | – | – | √ | – | – | – | – | – | – | √ | – | – | – |
| malaspina4* | – | – | √ | √ | √ | √ | √ | – | – | √ | √ | √ | √ | √ |
| manzanita* | – | – | – | √ | √ | √ | √ | √ | – | – | √ | √ | √ | √ |
| maple | – | √ | – | – | – | – | – | – | √ | – | – | – | – | – |
| mcken | – | √ | – | √ | – | – | √ | – | √ | – | √ | – | – | √ |
| medecin* | – | √ | – | √ | √ | √ | √ | – | √ | – | √ | √ | √ | √ |
| menzies | √ | – | – | – | √ | – | √ | √ | – | √ | √ | √ | √ | √ |
| millbay | – | – | – | √ | – | – | – | – | √ | – | √ | √ | √ | √ |
| miners | – | √ | – | – | – | – | – | – | √ | – | – | – | – | – |
| moh | – | – | – | √ | – | – | – | – | – | – | √ | – | – | – |
| mortimer | – | – | – | – | √ | – | – | – | √ | – | – | √ | – | √ |
| mud* | – | √ | √ | √ | √ | √ | √ | – | √ | √ | √ | √ | √ | √ |
| mudge1 | – | – | √ | – | – | – | – | – | – | √ | – | – | – | – |
| murchinson | – | – | √ | – | – | – | – | – | – | √ | – | √ | – | √ |
| musqueam | – | – | – | √ | √ | – | √ | – | – | – | √ | √ | – | √ |

| Site | Threshold = 5 (80th percentile) | | | | | | | Threshold = 4 (60th percentile) | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1: MaxEnt | 2: CPUE | 3: PA | 4: RSS | 5: WSG | 6: Mode | 7: Union | 8: MaxEnt | 9: CPUE | 10: PA | 11: RSS | 12: WSG | 13: Mode | 14: Union |
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| pender2* | − | √ | √ | √ | √ | √ | √ | − | √ | √ | √ | √ | √ | √ |
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| roche2* | √ | √ | √ | − | − | √ | √ | √ | √ | √ | √ | − | √ | √ |
| rock1 | √ | √ | − | − | − | − | √ | √ | √ | − | √ | √ | √ | √ |
| rocky | √ | − | − | − | − | − | − | √ | − | √ | − | − | − | √ |
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| roy | − | − | − | √ | √ | − | √ | √ | √ | √ | √ | √ | √ | √ |
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| Site | Threshold = 5 (80th percentile) | | | | | | | Threshold = 4 (60th percentile) | | | | | | |
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| | 1: MaxEnt | 2: CPUE | 3: PA | 4: RSS | 5: WSG | 6: Mode | 7: Union | 8: MaxEnt | 9: CPUE | 10: PA | 11: RSS | 12: WSG | 13: Mode | 14: Union |
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| snarrows2* | − | √ | √ | − | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ |
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| southgate | − | − | − | √ | √ | − | √ | − | − | − | √ | √ | − | √ |
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| Site | Threshold = 5 (80th percentile) | | | | | | | Threshold = 4 (60th percentile) | | | | | | |
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| | 1: MaxEnt | 2: CPUE | 3: PA | 4: RSS | 5: WSG | 6: Mode | 7: Union | 8: MaxEnt | 9: CPUE | 10: PA | 11: RSS | 12: WSG | 13: Mode | 14: Union |
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| victoria2 | – | – | √ | – | – | – | – | √ | √ | √ | – | – | √ | √ |
| vondonop1 | – | √ | – | – | – | – | – | √ | √ | – | – | – | √ | √ |
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| wigwam | – | – | – | √ | √ | – | √ | – | – | – | √ | √ | – | √ |
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Table A6. Predictions of highly suitable habitat (√) at all sites for mode models comprised of 4- and 3- model combinations, using the 80$^{th}$ percentile as the threshold for suitability. Sites are not shown if none of the models identify it as suitable, at that threshold. Site coordinates are shown in Table A2 and model numbers (along top row) can be looked up in Table A2.

