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PREDICTING THE CATCH POTENTIAL OF SKIPJACK TUNA IN THE WESTERN AND CENTRAL PACIFIC OCEAN UNDER DIFFERENT CLIMATE CHANGE SCENARIOS

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Key words: catch potential, climate change, generalized additive model, skipjack tuna.

ABSTRACT

Skipjack tuna (*Katsuwonus pelamis*) constitute an important migratory species that contributes significantly to the economy and the global fishery industry. Skipjack tuna play a vital role in the marine ecosystem, particularly in tropical waters of the western and central Pacific Ocean (WCPO). However, climate change may affect the characteristics of fishery resources, leading to substantial reallocation and reduction of the biomass of this species in the WCPO. In this study, catch and effort data for skipjack tuna were collected from a purse seine fishery and subsequently analyzed in combination with remote-sensing environmental variables and simulation data from climate models under various scenarios. Generalized additive models were developed to examine the relationships between environmental variations and the species' catch per unit effort and thus evaluate the potential effects of climate change. The catch potential of this stock was estimated under various greenhouse gas emission scenarios (2015-2050) currently under consideration by the Intergovernmental Panel on Climate Change (IPCC). The highest catch potential was associated with the highest greenhouse gas emissions, whereas the catch potential remained relatively stable under the scenario with lower emissions. To sustainably utilize skipjack tuna as a resource, the impact of climate change on the stock under various global warming scenarios should be considered in the assessment and management of fisheries for this species.

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I. INTRODUCTION

Climate change has continuously affected the marine ecosystem and has caused many disasters and changes (Scheffer et al., 2001), including nutrient loading (Schneider et al., 1997; Oguz and Gilbert, 2007; Ludwig et al., 2009), habitat fragmentation (Stempniewicz et al., 2007; Munday et al., 2009), and biotic exploitation (Hunsicker et al., 2013). The physical and chemical properties of the marine environment have been strongly altered by climate change, resulting in large-scale changes in primary productivity (Steinacher et al., 2010; Gruber, 2011) that have affected the catch of global fisheries over the past four decades (Cheung et al., 2013). These phenomena have led to enormous ecological and economic losses and may affect human society through the future response of ecosystems.

The annual catch of skipjack tuna (*Katsuwonus pelamis*) in the western and central Pacific Ocean (WCPO) reached more than 1,300,000 metric tons (mt) in 2005 (FAO, 2015), and canned skipjack tuna have become one of the most popular and recognized fish commodities globally (Mohan et al., 2015). Fishing access fees based on catches of foreign vessels, including purse seiners, are the main income for developing island countries in the WCPO. However, the annual total catch of skipjack tuna in exclusive economic zones (EEZs) varies among the different countries in the WCPO (Fig. 1). The movement of skipjack tuna among the EEZs of these island countries is the most important factor affecting the interests of and relationships between the relevant parties.

Tuna purse seiners constitute major fishing gear in the region and are operated actively in locations where the skipjack tuna schools aggregate. Thus, knowledge of the distribution of skipjack tuna could be associated with high fishing effort. Prior to the recent introduction of satellite telemetry and remote sensing technology to fisheries, the identification of fishing locations for tuna schools typically relied on surface-level indicators of

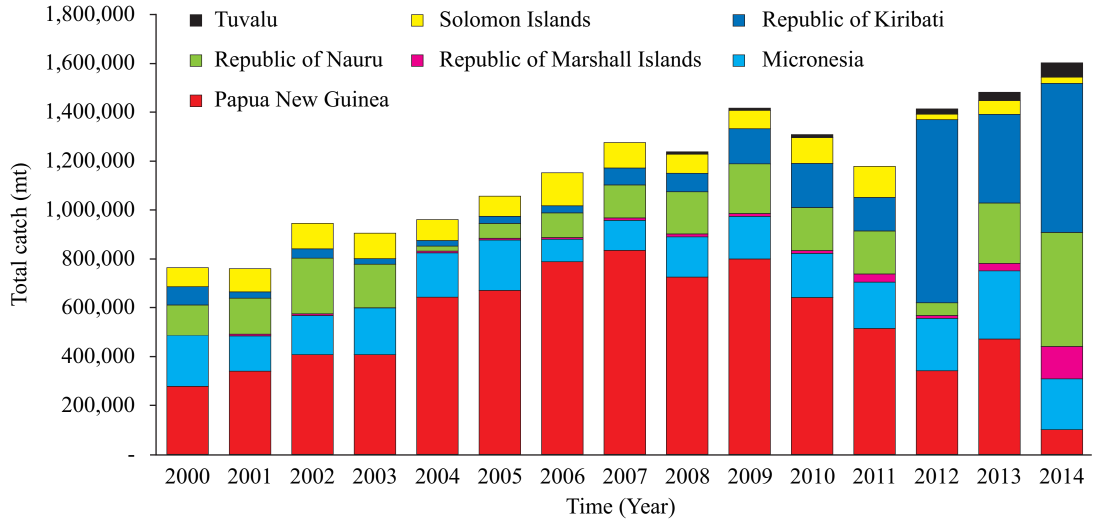

Fig. 1. Total catches (mt) of the Taiwanese purse seine fishery in the EEZ area of Pacific island countries during 2000-2014.

their feeding mechanisms and prey organisms (Blackburn, 1965; Sund et al., 1981). However, the interactions between fish and their environment can now be examined by incorporating a wide range of remote sensing oceanographic variables into fishery data. For example, a number of oceanographic environmental variables have been demonstrated to significantly affect the abundances and distributions of pelagic species, particularly tuna (Klemas, 2012).

