Methods for spatial survey modelling updates

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PURPOSE

To update the Scientific Review Board (SRB) on work related to space-time modelling of survey data undertaken or planned since SRB015.

INTRODUCTION

Since 2016, the IPHC has used spatio-temporal modelling to estimate weight and numbers per unit effort (WPUE, NPUE) indices of density and abundance of Pacific halibut, and to provide estimates of stock distribution among IPHC Regulatory Areas and Biological Regions. Recent work has included development of methods to make the space-time model output and diagnostics more easily available to scientists and stakeholders. In particular, an R Shiny app has been developed that allows users to output time series for any subset of survey stations included in the modelling, and to review maps of estimated Pacific halibut distribution since 1993. Making such information available through an online tool will allow scientists and stakeholders to examine trends in Pacific halibut density and distribution at any scale, while providing measures of uncertainty with which to judge the quality of the estimates. Such output has previously provided to stakeholders on request, but has not been made directly accessible to the public.

To date, space-time models have been fitted by individual IPHC Regulatory Area, with all parameters in the spatio-temporal correlation model being assumed constant within each area. Space-time models with spatially varying parameters are currently under investigation, with the expectation that this increase in model flexibility may lead to improved model fit. Ultimately such models will allow for data from all (or multiple) IPHC Regulatory Areas to be fitted within a single model, if computing power permits it. Results from work on IPHC Regulatory Area 4A are presented in this report.

METHODS

R Shiny app

Code for the R Shiny app was largely completed in 2019, and tested internally by IPHC staff. When space-time models are run each year, we store 2000 posterior samples of each of three density indices (O32 WPUE, and all sizes WPUE and NPUE). These stored data objects are now prepared for loading into the R Shiny app, and no new model fitting is required within the execution of the app itself. Once loaded, these samples are used for the calculation of posterior means and uncertainty measures (posterior standard deviations, coefficients of variation, and 95% credible intervals) from a user-selected group of survey stations (including National Marine Fisheries Service stations in the Bering Sea where the IPHC FISS has no annual coverage). Thus, the calculations are made on the fly within the app, using efficient matrix operations to keep computation time low (typically a few seconds, but longer for larger selections).

Spatially varying parameters

It was noted in IPHC-2019-SRB015-06 that there was evidence in some geographical areas of local lack of fit in posterior predictions of WPUE. A likely explanation for at least some of this lack of fit is that model parameters that quantify the strength of spatial dependence have been assumed to be constant throughout each IPHC Regulatory Area. However, factors that affect the strength of spatial dependence, such as habitat type and the strength of ocean currents, do vary spatially and by allowing the model parameters to vary, we may be able to improve model fit.

IPHC Regulatory Area 4A makes for a useful test case, as it comprises at least two distinct components, one along the Bering Sea shelf edge, and the other in the eastern Aleutian Islands. The latter can be further divided into two parts, a western subregion with high density, and a low density region in the southeast. We examined changes in parameters and model fit by fitting models with spatial parameters that varied among these three subregions of IPHC Regulatory Area 4A.

RESULTS

R Shiny app

At present, the R Shiny app for spatial modelling output has three main tabs, along with a tab with instructions. The first active tab allows users to select a subset of survey stations from a map, either by IPHC Regulatory Area or through polygon selection tools (Figure 1), with additional options to subset by depth and select a year range and input variable. From the selected stations, the app will compute the mean of the input variable by year, along with estimates of uncertainty (standard deviation, coefficient of variation (CV) and 95% intervals), and display the output in graphical and tabular form in the next tab (Figure 2). Output can also be downloaded from this tab. The third tab is independent of the previous two, and uses coloured circles to display predicted WPUE or NPUE by stations, with the colour gradient representing WPUE or NPUE (Figure 3). A year slider allows the use to visualize changes in the spatial distribution of Pacific halibut density over time. Menus also allow CVs to displayed, while a slider tool lets the user scroll through the years of the time series (1993-2019). The addition of

