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PRELIMINARY EVALUATION OF SEVERAL OPTIONS FOR REDUCING BIGEYE TUNA CATCHES

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CONTENTS

SUMMARY

The current management measures for bigeye tuna in the eastern Pacific Ocean (EPO) include, in addition to the 62-day general closures of the purse-seine fishery, a 30-day closure of a relatively small area of the EPO west of the Galapagos Islands, known informally as the "*corralito*", from the end of September to the end of October. However, there is the perception that additional management measures may be needed. This document presents the results of an analysis of areas of high catches of bigeye during 2001-2015, using data from floating-object sets by IATTC size Class-6[2] purse-seine vessels. The results of this analysis were used in a simulation to explore the potential of spatial closures to reduce catches of bigeye in the purse-seine fishery. The simulation results suggest that an annual closure of the equatorial EPO west of 120°W could potentially yield greater reductions in catch of bigeye than losses of catch of skipjack tuna. Future work should include optimization of the closure area boundaries and more realistic simulations of effort reallocation.

Also presented in this document is an update of analyses of the effect of environmental factors and gear characteristics on the probability of catching bigeye in floating-object sets by large purse-seine vessels, using data from 2012-2013. The results of this analysis are consistent with previous studies, and indicate that the location of fishing and environmental factors may have a greater effect than gear characteristics on the probability of catching bigeye. However, also consistent with previous studies, this analysis found that the probability of catching bigeye was greater with deeper purse-seine nets and with floating objects with greater underwater depth; an updated analysis of spatial patterns in these gear effects has not yet been done. Weekly environmental data for 2014 were used to illustrate the possibility of forecasting areas with high probability of bigeye catches in near real-time. The weekly forecasts show temporal changes in the areas

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with the highest estimated probability of bigeye catch, within a fairly stationary offshore region of the EPO. Future work should include validation of the forecasting results.

1. BACKGROUND

Recent increases in the number of sets on floating-objects by both small and large purse-seine vessels (Document SAC-07-07f(i)), and an increase in purse-seine fleet capacity (SAC-07-08), have prompted the need for further research on options to reduce catches of bigeye in the purse-seine fishery. Previous studies of time-area closures (Shelton and Suter 2007), which were based on data from 1995-2002, found that time-area closures alone were unlikely to provide a significant reduction in bigeye catch without also substantially impacting catches of skipjack. A seasonal closure of an area west of Galapagos (the "*corralito*") to reduce catches of bigeye was first proposed in 2008 (Document IATTC-77-04 REV), but this closure is estimated to have had little impact (Document SAC-05-16). Using floating-object set data from 2001-2005, a study of the effect of gear characteristics on the probability of catching bigeye (Lennert-Cody *et al*. 2008) found that in some areas of the EPO it was more likely that bigeye would be caught when fishing with deeper purse-seine nets and when using floating-objects with greater underwater depths.

This document presents an analysis of the areas of high bigeye catch, using purse-seine data from 2001-2015. The results of the analysis are used in a simple spatial closure simulation to evaluate the potential for bigeye catch reduction. In addition, an update of the analysis of the effects of environmental factors and gear characteristics on the probability of bigeye catch is presented. The results of this analysis were used to illustrate weekly forecasting of the spatial distribution of the probability of catching bigeye.

2. IDENTIFYING AREAS OF HIGH BIGEYE CATCH

2.1. Data and methods

Generalized additive models (GAMs) were used to summarize the spatial distribution of bigeye catch in floating-object sets by Class-6 purse-seine vessels during 2001-2015. Because of a high percentage of sets with no catch of bigeye (50%) during this time period, a delta-Gamma GAM was used. A logit link was used for the model of the presence/absence of bigeye catch, and a Gama distribution with log link for the model of catch-per-set of bigeye (catch = retained catch plus discards). For both the logistic and the Gamma GAMs, the right-hand side of the models had the following form:

~ te(latitude, longitude, by=ENSO category) + s(month, by=ENSO category)

where "te" indicates a tensor product smooth, and the smooth term for month was based on a cyclic cubic spline. The "by" parameter indicates that both smooth terms included an interaction with ENSO (El Niño-Southern Oscillation) period: El Niño (2003, 2007, 2010, 2015), La Niña (2008, 2011-2012), and ENSO-neutral (2001-2002, 2004-2006, 2009, 2013-2014) (ENSO information was obtained from www.esrl.noaa.gov).

2.2. Defining high-catch areas

To define high-catch areas based on the fitted GAMs, both presence/absence of bigeye and catch-per-set were predicted on a 1° spatial grid for April and September, for each of the three ENSO categories. The months of April and September were selected because these represent roughly the high and low months, respectively, of the predicted seasonal signal (Figure 1).

Maps of the estimated probability of catch of bigeye and catch-per-set (positives) were used to define three high-catch areas (Figure 2), based on the occurrence of high probabilities of catch and/or high catch rates in both months and all three ENSO periods. The three areas (Figure 2) were: 1) 5°S to the equator, 95°W-110°W (which overlaps with the *corralito*); 2) 5°S-5°N, and 120°W-150°W; and, 3) south of 15°S.

2.3. Preliminary evaluation of the potential of spatial closures

A simulation was implemented to determine if the high-catch areas identified by the GAMs (Figure 2) might result in a reduction in the overall purse-seine catch of bigeye if closed for a calendar year. The IATTC Catch-and-Effort data base for Class 1-6 purse-seine vessels was used for the simulation. For all 7 combinations of the three areas (1; 2; 3; 1 and 2; 1 and 3; 2 and 3; 1, 2, and 3), the following effort reallocation scenario was implemented for floating-object sets and unassociated sets (dolphin sets were excluded from the simulation because they rarely catch bigeye (Document SAC-07-03a)), by year, 2001-2015:

a. The number of sets inside the closed area(s) was reallocated outside to 5° areas and set types (floating-object or unassociated) based on the effort composition of those 5° areas outside the closed area(s);

b. Simulated tuna catch amounts, by species (bigeye, yellowfin, skipjack) and set type, for the reallocated sets were estimated from catch-per-set in each 5° area outside the closed area(s) (see Appendix for details);

c. The estimated purse-seine fleet catch for a given closed area(s) scenario, for each year, was the sum of the actual catch outside the closed area(s), plus the estimated catch from the reallocated sets;

d. The estimated annual effect of each of the 7 candidate closures was obtained by computing the difference between the actual total catch, by species and set type, and the estimated catch. The annual changes, in percent, for 2001-2015, were summarized with box-and-whisker plots, by species and set type, and by species.