Skipjack tuna are sensitive to changes in environmental conditions because they are capable of large-scale relocation in the search for suitable environmental conditions that satisfy their physiological needs (Yen et al., 2012a). For example, the chlorophyll-a concentration and primary productivity reflect the nutrient abundances in specific areas of the ocean, which can attract fish, indicating relationships between fish density and the environment (Lehodey et al., 1997). The exchange of heat between the atmosphere and ocean can be investigated based on mixed-layer characteristics and affects the physical environment, photic layer, and plankton growth (Ryan et al., 2002). This heat exchange may have a great influence on the spatial range and depth of the habitats of tuna and thus change the catchability of fishing operations (Bigelow et al., 1999). Sea surface temperature is one of the most commonly used environmental variables for investigating the distribution of tuna (Laurs et al., 1984; Maul et al., 1984). Variables such as surface height (Mugo et al., 2010) and current speed (Lehodey et al., 1998) have also been considered in studies of tuna distribution.

The skipjack tuna stock in the WCPO is considered reasonably and sustainably exploited but sensitive to changes in the environment. Because climate change and its impacts differ in different areas of the oceanic environment, any variation in environmental factors might be related to changes in fish stocks. Using the IPSL-CM4 model, Lehodey et al. (2013) predicted that the skipjack tuna catch potential will slightly increase in the WCPO through 2050. However, based on a newer version of this model, IPSL-CM5, the projected anomalies in skipjack habitat suitability are characterized by a declining trend during the same period, as reported by Dueri et al. (2014). The expected trend in the catch potential of skipjack tuna remains difficult to confirm at present due to the discrepancy between these two recently reported models. Moreover, Dueri et al. (2014) focused only on the suitability of skipjack tuna habitats, which may not be the sole factor affecting the catch potential of this species. The operating locations of the Taiwanese tuna purse seiners, which was initiated in 1982, are evenly distributed in the WCPO and could thus provide suitable indicators of the dynamics of skipjack resources in this region (Yen et al., 2012a).

To better understand the implications of climate change on the catch potential of skipjack tuna resources in the WCPO and provide a reference for research on long-term strategic approaches, we simulated the catch potential of skipjack tuna based on the IPSL-CM5 climate model using additional environmental factors and Taiwanese purse seine fishery data. Remote sensing oceanographic data were used in this study to explore the environmental characteristics of the warm pool and cold tongue regions in the WCPO. The cold tongue, as defined by Lehodey et al. (2010), refers to the area of relatively cold surface water (with a mean temperature of 25-27°C) extending from the Eastern Equatorial Pacific to the WCPO. In contrast, the warm pool, located west of the cold tongue, is the largest water body with the warm sea surface temperature (mean temperature of 28-29.5°C) on Earth (Oppo et al., 2009). To consider the future oceanographic conditions of the tuna fishing grounds located in these areas, various greenhouse gas emission scenarios were investigated by developing empirical generalized additive models (GAMs). These GAMs were then used to examine the potential impacts of future climate change and important environmental factors on the fishing conditions of skipjack tuna and the fishing effort in the WCPO under various climate scenarios.

II. MATERIALS AND METHODS

1. Study Area

The marine environment in the WCPO changes continuously due to the dynamic coupling between the atmosphere and the ocean. This coupling mechanism produces a strong climate-driven cold tongue and results in the El Niño-Southern Oscillation phenomenon in the Pacific Ocean. Most stocks of skipjack tuna by purse seine fisheries in the Pacific Ocean are distributed in the warm pool region located at 10°N-10°S and 130°E-165°E and the cold tongue region located at 10°N-10°S and 170°E-130°W (Lehodey et al., 2010). Thus, the study area comprised the warm pool and cold tongue regions located within 10°N-10°S and 130°E-130°W.

2. Fishery Data

Logbook data for skipjack tuna caught by the Taiwanese tuna purse seiners from 2000 to 2014 were studied. This dataset included information regarding fishing date, fishing location (longitude and latitude), fishing vessel name, catch, and fishing effort (fishing days). The catch and effort data were averaged to obtain monthly values on a 1°-by-1° grid to match the spatial and temporal scales of the environmental variables. The monthly catch per unit of effort (CPUE) of skipjack tuna at each fishing location was calculated as follow:

$$\mathrm{CPUE}_{mij} = \Sigma \mathrm{C}_{mij} / \Sigma \mathrm{E}_{mij}$$

where CPUE_{mij} is the nominal CPUE (mt/fishing day), $\Sigma\mathrm{C}_{mij}$ and $\Sigma\mathrm{E}_{mij}$ are the sums of the catch (mt) and fishing effort (fishing day), respectively, and *m, i* and *j* refer to the month, longitude and latitude, respectively.

3. Environmental Data

Environmental variables, including the sea surface temperature (SST), mixed-layer depth (MLD), sea surface chlorophyll-*a* concentration (SSC), sea surface salinity (SSS), net primary production (NPP), and u-component of the current (UCC)) were assumed to be related to the skipjack catch potential (Laurs et al., 1984; Maul et al., 1984; Lehodey et al., 1997; Lehodey et al., 1998; Bigelow et al., 1999; Ryan et al., 2002; Mugo et al., 2010) and were used in the following analyses. Data on these environmental variables were obtained from the NOAA Earth System Research Laboratory (http://www.esrl.noaa.gov). The remote sensing data were aggregated by month in 1°-by-1° square grid cells. Simulation data from the IPSL-CM5 climate model for the forecasted environmental variables under two different climate change scenarios—RCP 2.6 and RCP 8.5 (with radiative forcing levels by the end of 2100 of approximately 2.6 and 8.5 W/m^2, respectively; see Meinshausen et al., 2011)—were collected and incorporated into the analysis. The scenarios were selected to represent the possible scenarios with the lowest and highest greenhouse gas emissions. These data were generated from a model developed by the NOAA Geophysical Fluid Dynamics Laboratory (http://www.gfdl.noaa.gov).

