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Climate Change Potential Impacts on the Tuna Fisheries in the EEZ of Tonga

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Abstract: The potential impacts of climate change on the distribution of tuna in Pacific Island Countries' Exclusive Economic Zones have yet to be investigated rigorously, and so their persistence and abundance in these areas remain uncertain. Here, we estimate optimal fisheries areas for four tuna species; Albacore (*Thunnus alalunga*), Bigeye (*Thunnus obesus*), Skipjack (*Katsuwonus pelamis*), and Yellowfin (*Thunnus albacares*). We consider different climate change scenarios, RCP 2.6, RCP 4.5, RCP 6.0 and RCP 8.5, within a set of tuna catch records in the Exclusive Economic Zone of Tonga. Using environmental and CPUE datasets, species distribution modelling estimated and predicted these fisheries areas in the current and future climatic scenarios. Our projections indicate an expansion in area and a shift of productive areas to the southern part of this Exclusive Economic Zone of Tonga. This is an indication that future climatic scenarios might be suitable for the species under study however, changes in trophic layers, ocean currents and ocean chemistry might alter this finding. Information provided here will be relevant in planning future national actions towards proper management of these species.

Keywords: species distribution modeling; tuna species; climate change scenarios; potential suitability habitat; predictor variables; ensemble models

1. Introduction

Understanding species ecology, biogeography, and biodiversity over the past few decades has become the basis for modelling the distribution of marine species [1–3]. For future modelling, this needs to incorporate the vulnerability and impacts of climate change to marine ecosystems [4,5]. Tuna is greatly impacted by climate change, both in the Pacific Island Countries and at global scale [6–8]. These impacts include shifts in species biogeographical distribution and loss of suitability habitats due to changes of their biophysical environments such as an increase in water temperature and a decrease in oxygen concentrations [9–12].

Tuna are highly migratory species and widely distributed throughout the world's ocean mainly for feeding and spawning purposes [13,14]. The largest portion of the world's tuna catch (approximately 80%) is taken within the Western Central Pacific Ocean (WCPO) [15]. Importantly, the largest portion of this catch is taken within the Exclusive Economic Zone (EEZ) (65-75 %) of the Pacific Island Countries (PICs) in the WCPO [16–18]. Tonga (Figure 1) is enveloped within the geographical boundary of the WCPO. The most economically important tuna species in Tonga are Albacore (Thunnus alalunga), Bigeye (Thunnus obesus), Skipjack (Katsuwonus pelamis), and Yellowfin (Thunnus albacares) which account for over 95% of all tuna fisheries annual catch [19]. Tuna harvest is the largest commercial fishery in Tonga and is estimated at 2000 metric tons per year [19].

Climatic variabilities such as global warming [20,21] and the El Nino Southern Oscillation (ENSO) [22,23] threaten the global fisheries production [5,24]. These events have negative impacts which include increasing regional temperature, changing weather patterns, rising sea levels, ocean acidification, changing nutrient loads in ocean circulations, increasing stratification of the water

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column and changing of precipitation patterns [21,25]. Ocean circulation features such as upwelling, eddies, surface circulation, thermocline circulation, and gyres impact aquatic life, most importantly the distribution of primary productivity [26,27]. Under these circumstances, environmental stress on primary producers is transferred along the trophic webs and the impacts permeate throughout marine communities [28], including changes in tuna spatial and temporal distribution and abundance [25,29]. As a result, tuna catches are decreasing in many parts of the world [6,30]. Therefore, it is crucial for the PICs to establish proper management of the stocks so that harvesting is at sustainable level given the environmental conditions.

In this context, predicting future environmental conditions and their effects on species distribution is crucial to tuna species conservation and mitigation strategies of climate change impacts on biodiversity. Given the lack of non-extractive fish population data for the EEZ of Tonga, the work on species distribution modelling for the four tuna species is based on data from commercial catches. Models based on species catch data and environmental variables are essential tools to gain insight on species distributions and obtain crucial knowledge for biodiversity conservation and management [31,32]. The catch data used in this study were actual observation points collected by tuna longline fisheries in Tonga (noting that the catch is double verified by government officials, [19] and is considered a true representation of catch data. Sea surface temperature (SST), sea surface salinity (SSS) and sea surface current (SSC) were used as predictor variables and were extracted from the Bio-ORACLE version 2.0 dataset [33].

The goal of this study is to estimate the impacts of climate changes on the distribution of the four main tuna fisheries; Albacore, Bigeye, Skipjack and Yellowfin. We are searching for climatically stable areas where a long-term conservation strategy could be applied inside the EEZ of Tonga given different climate change scenarios. We expected an increase of climatically suitable areas for tuna in our study region, as the EEZ of Tonga envelops geologically bathypelagic features such as the famous Tonga Trench and the Tofua Volcanic Arc.

2. Materials and Methods

2.1. Study area

This study was conducted in the archipelago waters of Tonga (Figure 1), a small island country located 700 km south-west of Fiji and 1900 km north-west of New Zealand in the South Pacific Ocean. It covers an EEZ (latitude$14.15^0 - 20.22^0\ S$, longitude $171.31^0 - 179.10^0\ W$) of approximately 800 km^2. This EEZ envelops the northern end of the Tonga trench, Tonga Ridge, Tofua Arc Volcanic Front, northern end of the Tonga Kermadec Arc and the westward region of the Lau Basin [34]. Two geologically different parallel north to south chains of volcanic seamounts along the Tonga Ridge including the famous seamount of Capricorn 120 miles east of Vava'u island. These geologically bathypelagic features are part of the island nation's fishing ground and may influence its oceanic conditions such as surface water temperature, nutrient, salt content and mixed layer depth. Bathymetry may also play a role since volcanic seamount lines run through the fishing ground and includes very deep water more than 5000 m and very shallow seamounts and a large shelf that is about 2000 m deep. This fishing ground supports the nation's commercial tuna fisheries harvest of about two thousand tons per year [19].