Of the three areas, the results of the simulation suggest that a single-area closure based on the western-most area (Area 2) may have the potential for the greatest reductions of bigeye catch while limiting the impact on catches of skipjack (Figures 3-4). Combinations of closed areas, especially those that included Area 2, resulted in greater reductions in bigeye catch, but also greater reductions in the catch of skipjack (Figure 4a).

The reallocation method used in this simulation could be modified to reflect more complex fleet behavior. For example, the reallocation of sets from the closed area(s) might be done by vessel, according to each vessel's individual fishing habits. More complex reallocation schemes could be considered in the future.

Ideally, the candidate closure areas would be selected to produce stable results over time, including minimizing variability in the catch reductions for each of the three species. The high-catch areas selected for the simulation presented in this document were chosen by eye from the GAM results, and from inspection of weekly forecast maps (see below). Optimization of the boundaries of these areas might provide improved performance in terms of reduction of bigeye catch while minimizing the loss of skipjack catch.

3. ENVIRONMENTAL AND GEAR EFFECTS OF THE PROBABILITY OF CATCHING BIGEYE

3.1. Data and methods

A random-forest (classification) algorithm was used to predict the presence/absence of bigeye catch (retained catch plus discards) in floating-object sets by Class-6 vessels, using data from 2012-2013. In total, 65 predictors were considered in the random forest algorithm: current, first-differenced, and lagged environmental information; latitude, longitude and month; and several gear characteristics. Environmental data, roughly at a week-1° area resolution, were provided by the NASA Jet Propulsion Laboratory. Environmental data included: sea surface temperature (SST) and SST anomaly (SSTANOM), sea surface salinity (SSS), sea surface height (SSH), mixed layer depth (MLD), meridional (VVEL) and zonal (UVEL) velocities and velocity anomalies (VANOM and UANOM), probability of fronts, and wind speed (WNDSPD). From these data, first-differenced quantities were computed for SST, SSS, SSH, MLD and WNDSPD. In addition, lagged summaries (mean, standard deviation, and slope) were computed for lags of one and four months for all variables except probability of fronts, and UANOM and VANOM; lag periods were selected somewhat arbitrarily. Catch data were aggregated to the same resolution as the environmental data and a presence/absence response variable created (presence/absence of any catch in the week -1° area). Based on results of previous analyses (Lennert-Cody *et al*. 2008), four gear variables were included (as median values per week-1° area): purse-seine net depth, floating-object depth, the percentage of the floating-object covered with fouling organisms (a proxy for time at sea), and a proxy for local floating-object density. The purse-seine net depth is the hanging depth of the net (the actual fishing depth of the net was not available). The floating-object depth is the maximum depth of the floating-object below the water's surface (actual in-water depth was not available).

3.2. Results of predicting presence/absence of bigeye catch

The results of the random-forest analysis were generally consistent with previous studies of data from 2001-2005 (Lennert-Cody *et al*. 2008). Overall, set location and some environmental factors were more important for predicting presence of bigeye catch than any of the four gear characteristics (Figure 5), although correlation among predictors complicates the interpretation of variable importance. Of the four gear characteristics, net depth and floating-object depth were the most important for predicting the presence of bigeye catches. The presence of bigeye in the catch was more likely with deeper nets and deeper floating objects (Figure 6); spatial patterns in these relationships have not yet been evaluated for this analysis, but were observed previously (Lennert-Cody *et al*. 2008). Interestingly, lagged quantities for some environmental variables were more important than the variable value at the current week (Figure 5). It has yet to be determined whether the importance of lagged environmental information is a repeatable result with data from other years. The misclassification error rates from the random forest algorithm were 21% (predicting presence) and 26% (predicting absence).

3.3. Weekly forecasts of the probability of bigeye catch

To illustrate weekly forecasting of the spatial distribution of the probability of catching bigeye, a random-forest algorithm (without gear variables) was used to generate maps of the predicted probability of catching bigeye tuna for each week in 2014. At the first step, the random-forest algorithm was built on the data from 2012-2013, and used to predict the spatial distribution of the probability of catching bigeye for the first week of 2014, using the environmental data from that week. This process was iterated for each week of 2014, where the two-year block of data used to build the random-forest algorithm were advanced by one week, and predictions were made with the environmental data of the current week.

The forecasting results (Figure 7) highlight the effects of temporal changes in the environment over the course of the year within a larger, fairly stationary offshore region with higher estimated probabilities of catching bigeye. If a regular procedure were in place to receive and process environmental data, these types of maps could be made available to fishermen on a near-real-time basis as an additional piece of information to help them reduce catches of bigeye. Weekly forecasts have not yet been compared to actual distributions; however, an evaluation of algorithm performance can be undertaken if weekly forecasting is considered useful for future research. In addition, an evaluation of the optimal data window for generating weekly predictions could be conducted; the example above used a two-year moving data window. An alternative would be to fix the data set that is used to generate the model. Also, other lags and summaries of lagged variables could be explored.

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Lennert-Cody, C.E., Roberts, J.J. and Stephenson, R.J. 2008. Effects of gear characteristics on the presence of bigeye tuna (*Thunnus obesus*) in the catches of the purse-seine fishery of the eastern Pacific Ocean. ICES Journal of Marine Science 65: 970-978.