4. Fishing Effort and Construction of CPUE Model

GAMs were used to develop models of the CPUE and fishing effort for skipjack tuna in the WCPO. The month, longitude, latitude, and fish school type [free school, log school, or fish aggregating device (FAD) school] were treated as categorical variables, whereas environmental parameters were used as continuous variables in the models. The models, in which smoothing spline functions are used to model the CPUE and the fishing effort, can be written as follows:

$$\begin{aligned}\ln(\mathrm{CPUE}+0.01) \sim\ & \mathrm{CT}+\mathrm{school}+\mathrm{Month}\\ & +s(\mathrm{Longitude})+s(\mathrm{Latitude})+s(\mathrm{NPP})\\ & +s(\mathrm{MLD})+s(\mathrm{SSC})+s(\mathrm{SST})+s(\mathrm{SSS})\\ & +s(\mathrm{SSH})+s(\mathrm{UCC})+s(\mathrm{S105})\\ & +\mathit{Interaction}+\varepsilon\end{aligned}$$

$$\begin{aligned}\ln(\mathrm{Effort}+0.01) \sim\ & \mathrm{CT}+\mathrm{school}+\mathrm{Month}\\ & +s(\mathrm{Longitude})+s(\mathrm{Latitude})+s(\mathrm{NPP})\\ & +s(\mathrm{MLD})+s(\mathrm{SSC})+s(\mathrm{SST})+s(\mathrm{SSS})\\ & +s(\mathrm{SSH})+s(\mathrm{UCC})+s(\mathrm{S105})\\ & +\mathit{Interaction}+\varepsilon\end{aligned}$$

where $s(\,)$ denotes a smoothing spline function, *Interaction* denotes the interaction effect, ε is assumed to follow an $N(0, \sigma^2)$ normal distribution, CT denotes the effect of vessel size (CT number), school denotes the effect of school type (natural log, FAD, or free-swimming school), and S105 is the seawater temperature below the 105-m sublayer. A small constant (0.01) was added to the CPUE to avoid the possibility of taking the logarithm of zero. Fishery data for 2000-2010 were used as the training data, and data for 2012-2014 were used as observation data for comparison with the model output to verify the performance of the model. The “mgcv” package in the R Project statistical software environment (Wood and Augustin, 2002) was used to fit the model. The backward selection method with residual deviance was used, and the Akaike information criterion (AIC) was selected as the criterion for determining the best models for the CPUE and fishing effort.

5. Estimation of Catch Potential

The CPUE and fishing effort are expected to be affected by future changes in the oceanographic environment. Therefore, predictions of future CPUE and fishing effort were estimated based on the CPUE and fishing effort models developed by incorporating data from the climate change models. The catch potential was predicted using the following equation:

$$\Sigma \mathrm{C}_{mij} = \mathrm{CPUE}_{mij} \times \Sigma \mathrm{E}_{mij}$$

where *i* is the longitude, *j* is the latitude, *m* is the month, and $\Sigma\mathrm{C}_{mij}$ is defined as the catch potential within the corresponding

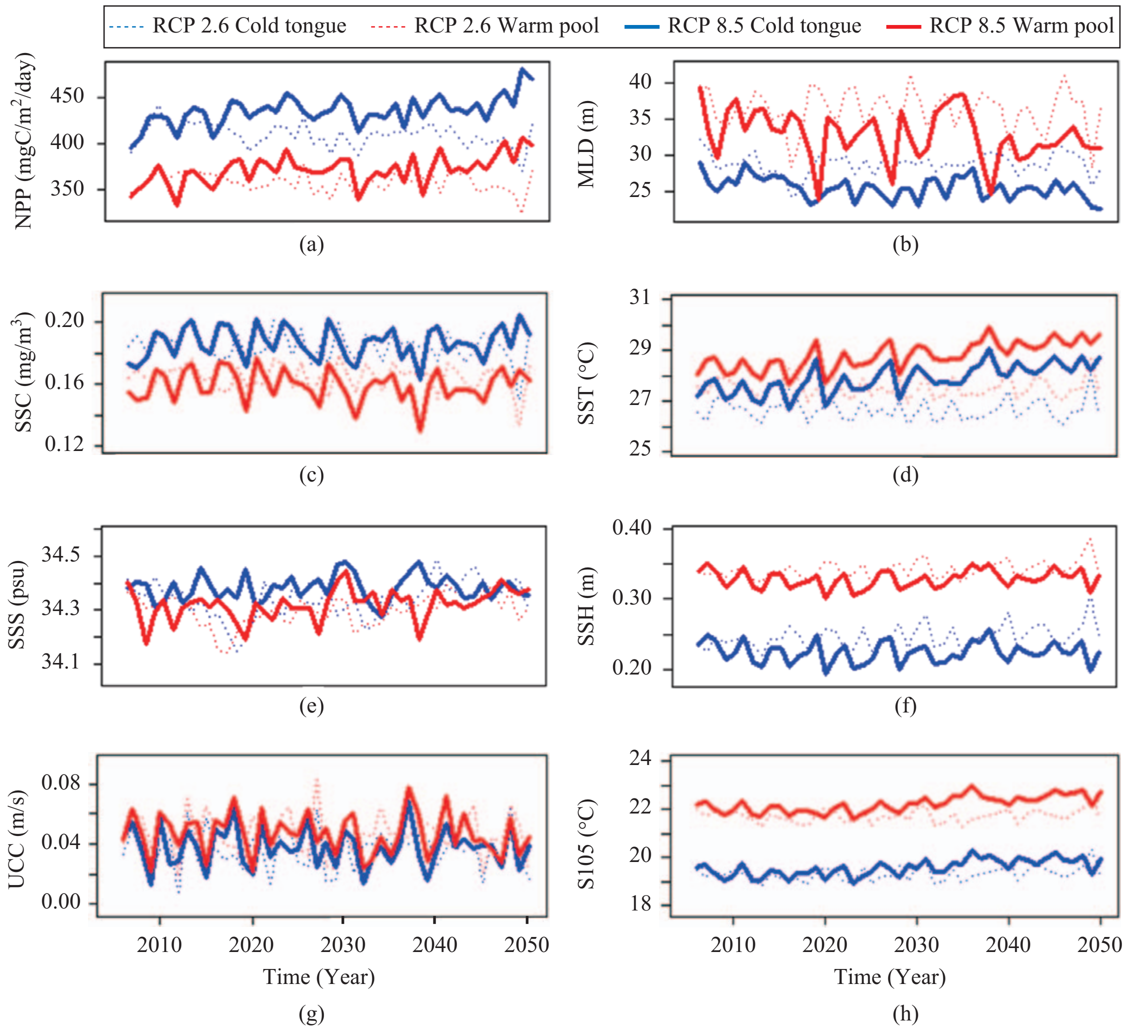

Fig. 2. Temporal variations in environmental variables for the following geographical regions under the RCP 2.6 and RCP 8.5 scenarios in IPCC AR-5: the cold tongue and the warm pool regions.