discrepancy statistics to allow the visualization of model fit is in progress at the time of writing.
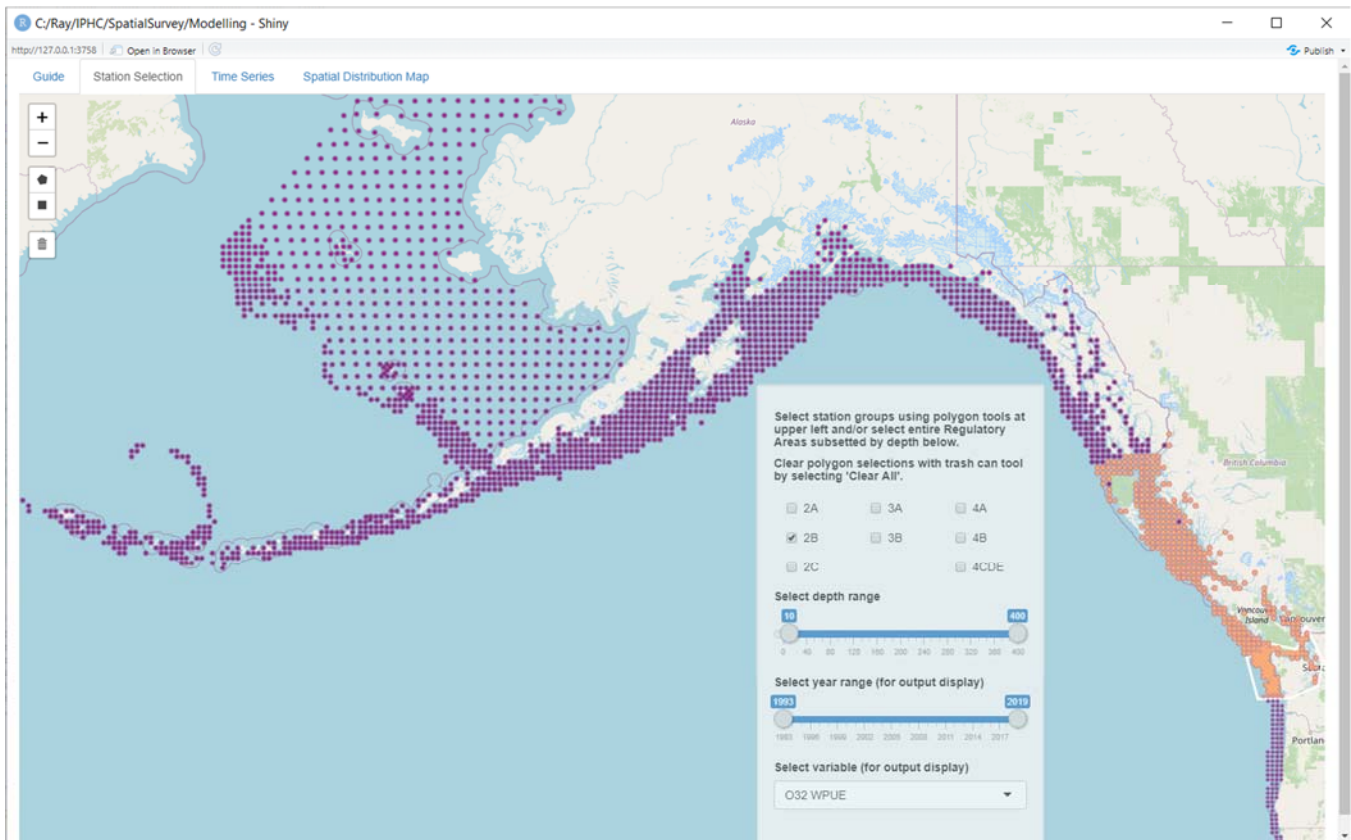