| Site | Mode of 4 models | | | | | | | | | | Mode of 3 models | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 | 34 | 35 | 36 | 37 | 38 | 39 | 40 | 41 | 42 | 43 | 44 | 45 | 46 | 47 | 48 | 49 | 50 | 51 |
| agamemnon | √ | √ | – | – | – | – | √ | √ | – | – | √ | √ | √ | √ | √ | – | – | √ | – | √ | – | – | – | – | – | – | – | √ | – | – | √ | – | – | – | – | – | – |
| albert | – | – | – | – | – | – | – | – | √ | – | – | – | – | – | – | – | – | √ | – | – | – | – | – | – | – | – | – | – | – | – | – | – | – | – | – | √ | – |
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| anderson2 | √ | √ | – | – | – | – | – | – | – | – | – | – | – | – | √ | – | – | √ | – | √ | √ | √ | – | – | √ | – | √ | – | – | – | – | – | – | – | – | – | – |
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| ashworth | – | – | – | – | – | – | √ | √ | – | – | – | √ | – | √ | – | – | √ | – | √ | – | – | – | – | – | – | – | – | – | – | – | – | – | – | – | – | – | – |
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| attwood | √ | – | – | – | – | √ | – | √ | – | √ | √ | √ | √ | √ | – | – | – | – | – | √ | – | – | – | – | – | – | – | √ | – | – | √ | – | – | √ | – | – | – |
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| becher4 | – | – | – | – | – | – | – | – | – | – | – | – | – | – | – | – | – | – | – | – | – | – | √ | – | √ | – | – | – | – | – | – | – | √ | – | – | – | √ |
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| bickley | √ | √ | √ | – | √ | – | – | – | √ | – | – | – | – | – | √ | – | – | √ | – | √ | √ | √ | – | – | √ | – | √ | – | – | – | – | – | – | – | – | – | – |
| boatcove | √ | – | – | √ | √ | – | – | – | – | – | √ | √ | – | – | – | – | – | – | – | – | – | √ | – | √ | – | – | √ | √ | √ | – | √ | √ | – | √ | – | – | √ |
| boundarybay | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ |
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| cadboro | – | √ | √ | – | √ | – | – | – | – | – | – | – | √ | √ | – | √ | √ | √ | √ | √ | – | – | √ | – | – | – | √ | – | – | – | √ | – | √ | √ | √ | – | √ |