grid at the corresponding time. The fishery and fleet dynamics and the variations in skipjack biomass in future predictions were assumed to remain equal to those in 2000-2010. The potential changes in catch data were thus determined and compared with the values in 2000-2010.

III. RESULTS

1. Changes in the Environment

The oceanographic characteristics of this region have presented variations over time, and these variations appear to be greater in the warm pool region than in the cold tongue region. However, the values of several environmental parameters have changed substantially since the beginning of the 2010s. Notably, the NPP and SSC values have considerably decreased since 2010, and the SSS has exhibited a clear change due to an increase in the velocity of the surface currents. The average SST and S105 have also exhibited increasing trends (results not shown).

The expected future temporal variations in environmental variables in the two geographical regions of interest are shown in Fig. 2. Increasing trends in the NPP (Fig. 2(a)), SSC (Fig. 2(c)), and SST (Fig. 2(d)) are expected over the next 30 years to 2050, and the degrees of increases are enhanced under the severe warming scenario (RCP 8.5). The trends for the change in the MLD under the two simulated scenarios in the cold tongue area are generally consistent, but the MLD under the RCP 8.5 scenario is relatively low. However, in the warm pool region, the trends for the change in the MLD are opposite under the two simulated scenarios, and the changes in the MLD under the RCP 8.5 scenario are more dramatic (Fig. 2(b)). The offset in the SSS time series between the warm pool and cold tongue regions is expected to briefly disappear and then increase to a high level by 2040 (Fig. 2(e)). The SSH is expected to remain stable in the future, even though the SSH values are slightly lower under the RCP 8.5 scenario (Fig. 2(f)). The changes in the UCC vary widely, and no significant trend is expected in the future (Fig. 2(g)). In general, no obvious future warming phe nomenon is expected

Table 1. Analysis of deviance explained by the CPUE and effort models for skipjack tuna in the WCPO.

Predictors	CPUE			Effort		
	Estimated degrees of freedom	F	*p*-value	Estimated degrees of freedom	Chi sq.	*p*-value
***s*(longitude)**	8.915	18.1	< 0.001	8.497	190.6	< 0.001
***s*(latitude)**	5.411	20.7	< 0.001	8.688	362.4	< 0.001
***s*(NPP)**	7.032	2.3	0.017	4.036	58.9	< 0.001
***s*(MLD)**	3.435	8.0	< 0.001	5.831	173.2	< 0.001
***s*(SSC)**	4.047	3.2	0.006	6.953	71.6	< 0.001
***s*(SST)**	8.796	40.9	< 0.001	6.887	47.3	< 0.001
***s*(UCC)**	3.213	3.5	0.007	8.608	61.3	< 0.001
***s*(SSS)**	8.581	5.6	< 0.001	2.784	33.9	< 0.001
***s*(SSH)**	2.567	30.2	< 0.001	8.100	185.6	< 0.001
***s*(S105)**	7.779	5.4	< 0.001	8.708	209.3	< 0.001
	R-sq. (adj.) = 0.132 Deviance explained = 13.3%			R-sq. (adj.) = 0.625 Deviance explained = 60.2%		

Table 2. Deviance explained by and AIC values of the CPUE and effort models obtained by sequentially adding each factor into the model.

CPUE model					Effort model				
Predictor	Residual deviance	AIC	ΔDeviance	ΔAIC	Predictor	Residual deviance	AIC	ΔDeviance	ΔAIC
+*s*(S105)	101621	135694.9	486.2	152.6	**+*s*(latitude)**	5426.5	90499.1	564.3	547.2
+*s*(SSH)	101450.9	135650.8	170.1	44.1	**+*s*(S105)**	5233	90322.9	193.5	176.2
+*s*(latitude)	101117.7	135548.5	333.2	102.3	**+*s*(longitude)**	5082.8	90190.1	150.2	132.8
+*s*(longitude)	100726.4	135432.5	391.3	116	**+*s*(SSH)**	4752.1	89873.8	330.7	316.3
+*s*(SSS)	100367	135323.8	359.4	108.7	**+*s*(MLD)**	4651.6	89786.3	100.5	87.5
+*s*(UCC)	100170.3	135267.2	196.7	56.6	**+*s*(SSC)**	4085.2	89234.8	566.4	551.5
+*s*(SST)	98554.2	134710.5	1616.1	556.7	**+*s*(UCC)**	4018.6	89185.3	66.6	49.5
+*s*(SSC)	98274.4	134618.5	279.8	92	**+*s*(NPP)**	3945.6	89120.1	73	65.2
+*s*(MLD)	98170.9	134589.5	103.5	29	**+*s*(SST)**	3900.2	89088.3	45.4	31.8
+*s*(NPP)	98124.8	134584.9	46.1	4.6	**+*s*(SSS)**	3863.7	89057.1	36.5	31.2

under the RCP 2.6 scenario, but the S105 appears to increase after 2030 under the RCP 8.5 climate change scenario (Fig. 2(h)).

2. Model Development and Outputs

The relationships among the catch potential of skipjack tuna, fishing effort, and environmental parameters were examined in this study. The variables incorporated in the models, the estimated degrees of freedom, the significance values and the explained variances for each model term in the two GAM models are summarized in Table 1. All predictor variables were found to be highly significant ($p < 0.01$) for both the CPUE and effort models, suggesting that all variables should be included in the models. The inclusion of all model variables was also supported by the AIC and deviance estimates (Table 2). The best model was determined to be the model with the lowest AIC value. The removal of any factor from the models reduced the model performance, as shown in Table 2.