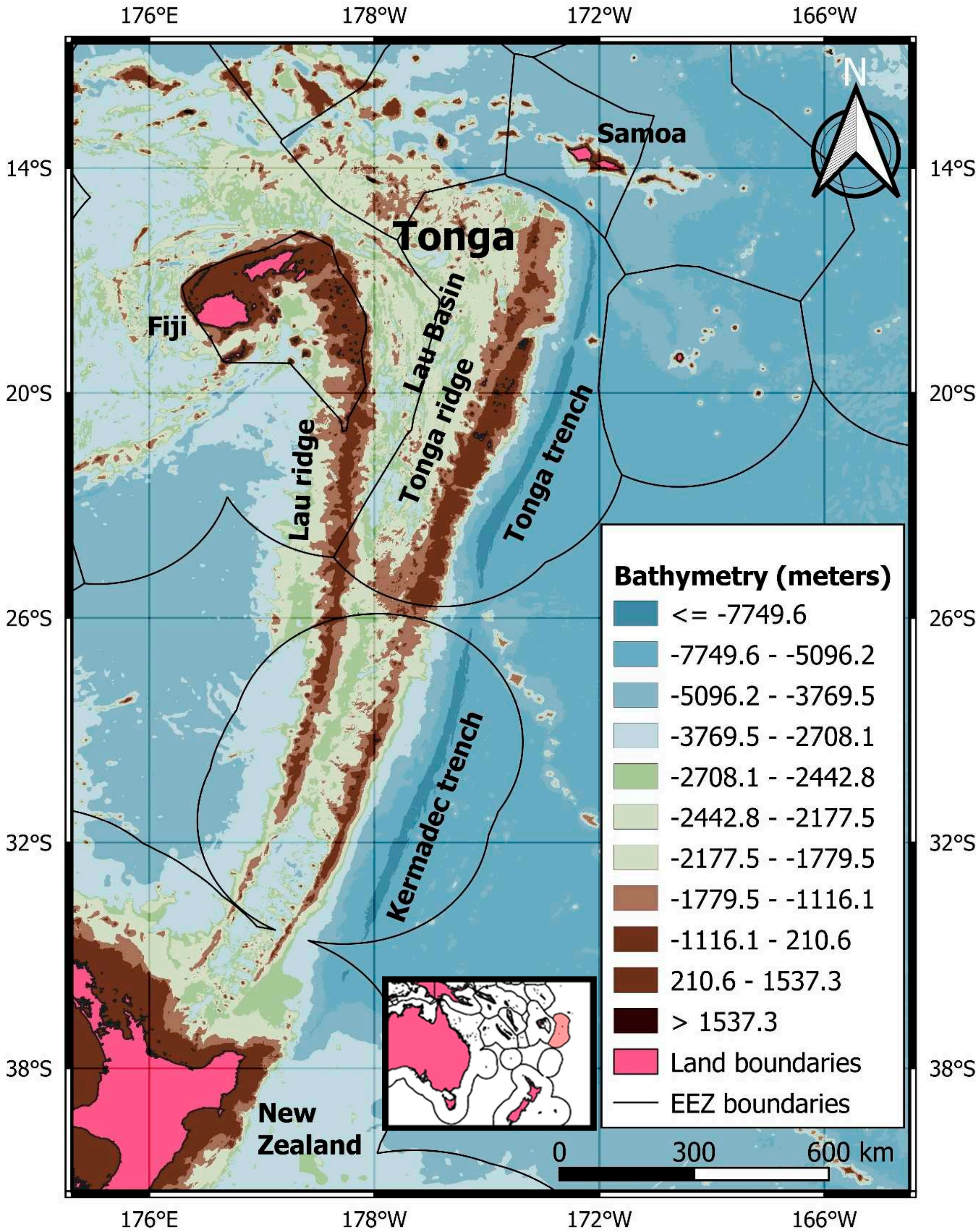

Figure 1. Map of the study region, Tonga Exclusive Economic Zone.

2.2. Study species and occurrence data

The catch (presence records only) data for Albacore, Bigeye, Skipjack and Yellowfin were recorded and compiled by the Tongan Long Line fishery from 2002 to 2018 and provided by the Tonga Ministry of Fishery and the South Pacific Community (SPC) Office in New Caledonia. The entire fish catch is checked by a minimum of two fisheries offices to ensure compliance [19]. The data's 1^0 spatial grid is comprised of daily fishing positions (latitude and longitude) and date (in day, month and year) (Table 1). For our study we used catch per unit effort (CPUE) which is calculated as the weight of the catch in metric tons divided by the number of hooks deployed per

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fishing record, providing a standardized measure of fishing efficiency and effort in capturing the target species [35,36]. The CPUE data were aggregated into monthly and annual resolved datasets to match the temporal scales of the predictor variables in Microsoft Excel [37]. The distributions of the CPUEs of Albacore, Bigeye, Yellowfin and Skipjack are shown in Figure 2 (a), (b), (c) and (d) respectively.