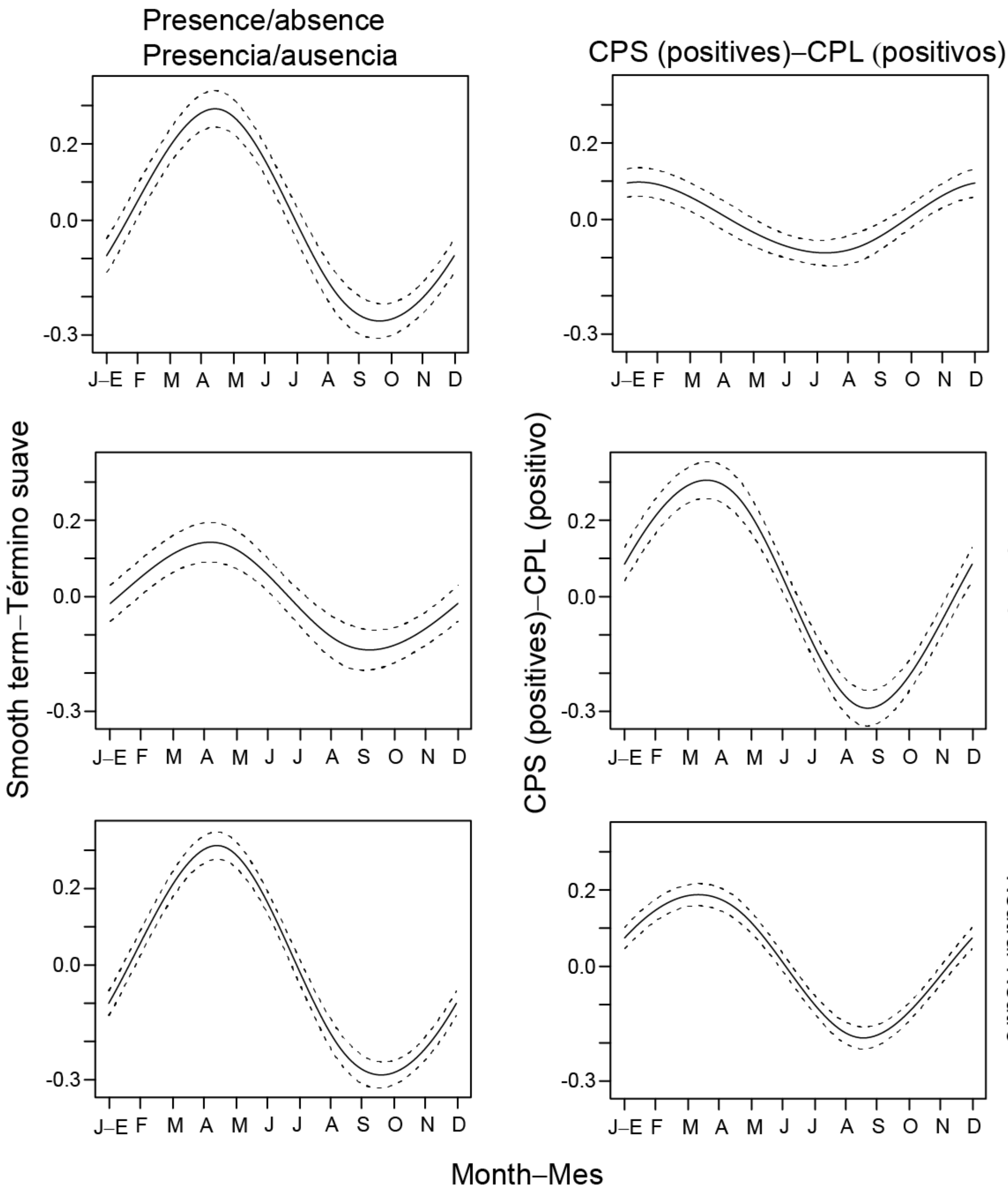

FIGURE 1. Smooth terms for month, by ENOS category, from the logistic GAM for presence/absence of bigeye tuna catch (left panels) and from Gamma GAM for catch-per-set (right panels).
FIGURA 1. Términos suaves de mes, por categoría de ENOS, del MAG logístico de presencia/ausencia de captura de atún patudo (paneles izquierdos) y del MAG gamma de captura por lance (paneles derechos).