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| chatham | – | – | – | – | – | – | √ | – | – | – | – | – | – | – | √ | – | – | – | – | – | – | – | – | – | √ | – | – | – | – | – | – | – | – | – | – | – | – |
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| evans1 | – | – | – | – | – | – | – | – | – | – | – | √ | – | √ | – | – | √ | – | √ | – | – | – | – | – | – | – | – | – | – | – | – | – | – | √ | – | – | √ |
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| sheer | − | − | − | − | − | − | − | − | √ | − | − | − | − | − | − | − | √ | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | √ | − |
| shoal | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ |
| shoalbay2 | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ |
| shorter | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | − | √ | √ | √ | √ | − | √ | √ | √ | √ | √ | − | √ | √ | − | √ | − | √ | − | √ | − | − | √ | √ | − | − |
| sidney3 | − | √ | − | √ | − | √ | − | √ | − | √ | − | − | √ | − | − | − | − | − | − | − | − | − | − | √ | − | − | − | − | √ | − | √ | √ | − | − | − | − | − |
| slab | − | √ | − | √ | − | − | − | − | − | − | − | − | − | √ | − | − | − | − | − | √ | − | − | √ | √ | − | − | − | − | − | √ | − | − | − | − | − | − | − |
| snarrows2 | − | √ | − | − | − | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | − | √ | − | √ | − | − | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ |
| sooke1 | √ | √ | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | √ | − | − | √ | √ | − | − | − | − | − | − | − | − | − | − | − | − | − |
| sooke2 | √ | − | √ | − | − | − | √ | − | √ | − | − | − | − | − | √ | − | √ | − | − | − | √ | − | √ | − | √ | √ | − | √ | − | √ | − | − | √ | √ | − | √ | − |
| sooke3 | − | √ | √ | − | √ | − | − | √ | √ | − | − | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | − | √ | √ | √ | √ | − | − | − | √ | √ | √ | √ | √ | √ |
| southgate | − | − | √ | √ | √ | − | − | − | − | √ | − | − | − | − | − | √ | √ | − | − | − | − | − | − | − | − | √ | − | − | √ | √ | − | − | √ | √ | √ | √ | − |