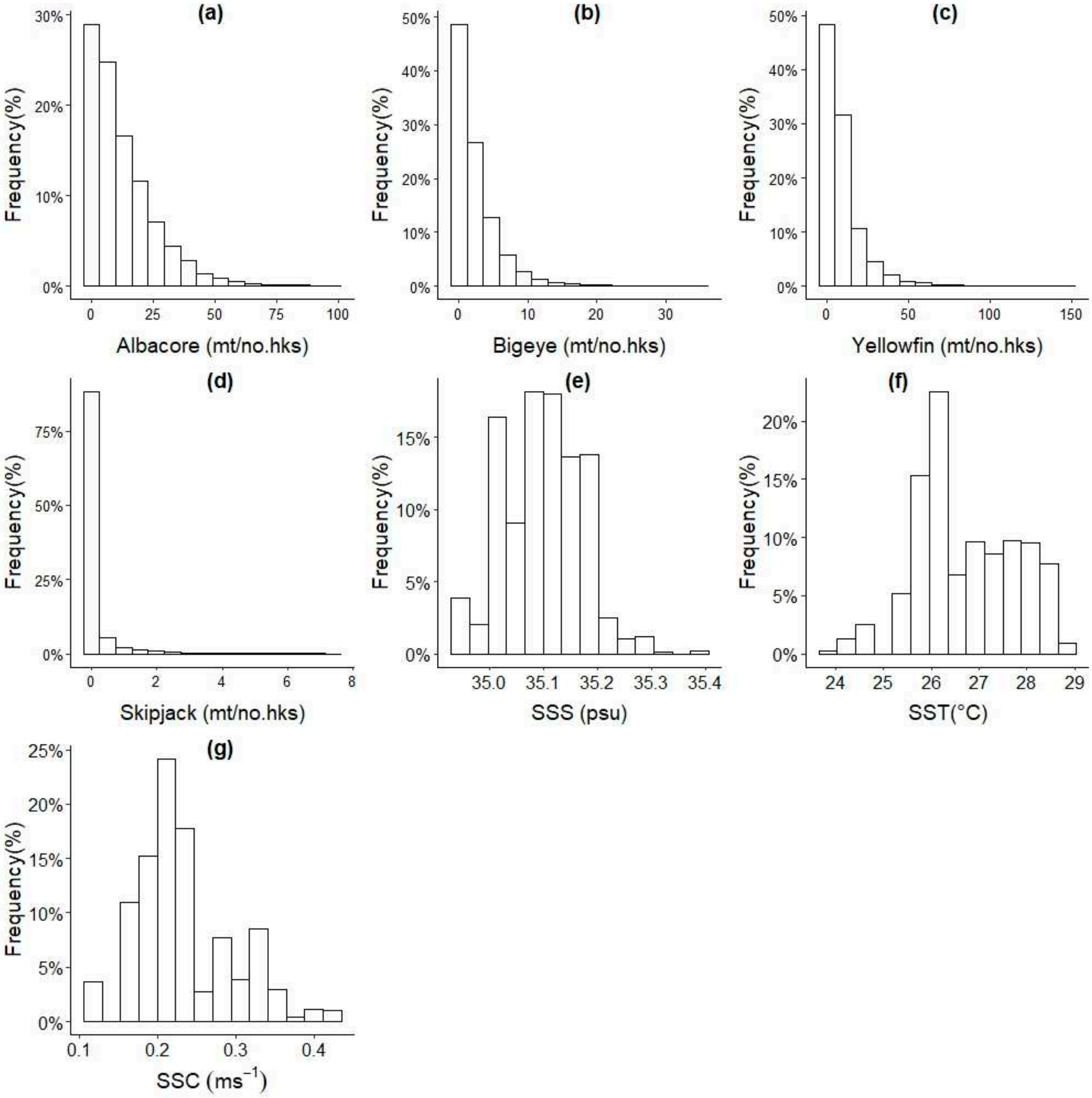

Figure 2. Histograms of CPUE (million tonnes per number of hooks, 2002 to 2018) of tuna ((a) Albacore, (b) Bigeye, (c) Yellowfin, (d) Skipjack) and environmental data ((e) SSS, (f) SST and (g) SSC) for 2010 as present time data of Bio–ORACLE version 2.0 dataset [33].

2.3. Predictor variables

We used the R packages *sdmpredictors* and *leaflet* to access potential predictor variables. We chose the Bio–ORACLE version 2.0 dataset [33] which provided the most complete set of variables for the study area both in the current and future projections. Variables selected (Table 1) were temperature, salinity, and current velocity, among other factors at sea surface. Secondly, we performed a statistical selection by employing the Variance Inflation Factor (VIF) method, utilizing the *usdm* package in the R environment [38,39]. We included all selected variables due to their low *VIF* (< 3) and Pearson correlation coefficients ($r < 0.7$). This ensures reduced dependence among variables

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and enhanced predictability. Present values refer to the period between 2010 and 2022 and future projections refer to the periods 2040–2050 and 2090–2100 under different greenhouse gas concentration scenarios based on different representative concentration pathways (RCP). We used the most optimistic scenarios ($2.6\,W/m^2$, $4.5\,W/m^2$, $6.0\,W/m^2$, and $8.5\,W/m^2$, respectively) to forecast the future distribution of the four tuna species across the range of climate change predictions. Variables were available at a spatial resolution of 5 arc–minutes (~0.083^0).

Table 1. Pre-selection environmental variables and Tuna Fisheries Data used to build species models.