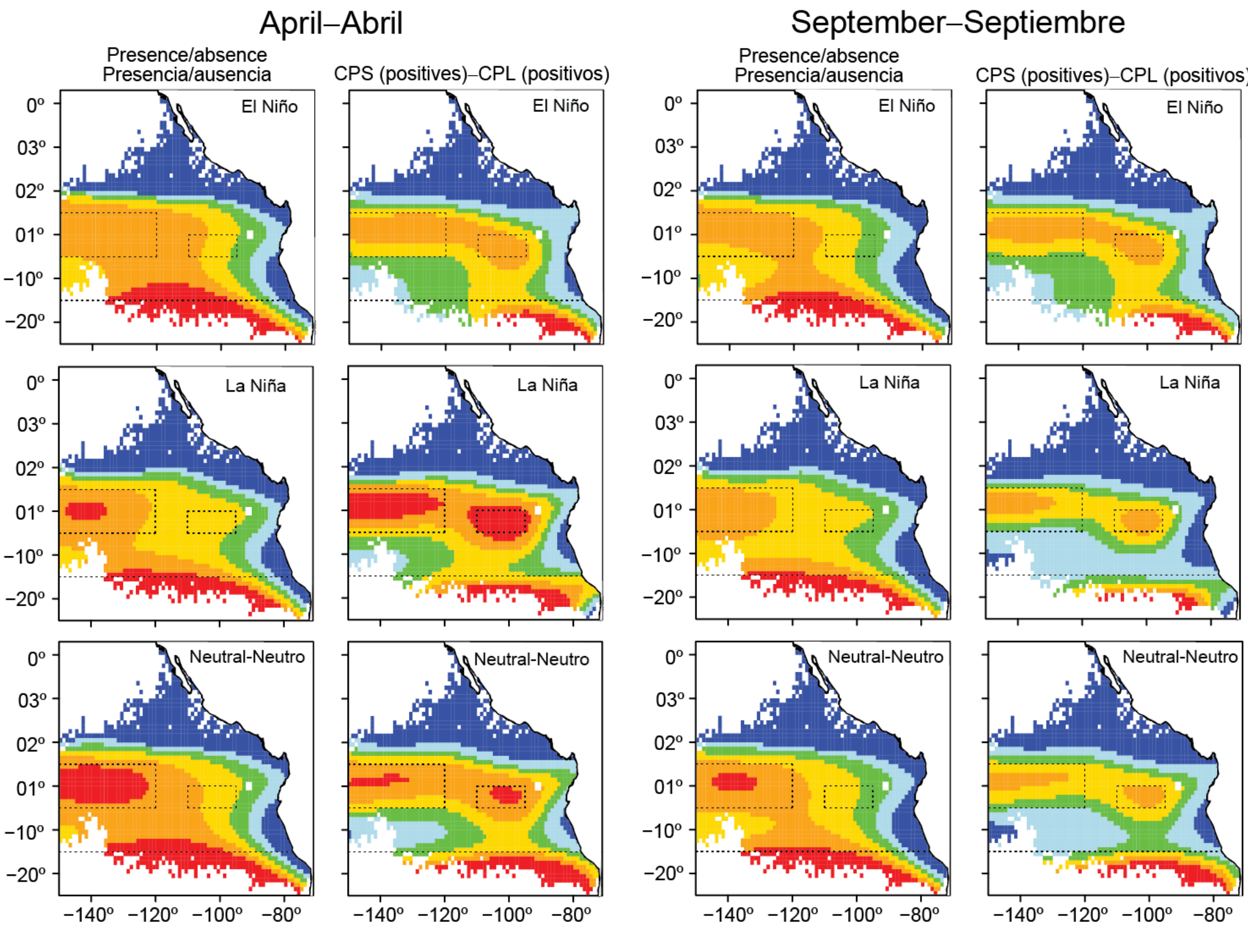

FIGURE 2. Maps of logistic and Gamma GAM predictions, for April and September, by ENOS category,. The areas delineated by dashed lines correspond to: 1) 150°W-120°W, 5°S-5°N; 2) 110°W-95°W, 5°S-0°; 3) south of 15°S. For the logistic GAM maps, the colors indicate the estimated probability of catching bigeye: dark blue: <0.1; light blue: 0.1-0.25; green: 0.25-0.50; yellow: 0.50-0.75; orange: 0.75-0.90; red: >0.90. For the Gamma GAM maps, the colors indicate the estimated bigeye catch-per-set, in metric tons (t): dark blue: < 5 t; light blue: 5-10 t; green: 10-14 t; yellow: 14-20 t; orange: 20-30 t; red: > 30 t.

FIGURA 2. Mapas de predicciones de MAG logístico y gamma, correspondientes a abril y septiembre, por categoría de ENOS. Las áreas delineadas con líneas de trazos corresponden a: 1) 150°O-120°O, 5°S-5°N; 2) 110°O-95°O, 5°S-0°; 3) al sur de 15°S. En los mapas de MAG logístico, los colores indican la probabilidad estimada de capturar patudo: azul oscuro: <0.1; azul claro: 0.1-0.25; verde: 0.25-0.50; amarillo: 0.50-0.75; naranja: 0.75-0.90; rojo: >0.90. En los mapas MAG gamma, los colores indican la captura por lance estimada de patudo, en toneladas (t): azul oscuro: < 5 t; azul claro: 5-10 t; verde: 10-14 t; amarillo: 14-20 t; naranja: 20-30 t; rojo: > 30 t.

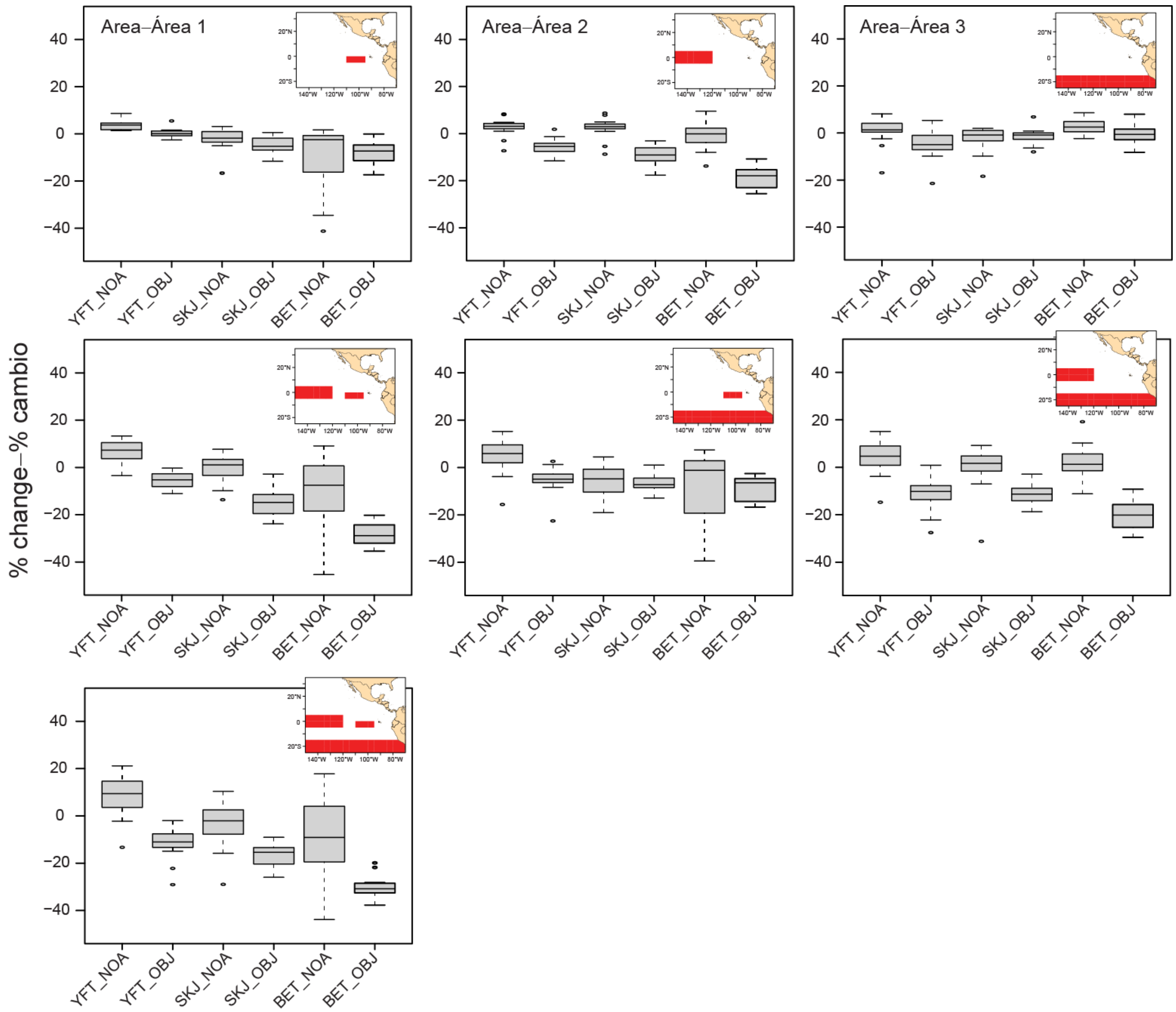

FIGURE 3. Box-and-whisker plots of the estimated percent change in total purse-seine catch, 2001-2015, for each combination of species and set type, as a result of effort reallocation from the closed area(s). The map in the upper right corner of each panel shows the closed area(s) (in red).