| steveston1 | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ |

| Site | Mode of 4 models | | | | | | | | | | Mode of 3 models | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 | 34 | 35 | 36 | 37 | 38 | 39 | 40 | 41 | 42 | 43 | 44 | 45 | 46 | 47 | 48 | 49 | 50 | 51 |
| steveston2 | − | √ | − | √ | √ | √ | − | √ | − | √ | − | − | √ | − | − | − | − | − | − | − | − | − | − | √ | − | − | √ | − | √ | − | √ | √ | − | − | √ | − | √ |
| stove | √ | − | − | − | − | √ | − | √ | − | √ | √ | √ | √ | √ | − | − | − | − | − | √ | − | − | − | − | − | − | − | √ | − | − | √ | − | − | − | − | − | − |
| sturt | − | − | √ | − | − | √ | √ | √ | √ | − | − | − | − | − | √ | √ | √ | √ | √ | − | − | − | − | − | − | √ | − | − | √ | √ | − | √ | √ | √ | √ | √ | √ |
| tallac | √ | √ | √ | √ | √ | √ | √ | √ | − | √ | √ | √ | − | √ | √ | √ | √ | − | √ | √ | √ | √ | √ | − | √ | √ | √ | √ | − | √ | − | − | √ | √ | √ | − | √ |
| thurston2 | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ |
| topaze | − | − | − | − | √ | − | − | − | − | − | − | − | − | − | √ | − | √ | − | − | − | √ | − | √ | − | √ | √ | √ | √ | − | √ | − | − | √ | √ | √ | √ | √ |
| tsawassen | − | − | √ | √ | √ | √ | − | − | √ | √ | − | − | − | − | − | √ | − | − | − | − | − | − | − | − | − | √ | − | − | √ | − | − | − | − | √ | √ | √ | − |
| twin | − | − | − | − | − | − | − | √ | − | − | − | − | − | − | − | − | − | − | √ | − | − | − | − | − | − | − | − | − | − | − | − | √ | − | − | − | − | √ |
| uganda | √ | − | − | − | − | √ | − | √ | − | √ | √ | √ | √ | √ | − | − | − | − | − | √ | − | − | − | − | − | − | − | √ | − | − | √ | − | − | − | − | − | − |
| vantreight | − | − | − | − | − | − | − | − | − | √ | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | √ | − | √ | − | − | − | − |
| vere | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | − | √ | √ | √ | − | √ | √ | √ | √ | √ | √ | √ | √ | − | √ | − | √ | √ | − | − | − | √ | √ | − | √ | − | √ |