The training data used to fit the models (2000-2010), observations for recent years (2011-2014) and outputs from the CPUE and fishing effort models are shown in Fig. 3. The predictions were compared with the observations to verify the results from both the CPUE (Figs. 3(d) and 3(f)) and fishing effort (Figs. 3(c) and 3(e)) models, which indicated that the effort model performed better than the CPUE model. In addition, the r^2 value for the CPUE model was 0.130, which is lower than that for the fishing effort model (0.625), indicating that the accuracy of the effort model is better than that of the CPUE model.

The effects of all environmental factors on the CPUE of skipjack tuna are shown in Fig. 4. A y-axis value greater than 0 indicates a positive effect, whereas a value less than 0 indicates a negative effect. Lower (< 200 mgC/m^2/day) and higher (> 300 mgC/m^2/day) NPP values exert negative effects on the CPUE of skipjack tuna (Fig. 4(a)). A deeper MLD exerts positive impacts on the CPUE of skipjack tuna (Fig. 4(b)). A positive effect on the catch of skipjack tuna was predicted at lower SSC values (< 0.1 mg/m^3), and a declining trend was predicted at higher values, as shown in Fig. 4(c). In contrast, a negative effect of the SST was predicted at SST values of 27.5-29°C;

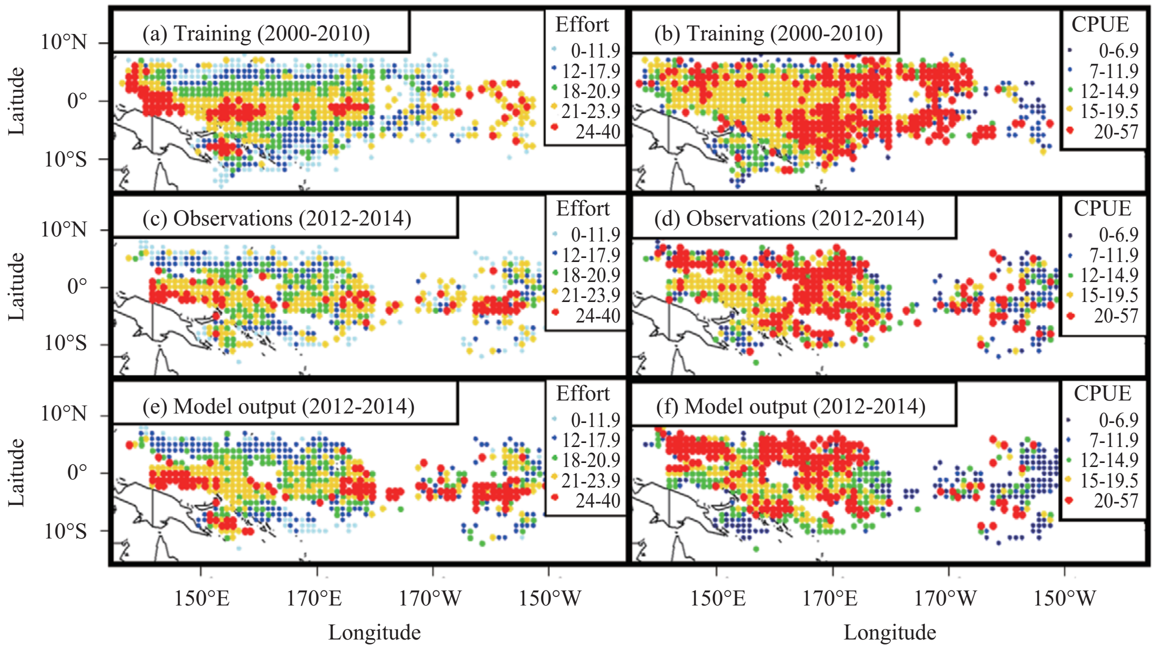

Fig. 3. Distributions of the training data, observation data and model outputs for the fishing effort (fishing days) and CPUE (mt per fishing day) for skipjack tuna in the WCPO.