Provider	Variable/code	Resolutions	Units
Tonga tuna longline fisheries	Catch per unit effort (CPUE)	Daily, 1 degree^2	mt/no. hks/ record
Bio–ORACLE version 2.0 dataset, bio-oracle.org	Sea surface salinity (SSS)	Long term mean, 5 arcmin, ≈ 9.2 km at equator, raster layers	PSU
	Sea surface current (SSC)		ms^{-1}
	Sea surface temperature (SST)		°C

2.4. Species distribution modelling

We built an ensemble model for each species using the selected predictor variables, the presence points of occurrence data, and 3 algorithms of the *sdm* R package version 1.0-67 [40]. These algorithms were; Generalized Additive Models (GAM, a nonparametric regression approach), Generalized Linear Models (GLM, a flexible generalization approach for ordinary linear regression) and Flexible Discriminant Analysis (FDA, a clarification approach for multiple predictors). For each species, we built an initial set of models in 4 independent cross validation runs selecting in each run 1000 pseudoabsences randomly distributed through different background areas in our study region. Each model run used sub-sampling and bootstrapping replications, each one reserving 25 % of the data for model testing and evaluation.

We computed the True Skill Statistic (TSS) to minimize the error for each model and created a weighted ensemble model by aggregating those with an optimal TSS. TSS is threshold-dependent, and we used the sensitivity-specificity sum maximization approach which selects the best thresholds (Table S1) for correct classification rates of presences and absences [41]. For the purpose of this study, we included in our analysis algorithms with a mean test TSS under 0.5 (Table S1) considering it has a large range (between -1 and 1) of variation than the AUC (between 0 and 1). We then used the selected algorithms and the complete modeling dataset to build a final ensemble model for each species, from which we calculated the mean of the predictions of the different algorithms. These models were then projected to current and four future scenarios RCP 2.6, RCP 4.5, RCP 6.0, RCP 8.5 [42] to the years 2050 and 2100 across the study area. Furthermore, based on these thresholds our distribution maps were developed with pixels greater than the threshold represented the presence of the species and pixels lower than the threshold indicated the absence of the species for all models. We then calculated an average value range for current and future projections, which returns both a prediction and a measure of uncertainty. For each cell value, a straightforward average of binary predictions is taken. The cells having values close to 1 indicate the areas where most models predict the presence, while the ones with values close to 0 represent the areas where most models predict the absence. Moreover, the cells with a value of 0.5 denote those areas where half of the models predict the presence while the other half predicts the absence. We finally used the results to develop binary maps to represent the distributions of each species in the current and future climatic scenarios.

2.5. Climatic suitable areas

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We obtained climatically suitable areas using a weighted method, where presence probability (obtained using *ensemble* function in the *sdm*) of each current and future scenario is multiplied by cell's area, then subsequently summing all raster values [43]. This approach results in a conservative area that considers that occupancy is not equal between cells hence the uncertainty underlying each cell in terms of presence probability. For example, if a cell had 0.1 value, that is 10 % chance of the species to occur in the cell, we calculated 10 % of the cell area and add it to the total area occupied by the species. We applied this weighted method to all current and future scenarios of all species.

3. Results

3.1. Performances of Species Distribution Modelling

The performances of *sdms* using different evaluation techniques for each species are presented in Table S1. The accuracy of our models was not very high (TSS range 0.40 to 0.44, deviance range 0.19 to 0.47, Table S1). However, model accuracy can also be evaluated using the receiver operator characteristics (ROC) curve as it has the capacity to show the proportion of the true presence rate (sensitivity, range 0.45 to 0.66) and the true absence rate (specificity, range 0.54 to 0.81) which were shown to be high (Table S1). The ROC curves for all models are presented in Figure S1. These high true presence and absence rates were validated by the prevalence scores (range 0.44 to 0.71) which indicate that species presence and absence cells were well identified and the proportion of correctly classified samples were maximized.

3.2. Relative contribution of predictor variables

In terms of variable importance, our results show SST (approximate range of 64.5 % to 74.2 %) has the highest contribution relative to SSS (30 % to 60 %) and SSC (32 % to 54 %) in predicting the distributional range of the four tuna species (Figure S3). In addition to the observed trends, the likelihood of encountering these species is strongly influenced by the selected of environmental factors. The optimal ranges for both SSC (around 0.25 ms^{-1} to 0.50 ms-^{1} and SST (about 23° C to 30° C for Albacore and Skipjack) (Figure S3) have been found to promote higher occurrences. On the other hand, the species distribution is negatively impacted by decreasing SSS values (roughly 34 PSU to 35.4 PSU for Skipjack and Yellowfin, and 34 PSU to 35.1 PSU for Bigeye), as well as SSS (approximately 34.9 PSU to 35.4 PSU for Skipjack and Yellowfin) and SST (within the temperature range of 23° C to 24.5° C for Bigeye and Yellowfin, and 25.5° C to 29.5° C for Albacore and Skipjack) (Figure S3).

3.3. Predicted suitability habitat

The results of predicted suitability habitats for both current and future projections are presented in Tables 2 and 3. Currently, our models unveiled that tuna has a potentially suitable habitat distribution ranging from 10,222 km^2 for Albacore to 32,876 km^2 for Skipjack of total of 78,951 km^2 (Table 2). Future scenarios showed generally an increase of suitability habitat for all species relative to their current conditions. The highest predicted suitability habitat for Albacore is 13,095 km^2 for RCP 8.5 in the year 2100, Bigeye is 54,537 km^2 for RCP 6.0 in the year 2050, Skipjack is 56,682 km^2 for RCP 8.5 in the year 2100 and 20,139 km^2 for Yellowfin in the year 2050 for RCP 8.5 (Table 2). The percentage increase of future scenarios relative to current scenario is presented in Table 3. The high percentage increase correspond to the increase in suitability habitats. Our results for future scenarios showed general expansion in stable areas for all species, ranging from 11,011 km^2 for RCP 4.5 in the year 2100 to 13,095 km^2 for RCP 8.5 in the year 2100 for Albacore, 33,558 km^2 for RCP 4.5 in the year 2100 to 48,053 km^2 for RCP in the year 2100 for Bigeye, 19,353 km^2 for RCP 4.5 in the year 2100 to 20,139 km^2 for RCP 8.5 in the year 2050 and 22,901 km^2 for RCP 2.6 in the year 2050 to 56,682 km^2 for RCP 8.5 in the year 2100 for Skipjack.