| vharbour | √ | √ | − | − | − | − | √ | √ | − | − | √ | √ | √ | √ | √ | − | − | √ | − | √ | − | − | − | − | − | − | √ | − | − | √ | − | − | − | − | − | − | − |
| victoria1 | − | − | − | − | − | − | − | √ | − | − | − | − | − | − | √ | − | − | √ | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − |
| waiatt2 | − | − | − | − | − | − | √ | − | − | − | − | √ | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | − | √ | − | − | − | − | − | √ |
| wellbore | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ |
| wigwam | − | − | √ | − | − | √ | − | − | √ | − | − | − | − | − | − | √ | − | − | − | − | − | − | − | − | √ | − | − | √ | − | − | − | − | − | √ | √ | √ | − |
| witty | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ | √ |

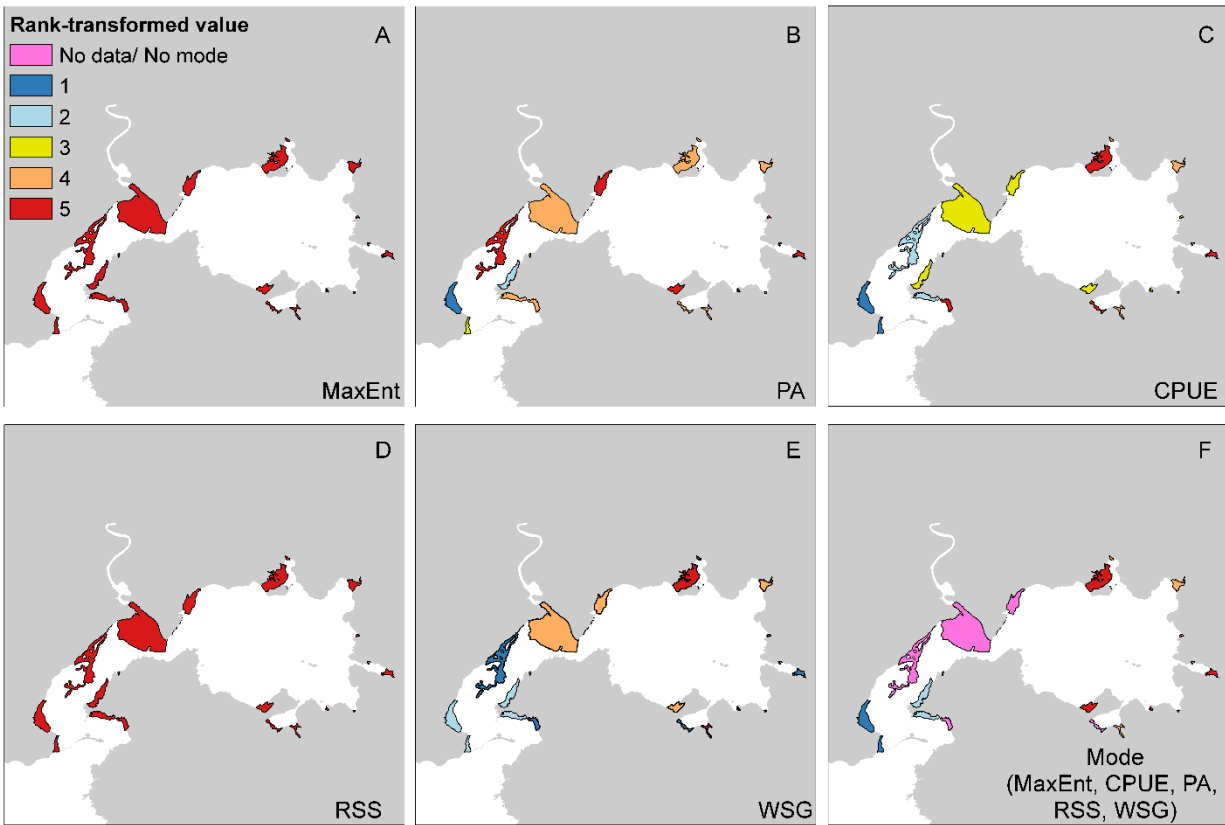# APPENDIX B. AREA-SPECIFIC PREDICTIONS WITHIN THE SALISH SEA



*Figure A1. Predictions from select models for Sooke. A-E) Individual models, showing quantiles (20th percentiles) of model values, where quantile 5 is interpreted as a site being highly suitable for EGC; F) Mode of the five individual models, where each site is assigned the most frequent value from the input models. "No mode" occurs when no value is the most frequent or if there is a tie.*
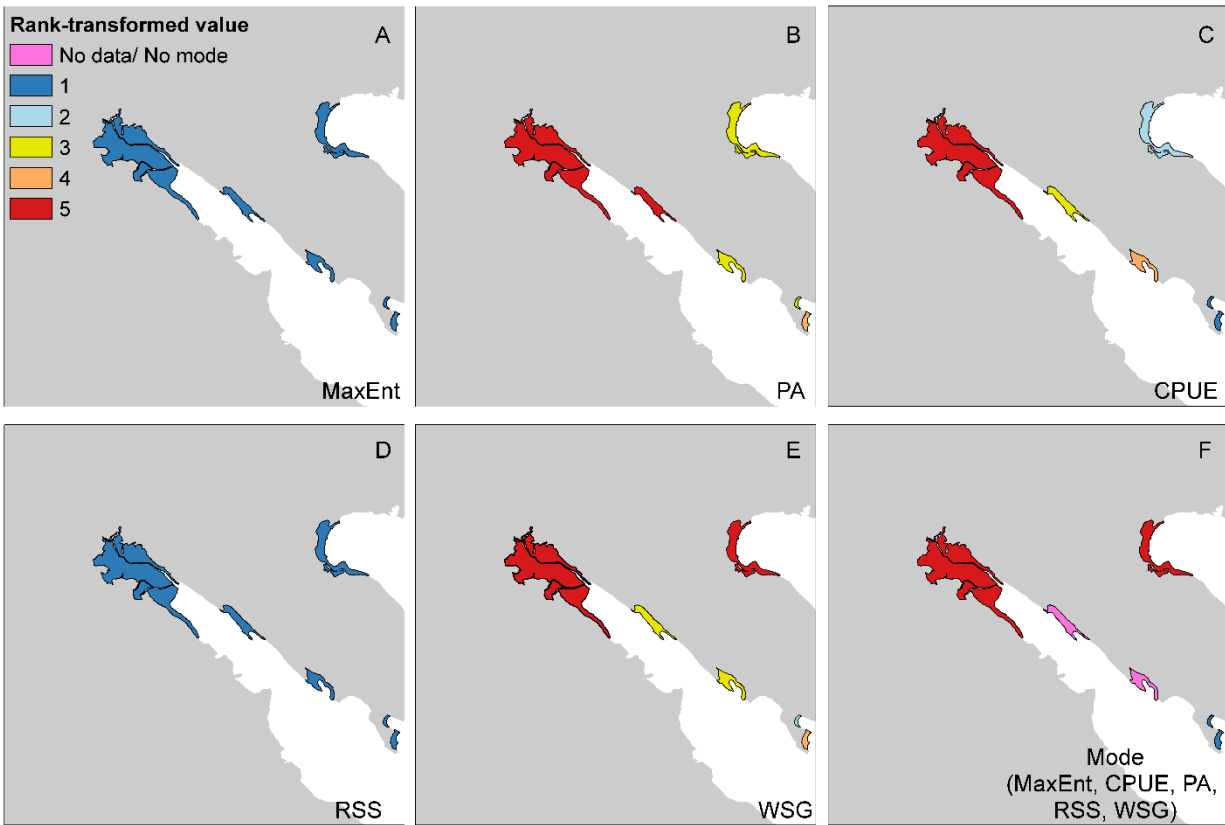
*Figure A2. Predictions from select models for Ladysmith. A-E) Individual models, showing quantiles (20th percentiles) of model values, where quantile 5 is interpreted as being highly suitable for EGC; F) Mode of the five individual models, where each site is assigned the most frequent value from the input models. "No mode" occurs when no value is the most frequent or if there is a tie.*
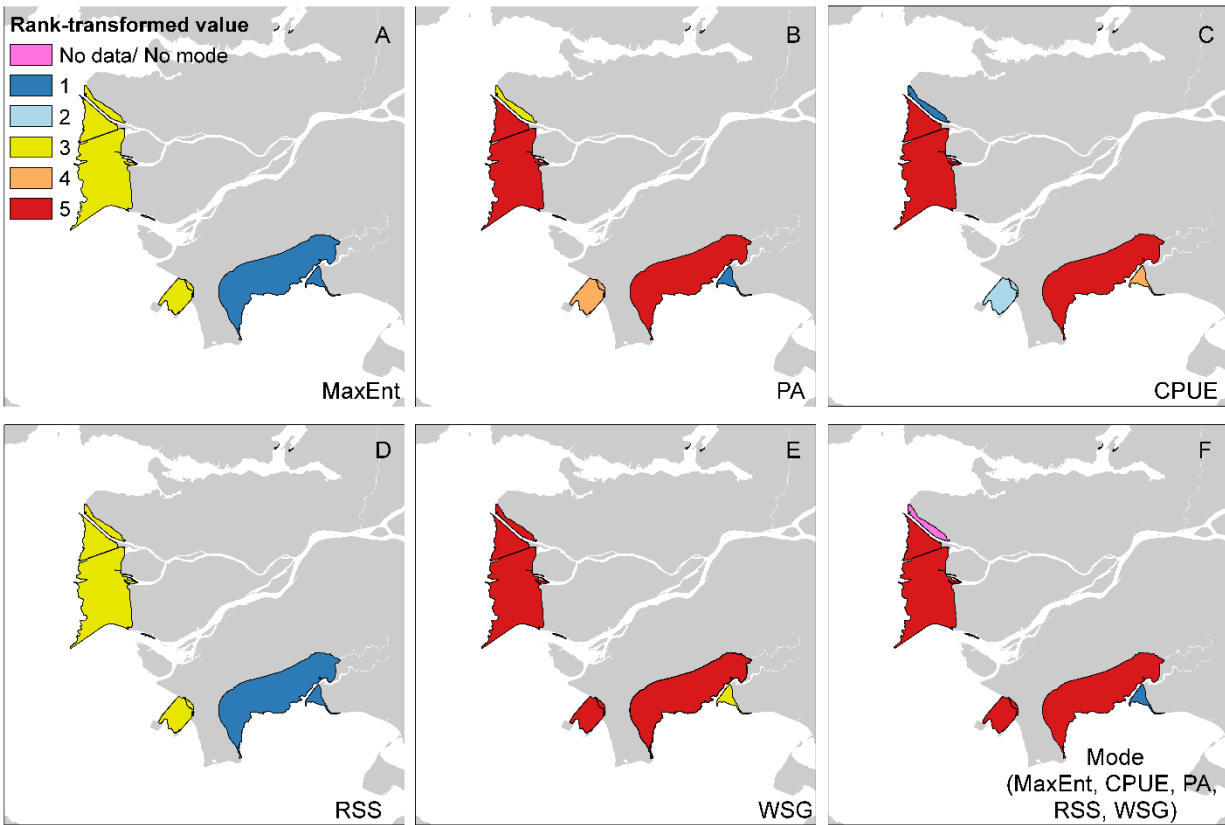
*Figure A3. Predictions from select models for Boundary Bay. A-E) Individual models, showing quantiles (20th percentiles) of model values, where quantile 5 is interpreted as being highly suitable for EGC; F) Mode of the five individual models, where each site is assigned the most frequent value from the input models. "No mode" occurs when no value is the most frequent or if there is a tie.*