Figure 1. Screenshot of the R Shiny app tab for station selection, showing an example where all stations in Regulatory Area 2B are selected using the check boxes, a subset of stations in Regulatory Area 2A are selected using the polygon selections tools at upper right, and the default depth range of 10-400 fathoms is selected (excluding two very shallow stations).
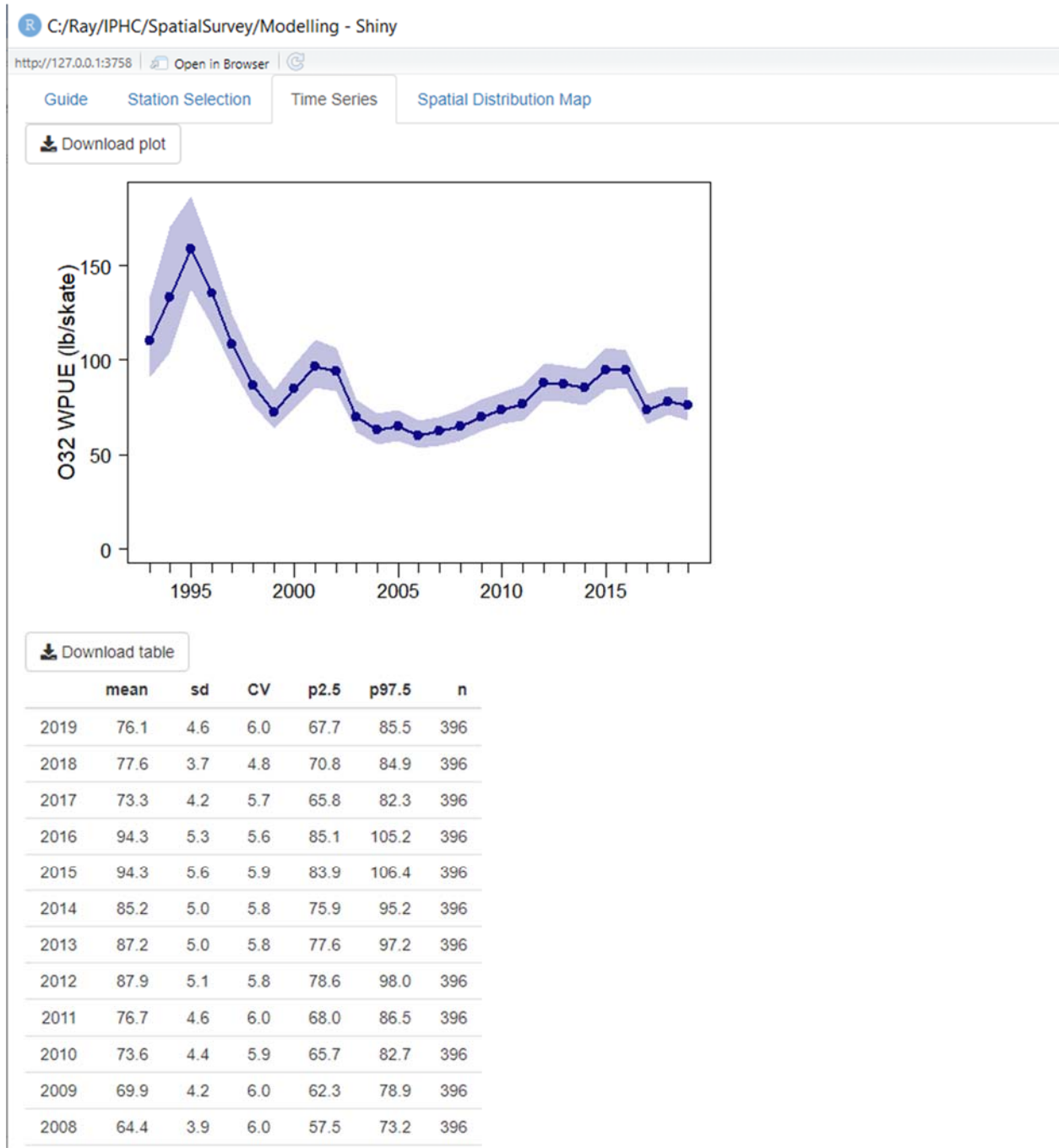
Figure 2. Screenshot of the R Shiny app output tab for the selected stations, showing the time series for over 32 inch (81.3 cm; O32) WPUE with 95% credible intervals shaded, along with tabular output.
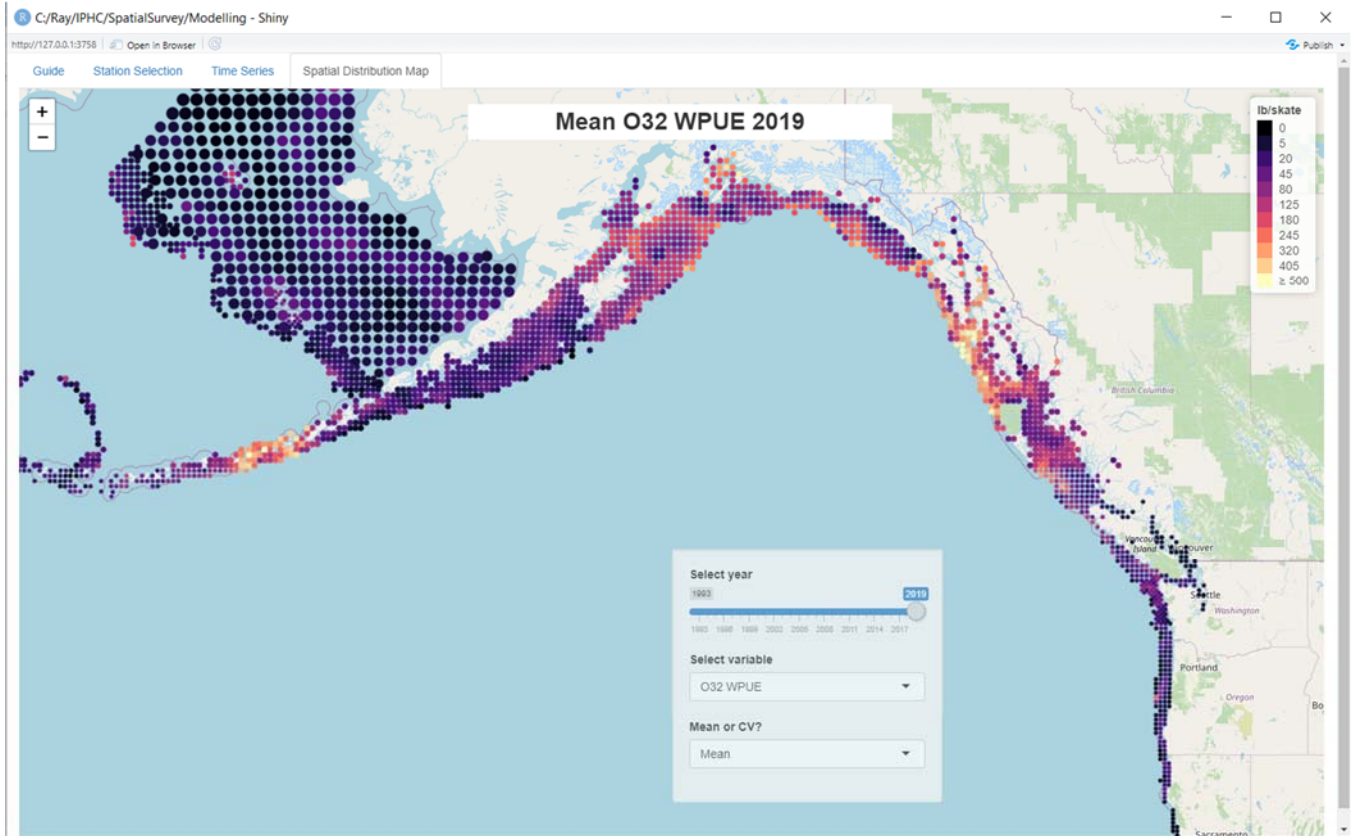
Figure 3. Screenshot of the R Shiny app Spatial Distribution Map tab, showing the distribution of O32 WPUE for 2019.