FIGURA 3. Gráficas de caja y bigote del cambio porcentual estimado de la captura cerquera total, 2001-2015, para cada combinación de especie y tipo de lance, como resultado de la redistribución del esfuerzo de las áreas vedadas. Se ilustran las áreas vedadas (en rojo) en el mapa en la esquina superior derecha de cada panel.

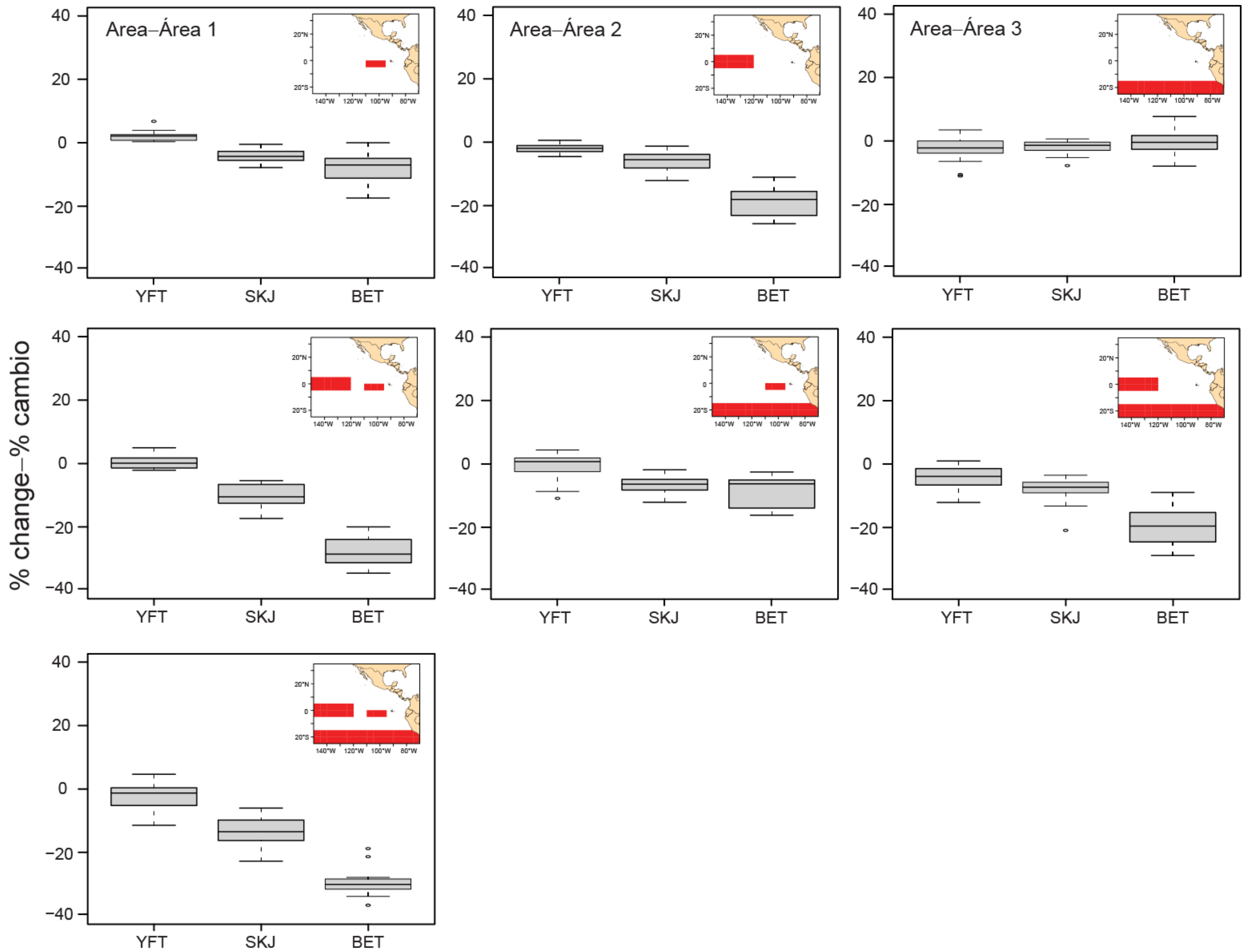

FIGURE 4a. Box-and-whisker plots of the estimated percent change in total purse-seine catch, 2001-2015, for each species, as a result of effort reallocation from the closed area(s). The map in the upper right corner of each panel shows the closed area(s) (in red).

FIGURA 4a. Gráficas de caja y bigote del cambio porcentual estimado de la captura cerquera total, 2001-2015, para cada especie, como resultado de la redistribución del esfuerzo de las áreas vedadas. Se ilustran las áreas vedadas (en rojo) en el mapa en la esquina superior derecha de cada panel.