Table 2. Total summed area in current and future scenarios using a weighted method described in Section 2.5.

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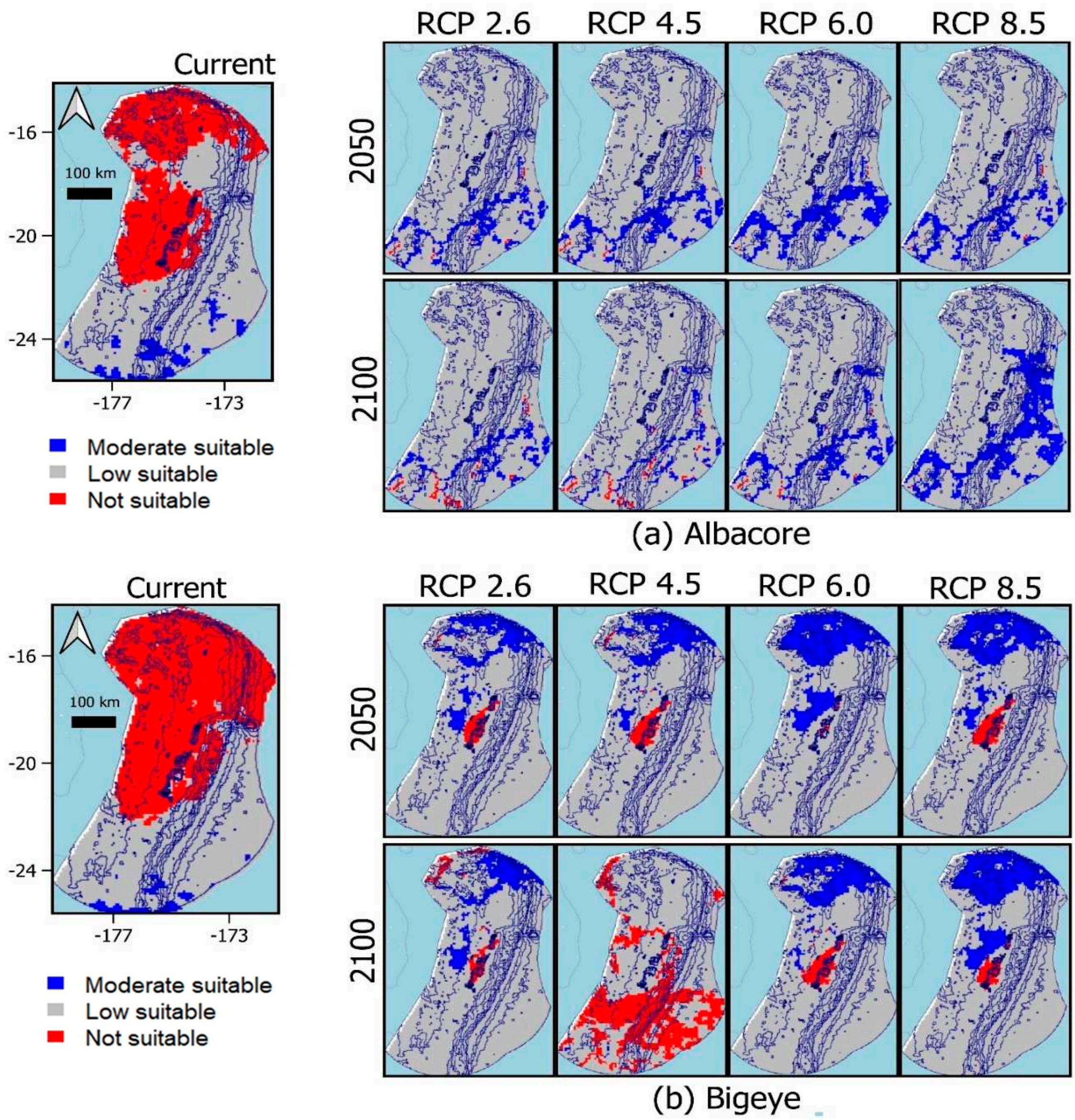
Scenario	Albacore (km^2)	Bigeye (km^2)	Yellowfin (km^2)	Skipjack (km^2)	Total (km^2)
Current	10,222	32,876	18,503	17,350	78,951
RCP 2.6/2050	11,338	39,758	20,064	22,901	94,062
RCP 2.6/2100	11,105	43,466	19,787	26,158	100,515
RCP 4.5/2050	11,549	40,012	20,123	24,059	95,744
RCP 4.5/2100	11,011	33,558	19,353	22,000	85,923
RCP 6.0/2050	12,317	54,573	20,143	32,725	119,759
RCP 6.0/2100	11,670	41,539	19,667	29,964	102,840
RCP 8.5/2050	11,542	37,452	20,139	25,422	95,555
RCP 8.5/2100	13,095	48,053	20,015	56,682	137,845

Table 3. The percentage increase of the future scenarios relative to the current scenario based on the assumption in maintaining present fishing effort. Percentage values are in terms of the area presented in Table 2.