Spatially varying parameters

Models that allowed spatial parameters to vary among the three subregions provided a better fit to the data than the model that assumed constant parameters throughout IPHC Regulatory Area 4A (ΔDIC = 66.5). Figure 4 shows that that the range parameter was much higher for the western Aleutian portion of IPHC Regulatory 4A than for other subregions, implying that spatial dependence remains strong for greater distances between two locations there. The variance parameter was also lower in this subregion. We also compared station-specific discrepancy statistics (Appendix A) to see if there were differences in local lack-of-fit between the models. Differences were generally small-to-modest at the station level (comparison of Figures 5 and 6), with improvements in local fit not occurring consistently across years or subregions (in several instances, local fit appeared to get worse).
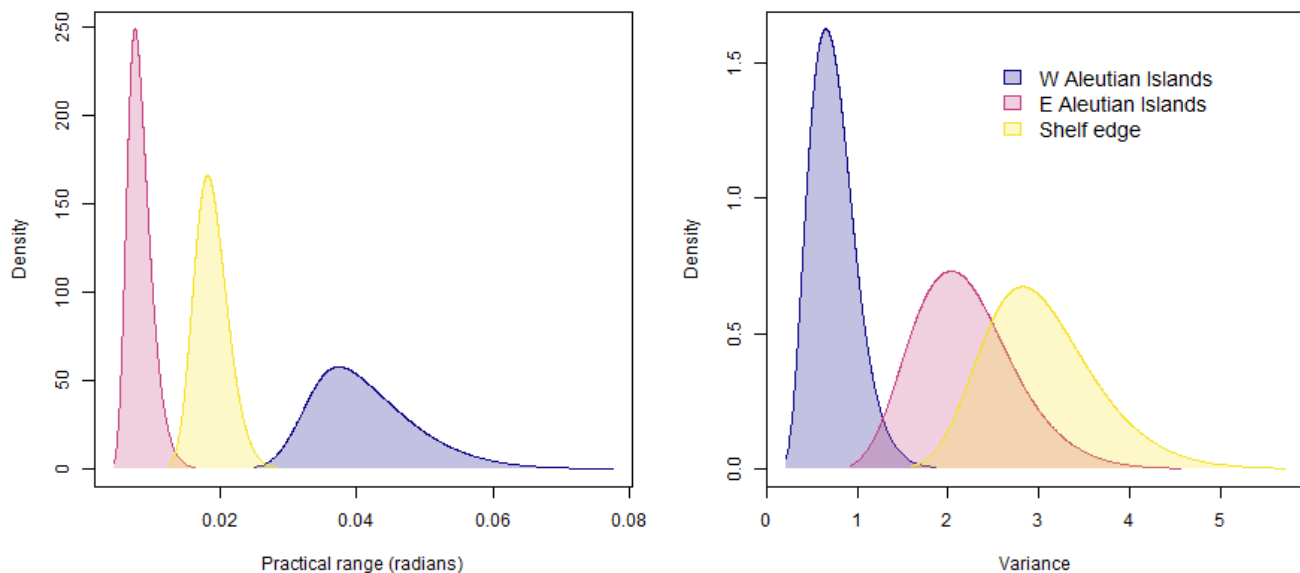

Figure 4. Posterior densities of spatial model parameters, practical range and variance, by subregion considered in the space-time modelling of Regulatory Area 4A data.