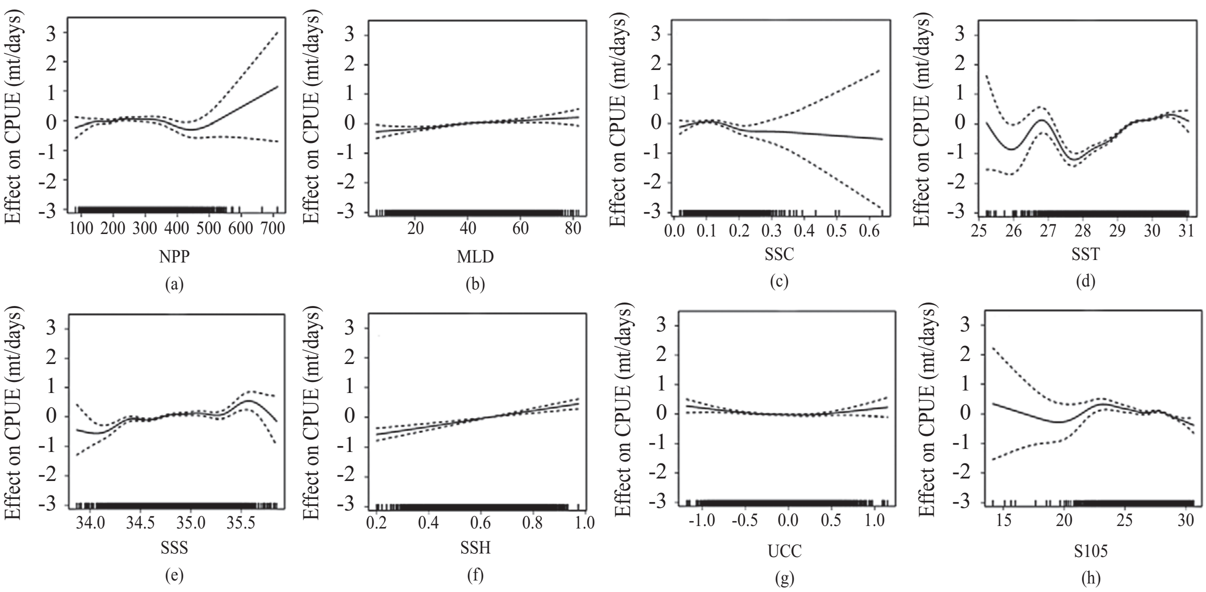

Fig. 4. Partial effects of environmental factors on the CPUE for skipjack tuna of the Taiwanese purse seine fishery industry in the WCPO. The dashed lines represent 95% point-wise prognosis intervals. The rug plots show the data distribution of the covariate.

thus, skipjack tuna appear to prefer the warm pool region, although the number of data points in areas of colder SSTs was relatively low (Fig. 4(d)). SSS values of less than 34.7 psu were estimated to have a negative impact on the catch of skipjack tuna (Fig. 4(e)). SSH values greater than 0.65 appeared to have a strong positive impact on the catch of skipjack tuna (Fig. 4(f)). The UCC with the lowest positive impact was estimated to be close to zero (Fig. 4(g)), supporting the preference of skipjack tuna for habitats with flowing waters. In contrast, high S105 values (higher than 20°C) were found to have a negative impact on the CPUE (Fig. 4(h)).

The greatest positive effect of the NPP on effort in the purse seine fishery was found at an NPP value of 250-300 mgC/m^2/day, as shown in Fig. 5. The positive and negative effects are consistent with the findings depicted in Fig. 4. The effect of the MLD was predicted to be similar. Higher SSCs had positive impacts on the fishing effort, whereas the SST had a negative effect on the fishing effort at SSTs lower than 28.5°C. Negative

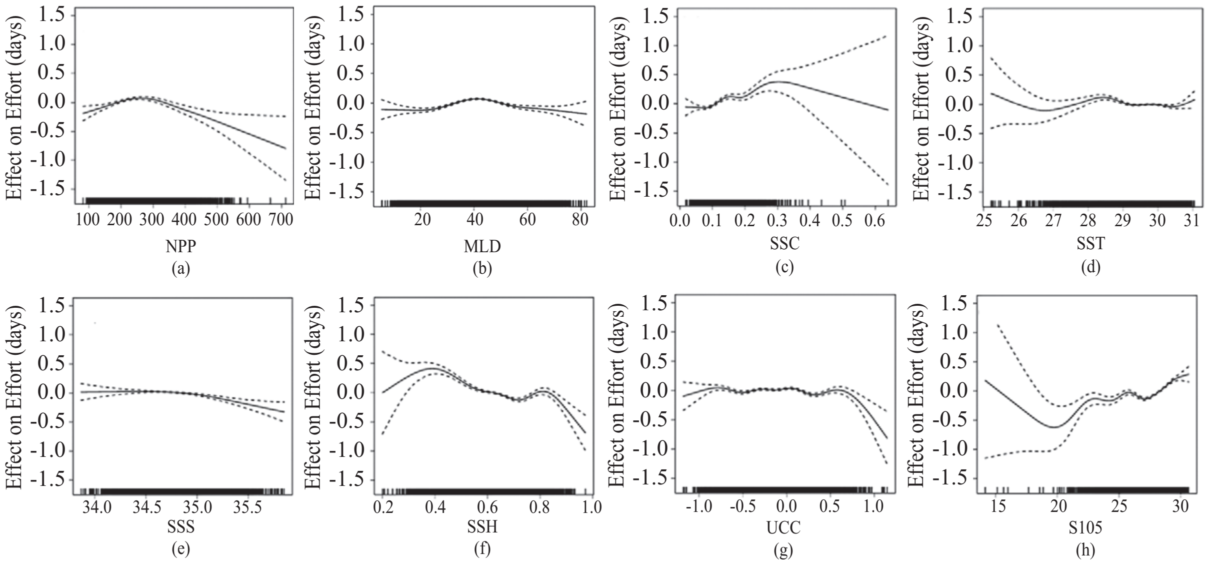

Fig. 5. Partial effects of environmental factors on the fishing effort of the Taiwanese purse seine fishery industry in the WCPO. The dashed lines represent 95% point-wise prognosis intervals. The rug plots show the data distribution of the covariate.