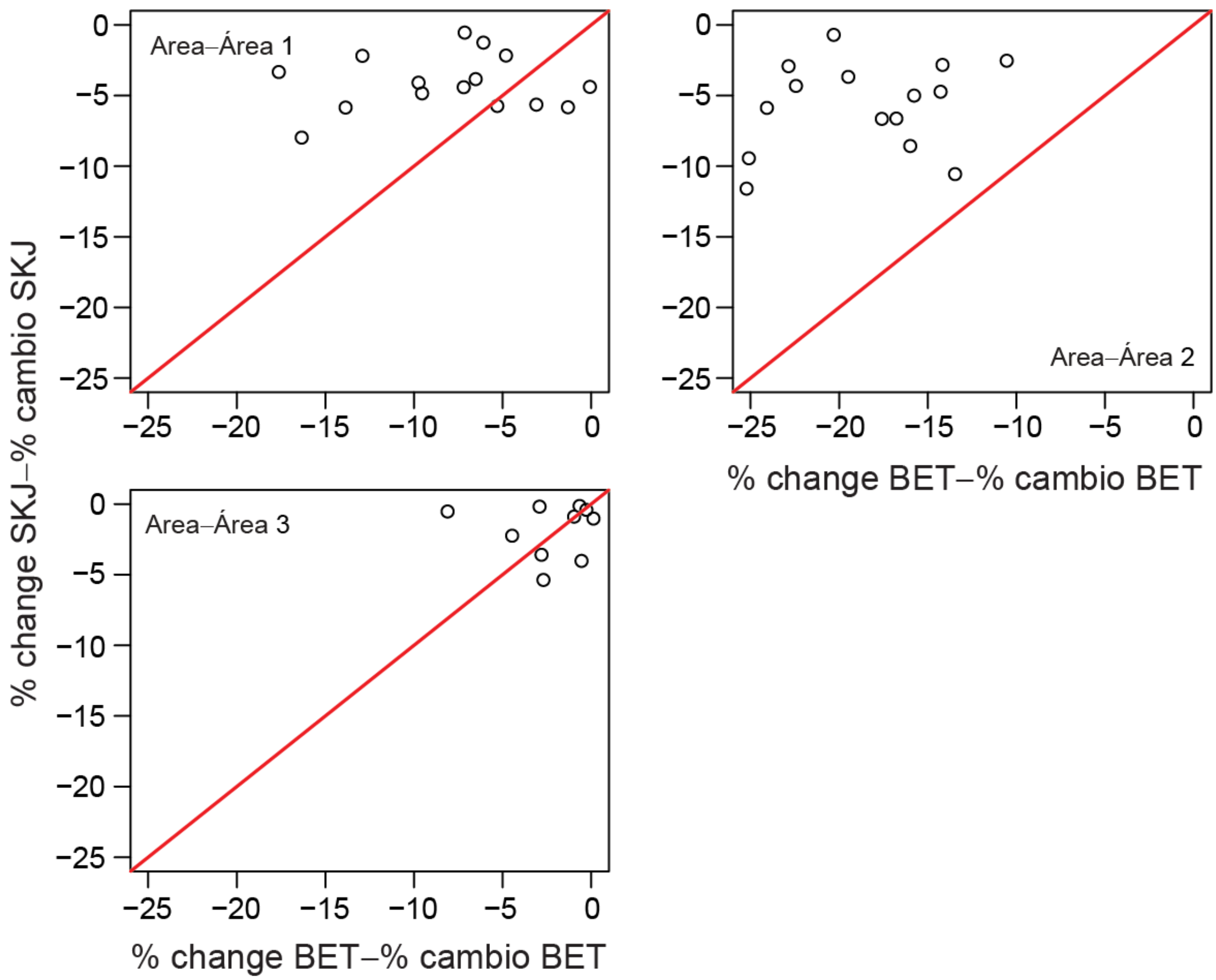

FIGURE 4b. Annual percent change in bigeye tuna catch *versus* annual percent change in skipjack tuna catch for the three single-area candidate closures; i.e., this figure shows plots of yearly points from the top row of Figura 4a. The red line is the one-to-one line.

FIGURA 4b. Cambio porcentual anual en la captura de atún patudo como función del cambio porcentual anual de atún barrilete correspondiente a cada una de las tres áreas de veda; o sea, esta figura grafica los puntos anuales de la fila superior de la Figura 4a. La línea roja representa la correspondencia de 1 a 1.

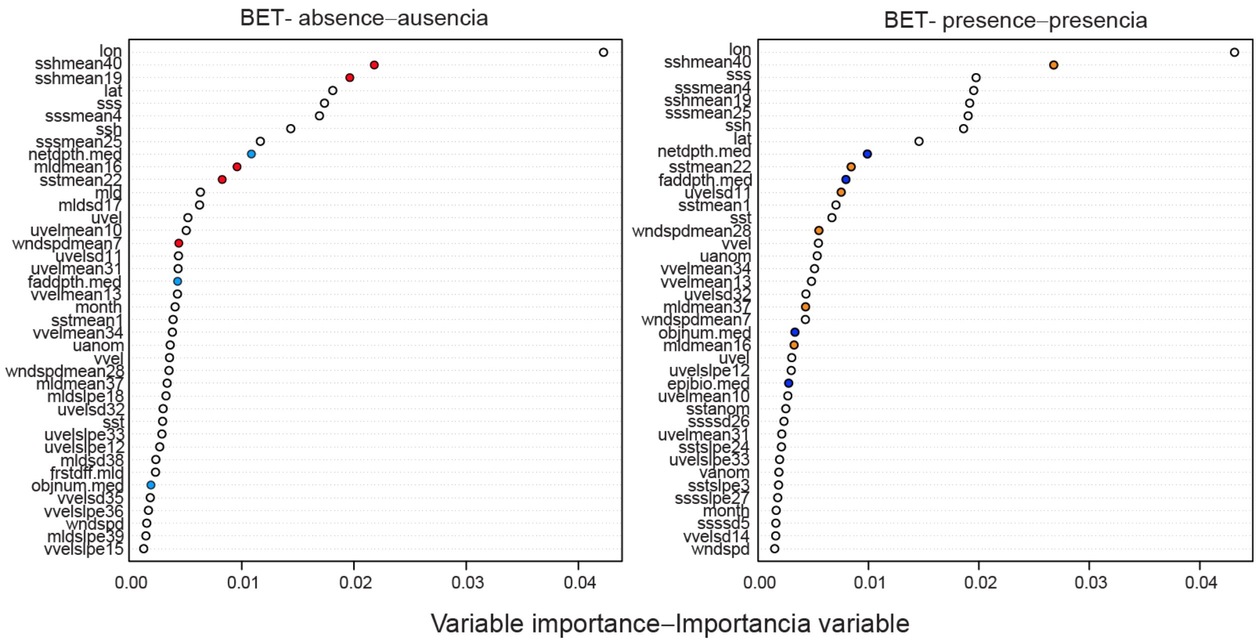

FIGURE 5. Variable importance plots from the random-forest algorithm for predicting presence/absence of bigeye in the catch, 2012-2013. The larger the value of variable importance (on the x-axis), the more influential the variable is with respect to correct classification. Only those 40 variables with the greatest variable importance values are shown. Red dots indicate influential lagged environmental variables; blue dots indicate gear variables. "lon": longitud; "lat": latitud; "netdpth.med": median purse-seine net depth; "faddpth.med": median floating-object depth; "objnum.med": median local floating-object density; "epibio.med": median percent coverage of fouling organisms; "frstdff": first-difference. Other variable names are de-coded as follows: variable name abbreviation + mean/standard deviation/slope ("mean"/ "sd"/ "slpe") + n (1-mes lag: n ≤ 21; 4-mes lag: n ≥ 22).