Regardless of the improvements to model fit in this example, the additional flexibility of using spatially-varying parameters in the models expands the options available for modelling Pacific halibut survey data. To date, we have modelled the data at the IPHC Regulatory Area level only (although always including a 'buffer' zone such that there are no edge effects in the predictions). With parameter estimates often varying among IPHC Regulatory Areas, this more flexible modelling approach will allow us to fit models simultaneously to multiple IPHC Regulatory Areas, or even to fit a coastwide model (provided present limitations on computer processing power can be overcome). Fitting models to multiple IPHC Regulatory Areas will mean that parameters that can be estimated only with one area can easily be applied to other areas within the model. For example, in 2019 we modelled differences between snap and fixed gears within the model for IPHC Regulatory Area 2C, where each station was fished twice, once with each gear type. If snap gear is used in other IPHC Regulatory Areas (for example, a planned comparison in Regulatory 2B in 2020), information on gear differences can be shared among areas, to improve

the precision of any gear covariate parameters, or to estimate spatial differences in those parameters.

DISCUSSION

The extent of fishery-independent surveys (IPHC and NOAA Fisheries) in 2020 remains uncertain (IPHC-2020-SRB016-05). However, the IPHC Secretariat plans to include spatio-temporal models that make simultaneous use of multiple IPHC Regulatory Areas where possible, particularly where residual patterns or gear-calibration warrant. With large portions of the survey design likely absent in 2020, modelled results will likely rely heavily on temporal correlations and previous observations. The IPHC Secretariat plans to make the R Shiny app publicly available at the time of release of the 2020 modelled survey results, likely in October 2020 after all 2020 observations have been included in the analysis. Progress on both of these topics will be revisited at SRB017.

RECOMMENDATION/S

That the SRB:

a) **NOTE** paper IPHC-2020-SRB016-06 which provides an update on spatio-temporal modelling and reporting development.

b) **REQUEST** any further analyses related to this work to be provided at SRB017.

REFERENCES

Cressie, N. and Wikle, C. K. (2011). *Statistics for Spatio-temporal Data*. John Wiley and Sons, Hoboken, New Jersey.

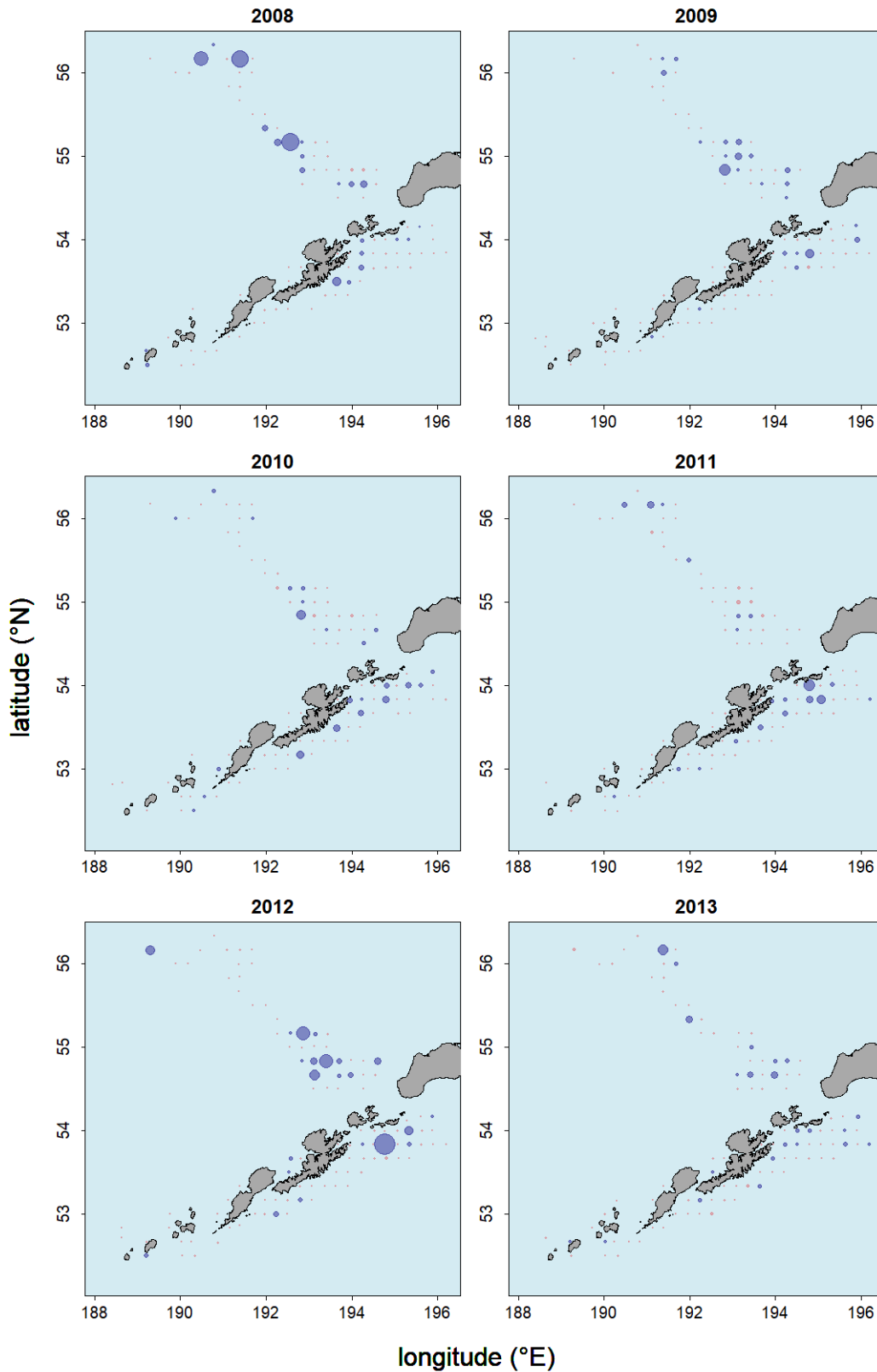Webster. R. 2020. 2021-2022 Fishery-Independent Setline Survey design evaluation. IPHC-2020-SRB016-05. 5 p.