Scenario	% Increase relative to current scenario				
	Albacore	Bigeye	Yellowfin	Skipjack	Total
RCP 2.6/2050	10.92	20.94	8.44	31.99	19.14
RCP 2.6/2100	8.65	32.21	6.94	50.76	27.31
RCP 4.5/2050	12.99	21.71	8.76	38.67	21.27
RCP 4.5/2100	7.72	2.08	4.59	26.80	8.83
RCP 6.0/2050	20.50	66.00	8.86	88.61	51.69
RCP 6.0/2100	14.17	26.35	6.29	72.70	30.26
RCP 8.5/2050	12.92	13.92	8.84	46.52	19.76
RCP 8.5/2100	28.11	46.16	8.17	226.69	74.60

3.4. Biogeographical distribution of species

The ensemble models of the species were used to produce maps (Figure 2) showing the suitability areas or presence (invaded area, colored grey and blue) of tuna species. The thresholds for the ensemble models of Albacore, Bigeye, Skipjack and Yellowfin were 0.23, 0.24, 0.26, 0.26 respectively (Table S1). Pixels below the threshold were considered not suitable (uninvaded, colored red) of the species. Future projections indicate a general expansion of suitability areas for all species (Table 2, Figure 3). Furthermore, our future projections also indicated a shift trend in suability areas to the south of the EEZ for Albacore and Yellowfin (Figure 3 (a) & (c)), towards the north for Bigeye (Figure 3 (b)). Skipjack suitability areas increase (Figure 3 (d)) in the northern, the central and along the western areas of the EEZ. These trends of suitability habitats, considering all species, are expected to increase and remain mainly in the central and towards southern part of the EEZ. Our projection show Skipjack has the highest suitability habitat areas then Bigeye and Yellowfin (Table 2 & Figure 3). Hence, we identified three main climatic stable areas from our future projection: the southern part (more pronounce for Albacore & Yellowfin), the northern part (more pronounce for Bigeye), the central and along western parts (more pronounce for Skipjack). Stable areas were generally higher in the year 2050 (for all RCPs for all species, except RCP 8.5 for Albacore and Skipjack), when considering all future scenarios agreeing with the size of tuna predicted suitability habitats areas (Table 2) for the species.