FIGURA 5. Gráficas de importancia variable del algoritmo de bosque aleatorio para predecir la presencia/ausencia de patudo en la captura, 2012-2013. Como más alto del valor de importancia variable (en el eje x), mayor la influencia de la variable con respecto a clasificación correcta. Se presentan solamente las 40 variables con los valores de importancia variable más altos. Los puntos rojos indican variables ambientales retardadas influyentes; los puntos azules indican variables de arte. "lon": longitud; "lat": latitud; "netdpth.med": profundidad mediana de la red de cerco; "faddpth.med": profundidad mediana del objeto flotante; "objnum.med": densidad mediana local de objetos flotantes; "epibio.med": cobertura porcentual mediana de epibiota; "frstdff": primera diferencia. Se descifran los nombres de las otras variables como sigue: nombre abreviado de la variable + promedio/desviación estándar/pendiente ("mean"/ "sd"/ "slpe") + n (retardo de 1 mes: n ≤ 21; retardo de 4 meses: n ≥ 22).

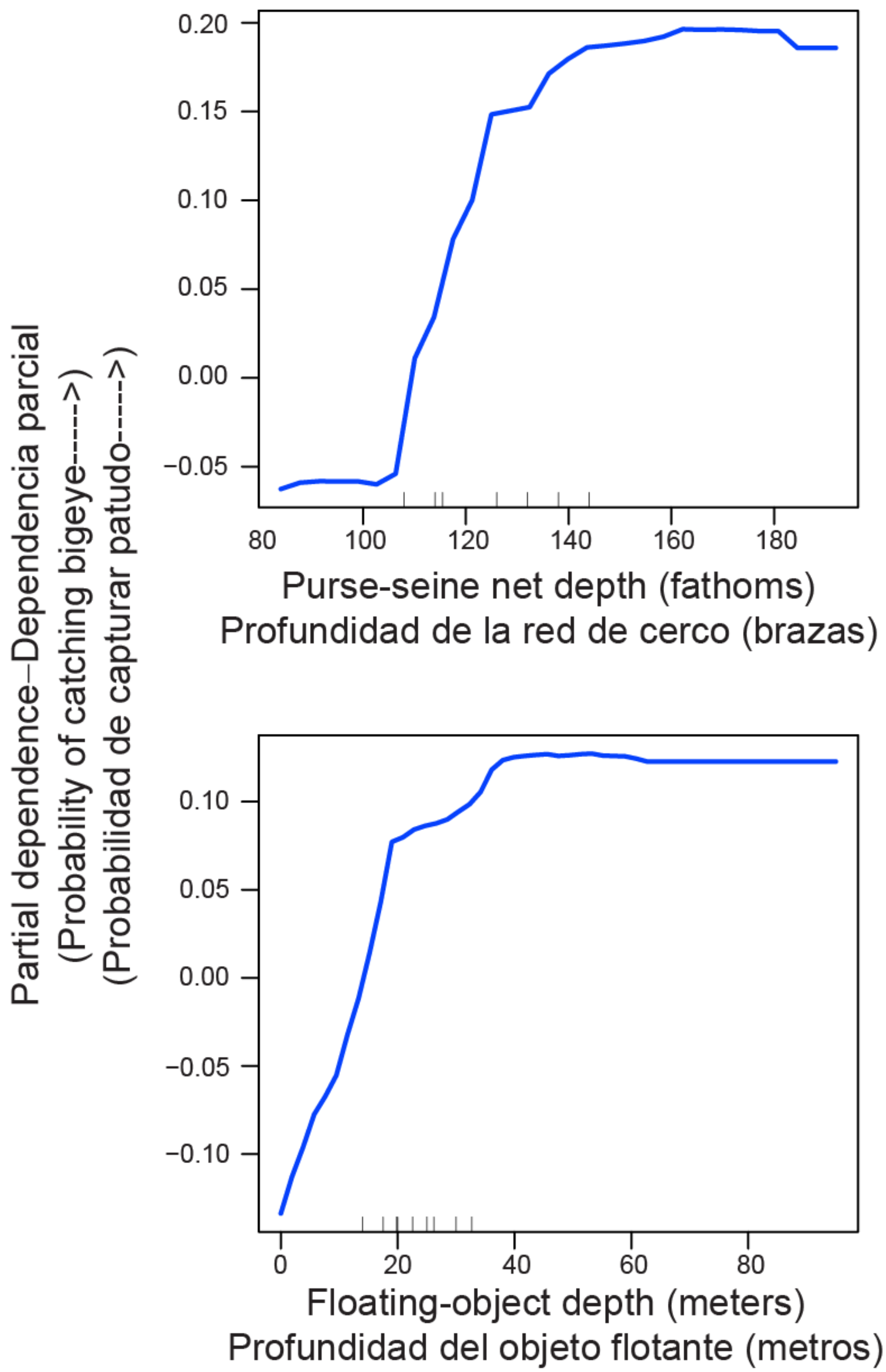

FIGURE 6. Random-forest partial-dependence plots for the probability of catching bigeye as a function of net depth and floating-object depth. The greater the value of partial dependence, the greater the odds of catching bigeye. The rug at the bottom of each figure shows the deciles of the variable values (1 fathom = 1.83 meters).