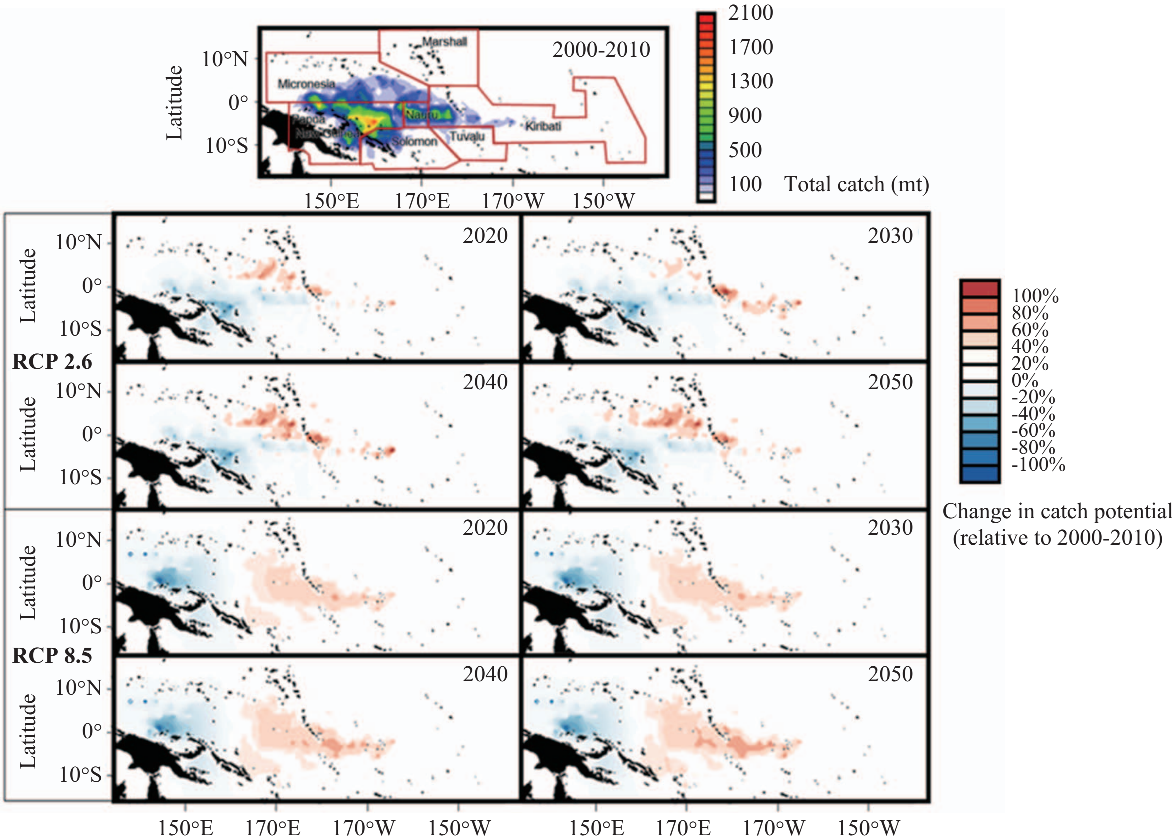

Fig. 6. Differences in the 10-year average catch potentials from 2000 to 2020, 2030, 2040, and 2050 under the AR5-RCP 2.6 and AR5-RCP 8.5 climate change scenarios.

effects on the fishing effort were predicted at SSS values greater than 35.2 psu and at UCC values greater than 0.5 m/s. The model indicated that the SSH exerts a positive effect values less than 0.6 m. As revealed by the GAM spatial plot for S105, a high fishing effort for skipjack tuna is expected for waters with temperatures ranging from 26°C to 30°C.

3. Catch Potential of Skipjack Tuna

The catch potential of skipjack tuna was calculated using the two developed models for each grid cell (1° × 1°) on a monthly basis. The values averaged over 2000-2010 were used as the baseline to assess the possible impacts on catch potential for the years 2020, 2030, 2040, and 2050. The model-predicted catch distribution for the 2000s was very similar to those for 2010 to 2014 (Fig. 6), which can be generally divided into two main catch distributions, one in the northeastern waters of Papua New Guinea and one in the waters off the Kiribati EEZ.

Eight figures are presented to depict the future changes in the catch potential of skipjack tuna for the years 2020, 2030, 2040, and 2050 under the RCP 2.6 and RCP 8.5 scenarios (Fig. 6). A large decline in the northeastern waters of Papua New Guinea is expected, with an intense recession during 2020-2030. This recession is then predicted to slow slightly, yielding an overall declining trend. This decline will lead to a more even distribution of skipjack catches. In contrast, the catch potential is expected to increase in other areas, mainly within 0-10°N and 160°E-179°E, indicating the potential for a catch increase in 2020. The catch potential is expected to shift eastward to 175°E-170°W beginning in 2030 and to increase at 0-4°S in 2040; these changes represent the largest increase in the catch potential observed in both the RCP 2.6 and RCP 8.5 scenarios. The shift in the fishing effort areas indicates an increase in the catch potential at 0-10°N and 160°E-179°E in 2050. Overall, the model-predicted productive area that is suitable for fishing is observed to move eastward and toward higher latitudes (Fig. 6).

A comparison of the two considered scenarios (RCP 2.6 and RCP 8.5) revealed spatial and temporal variations in the predicted outputs (Fig. 6). The catch potential for skipjack tuna is expected to increase in the waters at 2°N-2°S and 165°E-175°E under the RCP 8.5 scenario, whereas the catch potential in the same area declines under the RCP 2.6 scenario. The variation in the catch potential in the study area as a whole and separately in the cold tongue and warm pool regions is shown in Fig. 7. The production of skipjack tuna in this area exhibits an upward trend under the RCP 8.5 scenario, whereas no changing tendency is clearly observed under the RCP 2.6 scenario.

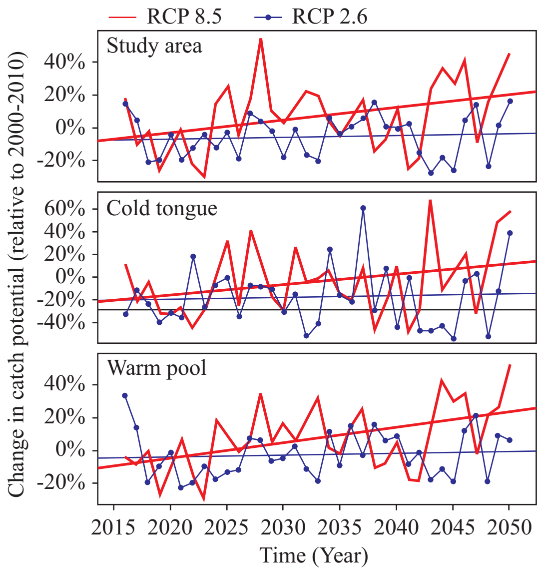

Fig. 7. Changes in the catch potential (2016-2050 relative to 2000-2010) in the following three geographical regions under the AR5-RCP 2.6 and AR5-RCP 8.5 climate change scenarios: the entire study area, the cold tongue region and the warm pool region.