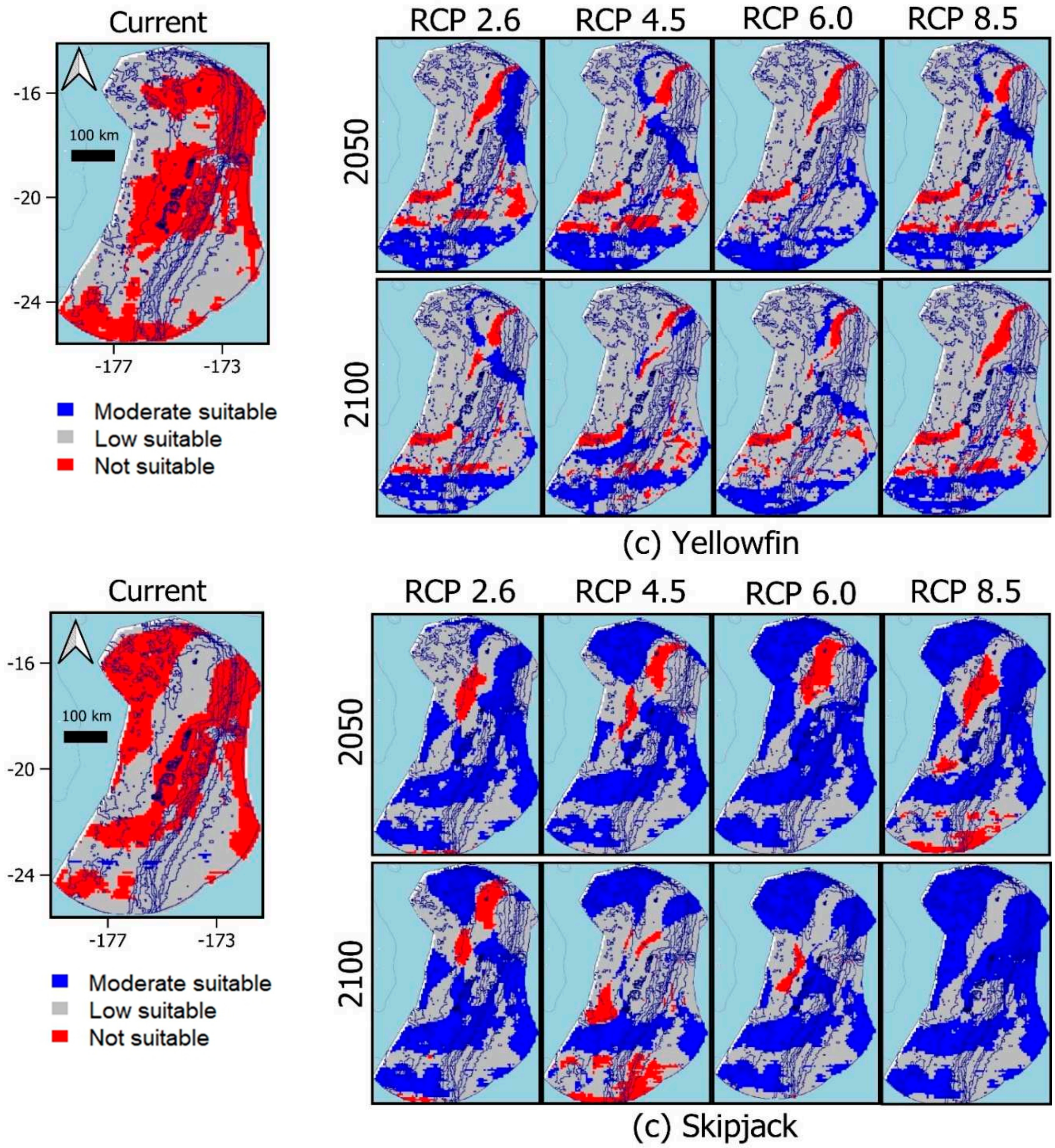


Figure 3. Projection distribution of suitability areas(invaded, indicated by blue and grey colors) and not suitable areas (uninvaded indicated by red color) for the current and future times for (a) Albacore, (b) Bigeye, (c) Skipjack and (d) Yellowfin yielded by our ensemble niche models of each diagnostic species (see Table 1). Shown also is bathymetry contours (indicated by soft colored blue lines) from the National Oceanic and Atmospheric Administration [44] data.

4. Discussion

We predicted the climate adjusted optimum fisheries areas for Albacore, Bigeye, Skipjack and Yellowfin tuna in the EEZ of Tonga in the current and future scenarios. Similar studies have been done in other areas [8,32,45] including the South Pacific [8] and WCPO [46] on different tuna species. Our selected predictor variables have been used in previous studies [8,47] but these studies were not done in countries local EEZs. Furthermore, when conducted, these studies were limited to a single species [48]. In our study, we used a common dataset (both in the current and future scenarios) and consistent approaches (using of GAM, GLM and FDA in the *sdm* package) to provide a comprehensive view of suitability habitat areas of four tuna species under current and future climatic conditions anticipating climate change effects on population species. We believe there have been no scientific studies done on tuna suitability habitat nor on our selected predictor variables in Tonga [19,49]. Hence it may be too early to use our results for practical applications regarding the impacts of climate change on tuna species distribution, even so, our results showed strong indication of suitability stable areas both in our current and future projections(see Results sections 3.3 and 3.4, Figure 2). Similar studies have been conducted elsewhere, employing comparable methodologies on marine and land species [47,50–52]. Our selected environmental variables indicated that the four tuna species occurrences can either increase or decrease at certain predictor variable ranges (Figure S3). This might be due to the fact that tuna species prefer certain environmental conditions for feeding [53,54], migration [55] and spawning [56]. Hence, changes in environmental conditions can significantly alter the presence of tuna. From our variable response curves (Figure S3), tuna were caught in temperature range $23^0\ C$ and $30^0\ C$, salinity range 34.6 PSU and 35.6 PSU and ocean current range $0.08\,ms^1$ and $0.48\,ms^1$. These correspond to the world's tropical-subtropical and temperate tuna preferences range of $20^0\ C$ to $30^0\ C$ and $\leq 25^0\ C$ [57] respectively. Bigeye and Yellowfin have less clearly defined salinity preference and tolerate water salinity as low as 33 PSU [57,58].

However, Albacore and Skipjack still caught in Tonga in salinity range 35 - 37 PSU (Figure S3) even when previous finding stated their salinity preference is much more well defined [57–59]. Our results showed that SST has the highest contribution in predicting suitability habitat followed by SSS for all species (Figure S3). Furthermore, probability of tuna occurrence is higher in lower sea surface temperature and sea surface salinity but in higher sea surface current (Figure S3). The lack of studies in the area on tuna species distribution, environmental preferences and climate change impacts on tuna limits our discussion to comparable and corresponding studies. Although tuna is well known as a migratory species, little is known about its local distribution such as the EEZ of small Pacific Island Countries like Tonga [60,61]. Distribution modeling studies are thus essential for optimizing the necessary information on potential productive sites and their environmental traits to enable prediction of suitable areas for the current and future occurrence of these species.

In terms of current and future projections of stable areas, we presented the results of ensemble models built from machine learning algorithms (GAM and GLM) and regression algorithm (FDA). Our current predictions show mostly areas of low and not suitable conditions (mainly in the northern part for all species) and only small patches of moderate suitability in the southern part of the EEZ. On the other hand, our results show an increase of fisheries suitable areas for the future relative to the current conditions for all species mainly in the year 2050 (see results sections 3.3 and 3.4).

These predicted high stable areas could be attributed to; i) environmental preferences of the species. ii) geologically bathypelagic features of the fishing ground and, iii) the presence of pelagic prey species in the fisheries area. As previously stated (see Study area section 2.1), the EEZ of Tonga partly envelops the; famous Tonga Trench, Tonga Ridge, Tofua Arce Volcanic Front, northern end of the Tonga Kermadec Arc, the westward region of the Lau Basin, the northern end of the Louisville Seamount Chain and the parallel north to south chains of volcanic seamounts along the Tonga Ridge. Studies have shown [62,63], that geologically bathypelagic features of the fishing ground, such as underwater mountains and canyons, have a significant influence on the presence and distribution of tuna in the ocean. Variability in ocean bottom depth in the South Pacific Ocean influence the vulnerability of Albacore tuna [64]. At tropical latitudes, Albacore tuna showed a distinct diel pattern in vertical habitat, occupying shallower, cooler waters above the mixed layer depth [65]. These features can create areas of upwelling and nutrient-rich waters, which can attract tuna and other pelagic species [66]. In addition, the physical characteristics of the seafloor, such as depth and substrate type, can also play a role in tuna habitat selection and movement [67].