FIGURA 6. Gráficas de dependencia parcial de bosque aleatorio de la probabilidad de capturar patudo como función de la profundidad de la red y la profundidad del objeto flotante. Como mayor el valor de dependencia parcial, mayor la probabilidad de capturar patudo. La alfombra al pie de cada figura indica los déciles de los valores de las variables (1 braza = 1.83 m).

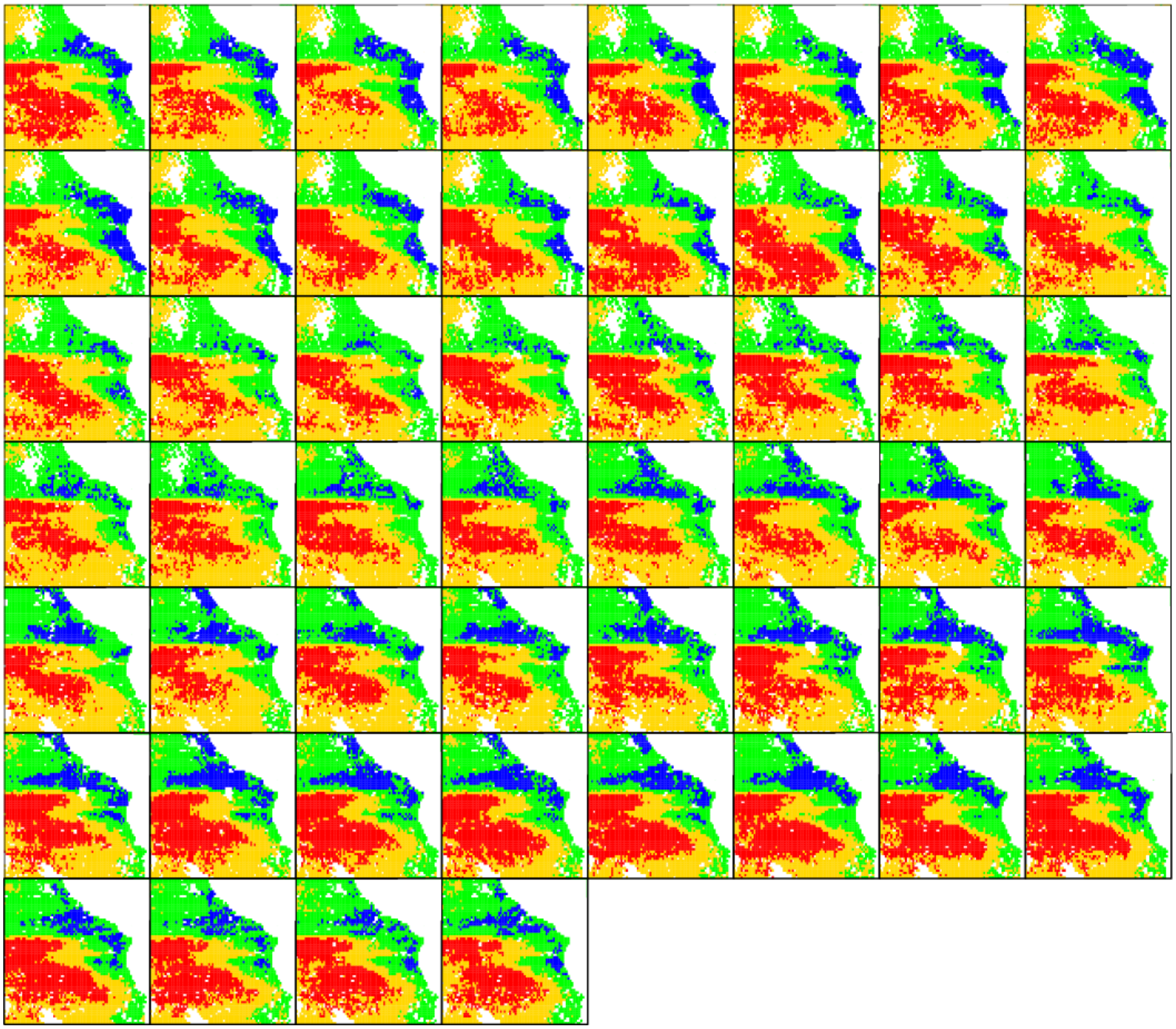

FIGURE 7. Weekly prediction maps for 2014 of the probability of catching bigeye: blue: < 0.25; green: 0.25-0.50; yellow: 0.50-0.75; red: ≥0.75. The map in the upper left corner corresponds to the predictions for the first week of 2014, and time progresses from left to right, and top to bottom.

FIGURA 7. Mapas de predicciones semanales para 2014 de la probabilidad de capturar patudo: azul: < 0.25; verde: 0.25-0.50; amarillo: 0.50-0.75; rojo: ≥0.75. El mapa en la esquina superior izquierda corresponde a las predicciones para la primera semana de 2014, y el tiempo avanza de izquierda a derecha, y de arriba hacia abajo.

Appendix

Equation used to estimate total catch for a particular closure scenario

Total catch, by set type, of tuna species in each 5º area after set reallocation resulting from a spatial closure of the purse-seine fishery

$$C_{TOT,i,t,sp} = \left[\underbrace{\overbrace{\left(\sum_{i\epsilon closure} k_i\right)}^{\text{Total number of sets from closure area}} \overbrace{\left(\frac{k_{i\epsilon open}}{\sum_{i\epsilon open} k_i}\right)}^{\text{Proportion of sets by 5º squared area against sets made in the open area}} \overbrace{\left(\frac{k_{i\epsilon open,t}}{k_{i\epsilon open}}\right)}^{\text{Proportion of sets by type against all the sets made in a 5º squared open area}}}_{\text{Reallocated number of sets by set type by 5º squared area}} + \overbrace{k_{i\epsilon open,t}}^{\text{Existing number of sets by type made in a 5º squared open area}} \right] \overbrace{\left(\frac{\sum_{j=1}^{k_{i\epsilon open}} y_{i\epsilon open,t,sp,j}}{k_{i\epsilon open,t}}\right)}^{\text{CPS by tuna sp., by set type, by 5º squared area}}$$

$k_{i,t}$ is the number of sets, by type t, that occurred in the i^{th} 5º area

$y_{i,j,t,sp}$ is the catch of the sp^{th} tuna species (t) caught in the j^{th} set, by type t, that occurred the i^{th} 5º area