Figure 5. Discrepancy statistics by station for IPHC Regulatory 4A from 2008-13 for the model with constant parameters constant. The larger blue circles represent data that are most inconsistent with the space-time model's posterior predictive distribution (p<0.05).
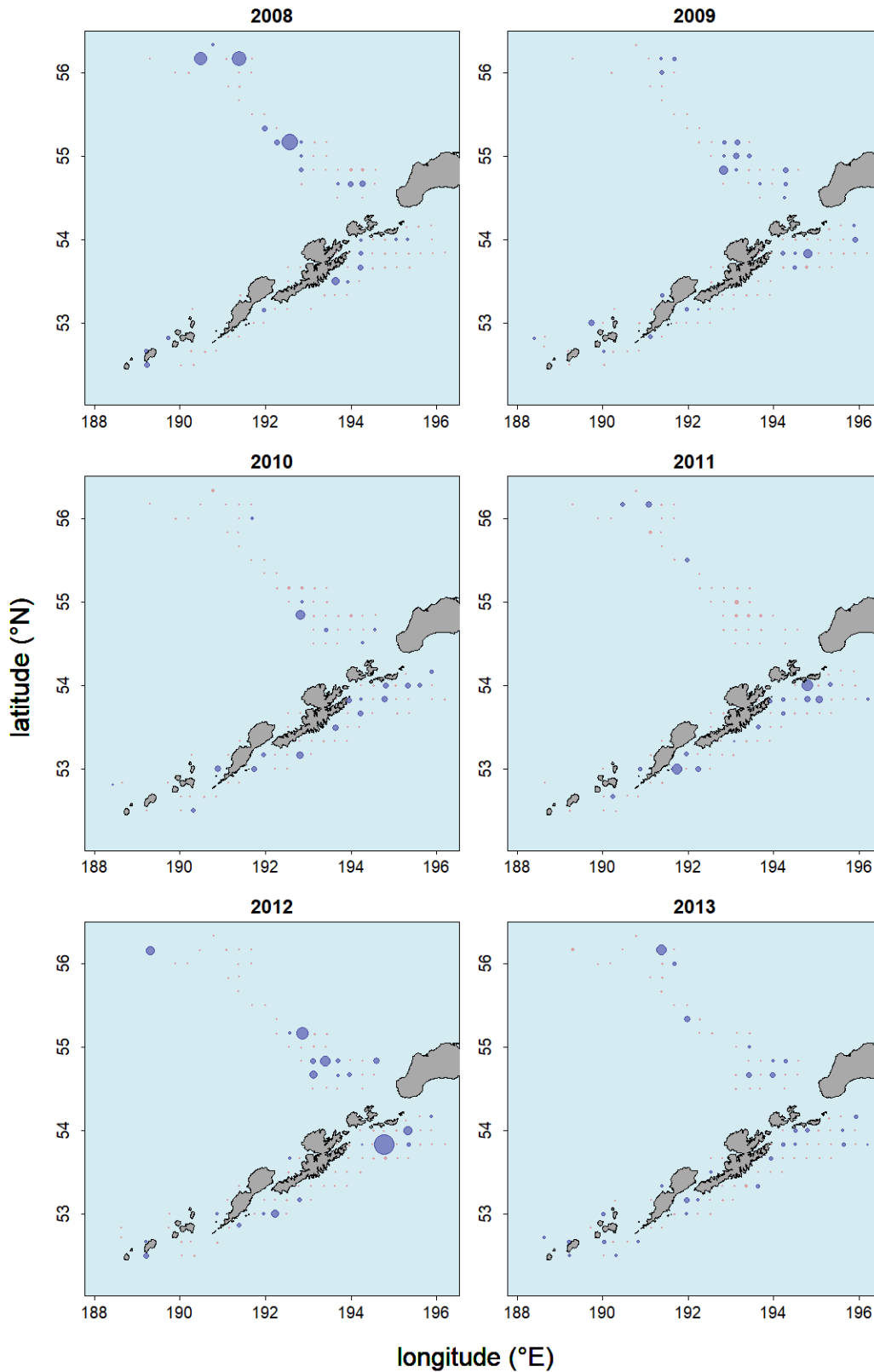
Figure 6. Discrepancy statistics by station for Regulatory 4A from 2008-13 for the model with spatially-varying parameters. The larger blue circles represent data that are most inconsistent with the space-time model's posterior predictive distribution (p<0.05).