Furthermore, presence of pelagic prey species can have a significant influence on the abundance and distribution of tuna [68]. For example, studies have shown that the availability of small pelagic fish, such as anchovies and sardines, can be a key factor in the movement and aggregation of tuna schools [69]. Environmental factors such as temperature and salinity affect the distribution and abundance of both tuna and their prey [70]. Tuna species prefer cooler ocean areas as compared to warmer areas as cooler waters tend to be more nutrient-rich, which supports the growth of the small

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fish and squid that make up their diet [71,72]. A better understanding of the dynamics between tuna and their prey species is essential for effective fisheries management and conservation.

Increase in stable habitat area for Skipjack happens along the west in the north-south direction which are areas occupy by the Tonga Ridge and the famous Tonga Trench and the northern end of the Louisville Seamount Chain (Figures 1 & 2). These oceanic features may influence environmental conditions such as surface water temperature, nutrient, salt content, upwelling and mixed layer depth, which are preferred habitats for pelagic species such as tuna [62,64,65]. Furthermore, studies have shown that large offshore fishes are well known to habit in these areas principally due to foraging advantages [62] and possibly for reproductive and navigational benefits [62,73,74]. This may also be the reason for persistent presence of the four tuna species in their current conditions and their expansion in future projections (Figure 2).

It is important to acknowledge the limitations of this study. The short time series of our dataset may not capture the full range of the expected variability and trends of climate change impacts on our studied species, making it difficult to identify meaningful patterns [75]. Additionally, statistical analyses may be limited in their ability to detect significant effects or relationships due to insufficient data points [75]. The moderation effect of travel costs on tuna catch could also be a limitation in this research study. It may be difficult to accurately measure and control for the various factors that influence travel costs [76], such as fuel prices, distance to fishing grounds [77], and vessel efficiency [78] which are information not available to our study. This can make it challenging to isolate the true effect of travel costs on tuna catch [79], and to generalize findings to other contexts with different travel cost structures. Additionally, the relationship between travel costs and tuna catch may be subject to nonlinear or threshold effects [80], which can further complicate interpretation and analysis.

The study of marine ecosystems and their inhabitants is of paramount importance due to their ecological and economic value [81,82]. Tuna species, in particular, are widely exploited for commercial purposes, making it imperative to understand their population dynamics [83,84]. However, obtaining accurate information on their population trends has proven to be challenging due to the species' migratory behavior and high mobility [84–86]. To address this issue, it is important to conduct studies on species population genetics, isotopic trophic food, and investigations on ocean current variability and chemistry of our study area. Population genetic provide information on genetic diversity, gene flow, and population structure [57]. Isotopic trophic food studies provide information on the feeding habits, trophic position, and migration patterns of the studied species, which can help identify critical habitats and inform conservation efforts [87,88]. Ocean current variability and chemistry is important provide information on the distribution and migration patterns of the species, as well as their physiological responses to changes in ocean conditions [89,90]. Also, social and economic factors such as tuna fisheries effort constraints should be taken into consideration as these factors can have a significant impact on the fishing pressure exerted on the species [91,92]. Therefore, we recommend further researches to be conducted in light of the above stated areas, which could provide valuable insights on the goals of this study.

5. Conclusion

We predict suitable habitats for four tuna species; Albacore, Bigeye, Skipjack and Yellowfin in the current and future scenarios which may conserve species populations in the EEZ of Tonga. Considering environmental variation from current conditions to future scenarios of climate change in our models, RCP 8.5 in the year 2100 is likely to be more climatically stable for all the four tuna species. It is also shown (Table 2 & Figure 2 (b), (c) and (d)) that tropical-subtropical tuna (Bigeye, Skipjack & Yellowfin) have more future occurrences and stable areas than temperate tuna (Albacore) due to their ability to tolerate environmental habitats in our study region. Furthermore, as discussed, we attributed climatically stable areas predicted in the current and future times to the environmental preferences of the species, the geologically bathypelagic features of the fishing ground and the presence of pelagic prey species in the fisheries area.

Because our results were largely based on use of environmental variables and catch data, our findings should not be treated as ready-made for on-the-ground application but could be used as one of many tools to help in conservation planning of the studied species. We recommend that further studies on habitat suitability in the current study site be carried out for further quantification of predicted occupancy status shown here. Furthermore, we also recommend that these future studies consider the inclusion of other environmental variables such as dissolved oxygen, mixed layer depth, sea surface height and chlorophyll-a concentration as predictor variables. These variables have been shown as preferred habitats for various tuna species [93–95]. The application of species distribution modelling can be limited for example by; model performance and the reliability of climatic future predictions [96] and by assuming there is a balance between environmental changes and spatial distribution of the species [97]. Nevertheless, our study provides a solid foundation for future development of conservation measures aimed at sustainable harvesting and management of the species populations. These findings are of relevance for conservation planning predicated on the protection of biodiversity under climate change scenarios.

Supplementary Materials: The following supporting information can be downloaded at the website of this paper posted on Preprints.org, **Figure S1**. Receiver operator characteristics using bootstrap and subsampling replication methods for different *sdms* for Albacore, Bigeye, Skipjack and Yellowfin: **Figure S2**. Response curves from the ensemble models to the three selected environmental variables for Albacore, Bigeye, Skipjack and Yellowfin; **Figure S3**. Variable importance for three less correlated environmental variables of the ensemble species distribution model for Albacore, Bigeye, Skipjack and Yellowfin; **Table S1**. Predictive models from machine learning (FDA), regression (GAM and GLM) and their performance evaluation of *sdms*.

Data Availability Statement: All species data and extracted predictor variables are available in: VAIHOLA, SIOSAIA (2023), Tonga tuna, Dryad, Dataset,

https://datadryad.org/stash/share/Bkhr8-Suq6P0M3Q8MZ7XYymkqiy4kl2DQwfk39c5MhQ

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