IV. DISCUSSION

Standardized fishery data such as CPUEs for purse seine fisheries can be used as abundance indices to investigate the changes and shifts in fish stock. By analyzing environmental variables and fishery data using the empirical GAMs developed in this study, we modeled the changes in the spatial and temporal distributions of skipjack tuna schools. In contrast to passive fishing vessels such as longliners, the fishing effort of purse seiners is correlated with the fish density (Yen et al., 2012b) because purse seiners operate only when a large school of fish is found due to the high costs and large amount of fishing effort required. Fishermen must maneuver the fishing vessel and throw the nets to surround the fish school as soon as possible after the fish are located to ensure a catch. Before casting a net for fishing, purse seine fishermen are pretty sure where skipjack tuna aggregate and a group of fish has formed, thereby substantially increasing the likelihood of catching fish during each operation. Therefore, locations of high fishing effort can be used as excellent indicators of areas with a high density of fish schools. This correlation explains why the amount of deviance explained and accuracy are greater for fishing effort models than for CPUE models. This finding suggests that some factors, such as technology and fishing vessel operation, remain to be included in CPUE models. The probability approach of successful catch is considered an ideal approach for addressing complicated fishery data and zero-catch scenarios because the models incorporate information of both fish density and fishing effort (Maunder and Punt, 2004; Bordalo-Machado, 2006; Yen et al., 2012b). A CPUE model can be used to determine the size or density of fish schools, whereas a fishing effort model can be used to assess the presence or absence of fish (Ellis and Wang, 2007). Due to the small proportion (< 10%) of zero-catch observations in our dataset, we simply added a small constant (Su et al, 2008) to all catch data to model the CPUE and fishing effort.

To investigate the uncertainty of the modeling approach used, both CPUE- and effort-based models were developed in this study. CPUE-based models are usually utilized to explore the distribution of fish abundance through the incorporation of environmental variables in the model (Su et al., 2008), whereas effort-based models are used to explore the distribution of fishing vessels (effort), which directly reflects the experience of fishermen (McCluskey and Lewison, 2008). CPUE-based models are suitable for investigating abundance distribution patterns related to environmental variables because these models provide useful information regarding the location of fish and where these can be caught by vessels. However, effort-based models possess higher explanatory power for predictions than CPUE-based models because purse seiners are active vessels and are operated only when fish schools have been located. Effort-based models are therefore the most suitable approaches for characterizing potential habitats and abundances for the fishery of interest. Consequently, data on operation locations can provide useful information regarding the experience of fishermen and the locations of habitats that can suitably serve as the main targets of purse seiners (Yen et al., 2012b).

The trends and variations in catch potential for both short-term (2020-2025) and long-term (2030-2050) periods were predicted in this study. Although the predictions for 2030 to 2050 exhibited large fluctuations, the habitat characteristics could be examined based on the results of the empirical GAMs to further elucidate the impact of different greenhouse gas emissions scenarios on the catch rate of skipjack tuna. Loukos et al. (2003) assessed the impact of climate change on skipjack tuna and predicted an increasing trend in habitat suitability in the eastern Pacific Ocean under global warming conditions. These results were similar to those reported by Lehodey et al. (2013), who examined the temporal distribution of skipjack tuna based on the most extreme simulation (A2) from the IPSL-CM4 model. The Apex Predators ECOSystem Model (APECOSM) has also been used to evaluate the future impacts of climate change on the abundance and spatial distribution of skipjack tuna (Dueri et al., 2014). In addition to the horizontal distribution, the vertical fish distribution was fond to be particularly important in this study. Skipjack tuna are predominantly distributed in the mixed layer or in layers above the thermocline (Matsumoto et al., 2014). A deepening of the mixed layer could increase the habitat range in vertical space and thus reduce the likelihood of catching a large school of skipjack tuna. Therefore, oceanographic variables related to the vertical distributions (e.g., underwater sea temperature and MLD) are important factors and should be included in catch potential analyses.

Cheung et al. (2010) predicted a shift in space and time of catch potential in the global ocean under the extreme climate change scenario (analogous to the RCP 8.5 scenario used in this study), which suggests that the catch potential will considerably decline in this region of the WCPO, and indicated a shift in the distribution of the skipjack tuna habitat toward the eastern Pacific Ocean, with an extension to higher latitudes. This result is reasonable because the habitat suitability for skipjack tuna decreases in environments with the characteristics of the western equatorial warm pool (Dueri et al., 2014), as demonstrated in this study.

Various aspects of uncertainty should be addressed when conducting analyses. For example, anthropogenic impacts, the development of fishing techniques and management policy are usually assumed invariant, but these factors may change in the future due to practical realities. Furthermore, several factors that might compromise the reliability of a model were investigated. The removal of the SSC from the effort-based model decreased the proportion of deviance explained from 0.625 to 0.421. Similarly, removing the SST from the CPUE model slightly reduced the proportion of deviance explained (~3%). However, additional unknown important factors should be examined in future analyses to reduce the uncertainty and increase model performance. The skipjack tuna fishing ground was predicted to shift eastward and move to high latitudes, consistent with the results of previous studies (Lehodey et al., 2013; Dueri et al., 2014), but the differences among and the uncertainty in various climate warning levels, such as the RCP 2.6 and RCP 8.5 scenarios, need to be further investigated. Under a low greenhouse gas emissions scenario (i.e., RCP 2.6), the increase in the catch potential favors the movement of fish to higher latitudes in the northern hemisphere, whereas under the scenario comprising high greenhouse gas emissions (i.e., RCP 8.5), the areas with increased catch potential are predicted to be located in the southern hemisphere. However, all analyses suggest a decline in the catch potential in waters northeast of Papua New Guinea based on a reduction in the habitat suitability of this area for skipjack tuna under various climate change scenarios.

An indirect but effective approach was used and validated in this study to estimate the catch potential of an important fishery resource. However, the results and analyses could be improved by incorporating remote sensing and climate change scenario data at a finer scale, such as by downscaling. In summary, we have demonstrated that climate change might result in substantial changes in the catch potential and fishing grounds of a pelagic species, emphasizing the need for further research to guide the imperative development of adaptation management strategies.

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