APPENDIX A
Posterior predictive diagnostics

The request to examine spatio-temporal residual patterns falls within the area of posterior predictive diagnostics, in which discrepancy measures are used to assess model fit (Cressie and Wikle, 2011). Using the notation of Cressie and Wikle (2011), we make use of the discrepancy measure, T, for assessing local model fit:

$$T(Z_i; Y, \theta) = \frac{(Z_i - E(Z_i \,|\, Y, \theta))^2}{\text{var}(Z_i \,|\, Y, \theta)}$$

Here Z_i is observation i (i.e., observed WPUE or NPUE), Y is the underlying process, and θ is the vector of model parameters. $E(Z_i \,|\, Y, \theta)$ and $\text{var}(Z_i \,|\, Y, \theta)$ are the mean and variance respectively of the posterior predictive distribution of Z_i. The value of T for the observed Z_i can be compared to the values computed by substituting the samples from the corresponding posterior distribution (we save 2000 such samples as part of the model output). As a measure of "extremeness" we compute the posterior predictive p-value for each observation Z_i,

$$P\big(T(Z_{i,rep}; Y, \theta) \geq T(Z_i; Y, \theta) \,|\, Z_i\big)$$

where the $Z_{i,rep}$ are the posterior samples. Very small p-values are indicative of local lack of fit. In this report, we spatially visualise the discrepancy values by mapping T for each observed station over several years.