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Climate Change Potential Impacts on the Tuna Fisheries in the Exclusive Economic Zones 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. The information provided here will be relevant in planning future national actions towards the proper management of these species.

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

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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 of and impacts of climate change on marine ecosystems [4,5]. Tuna is greatly impacted by climate change, both in the Pacific Island countries and at a global scale [6–8]. These impacts include shifts in species biogeographical distribution and the loss of suitable habitats due to changes to their biophysical environments such as an increase in water temperature and a decrease in oxygen concentration [9–12].

Tuna, highly migratory and widely distributed across the world's oceans for feeding and spawning [13,14], are predominantly captured in the Western Central Pacific Ocean (WCPO) [15], which accounts for approximately 80% of the global tuna catch.

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].

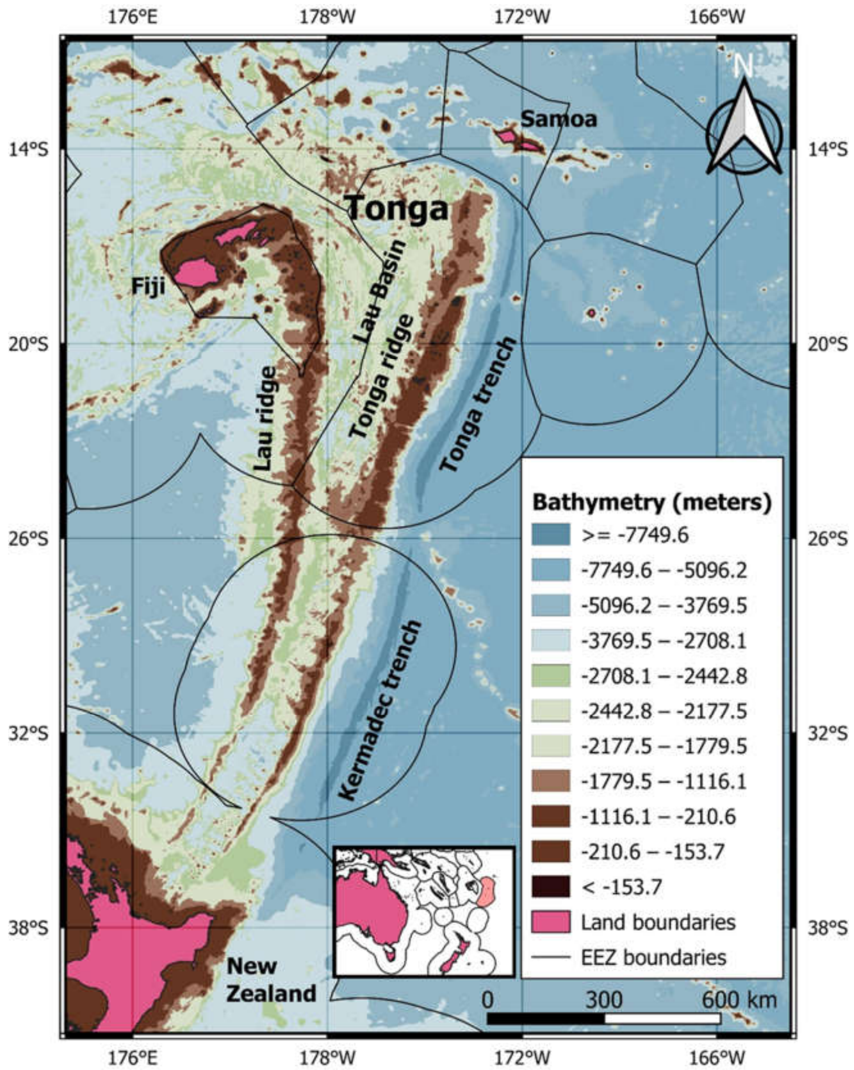

Figure 1. Map of the study region, Tonga exclusive economic zone.

Given Tonga's geographical location within the WCPO, which accounts for the largest portion of the world's tuna catch, the country's tuna fisheries face the challenge of climatic variabilities such as global warming [20,21] and the El Nino Southern Oscillation (ENSO) [22,23], which threaten global fisheries production and impact the distribution and abundance of tuna [5,24]. These events have negative impacts which include increasing regional temperatures, changing weather patterns, rising sea levels, ocean acidification, changing nutrient loads in ocean circulations, increasing stratification of the water column, and changing 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]. One of the most prominent impacts of climate change on tuna is the alteration of ocean temperatures. Rising water temperatures can affect the distribution and migration patterns of tuna, as they are highly sensitive to temperature changes [28]. As their preferred temperature ranges shift, tuna populations may move to different areas, potentially disrupting their normal breeding and feeding grounds. Changes in ocean currents and nutrient distribution can cause variations in the abundance and distribution of phytoplankton and zooplankton, which serve as vital prey for tuna [29]. These disruptions in the food chain can result in reduced growth rates and lower survival rates for tuna, thereby impacting their population dynamics. Climate change can alter the preferred range of salinity for tuna by changing precipitation patterns and freshwater input into the oceans, leading to shifts in surface water salinity levels [30,31]. These changes can disrupt the availability of prey species and affect the suitability of habitats, ultimately influencing the distribution and behavior of tuna populations [32,33]. Moreover, ocean acidification resulting from increased carbon dioxide absorption by seawater poses a threat to tuna. Acidic waters hinder the development and survival of tuna larvae, which consequently affects their recruitment and overall population numbers [34]. Under these circumstances, environmental stress on primary producers is transferred along the trophic webs and the impacts permeate throughout marine communities [35]; including changes in tuna spatial and temporal distribution is crucial for tuna species conservation [25,36]. As a result, tuna catches are decreasing in many parts of the world [6,37]. Therefore, it is crucial for the PICs to establish proper management of the stocks so that harvesting is at a sustainable level given the environmental conditions.

In this context, predicting future environmental conditions and their effects on species distribution is crucial for 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 into species distributions and obtain crucial knowledge for biodiversity conservation and management [38,39]. The goal of this study is to estimate the impacts of climate change 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 in 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 southwest of Fiji and 1900 km northwest of New Zealand in the South Pacific Ocean. It covers an EEZ (latitude 14.15°S–20.22°S, longitude 171.31°W–179.10°W) of approximately 800 km^2. This EEZ envelops the northern end of the Tonga trench, the Tonga Ridge, the Tofua Arc Volcanic Front, the northern end of the Tonga Kermadec Arc, and the westward region of the Lau Basin [40]. There are 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 the surface water temperature, nutrients, 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].

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 was checked by a minimum of two fisheries offices to ensure compliance [19]. The data's 1° spatial grid comprises 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 fishing record, providing a standardised measure of fishing efficiency and effort in capturing the target species [41,42]. The CPUE data were aggregated into monthly and annual resolved datasets to match the temporal scales of the predictor variables in Microsoft Excel [43]. The distributions of the CPUEs of albacore, bigeye, yellowfin, and skipjack are shown in Figure 2a–d, respectively.

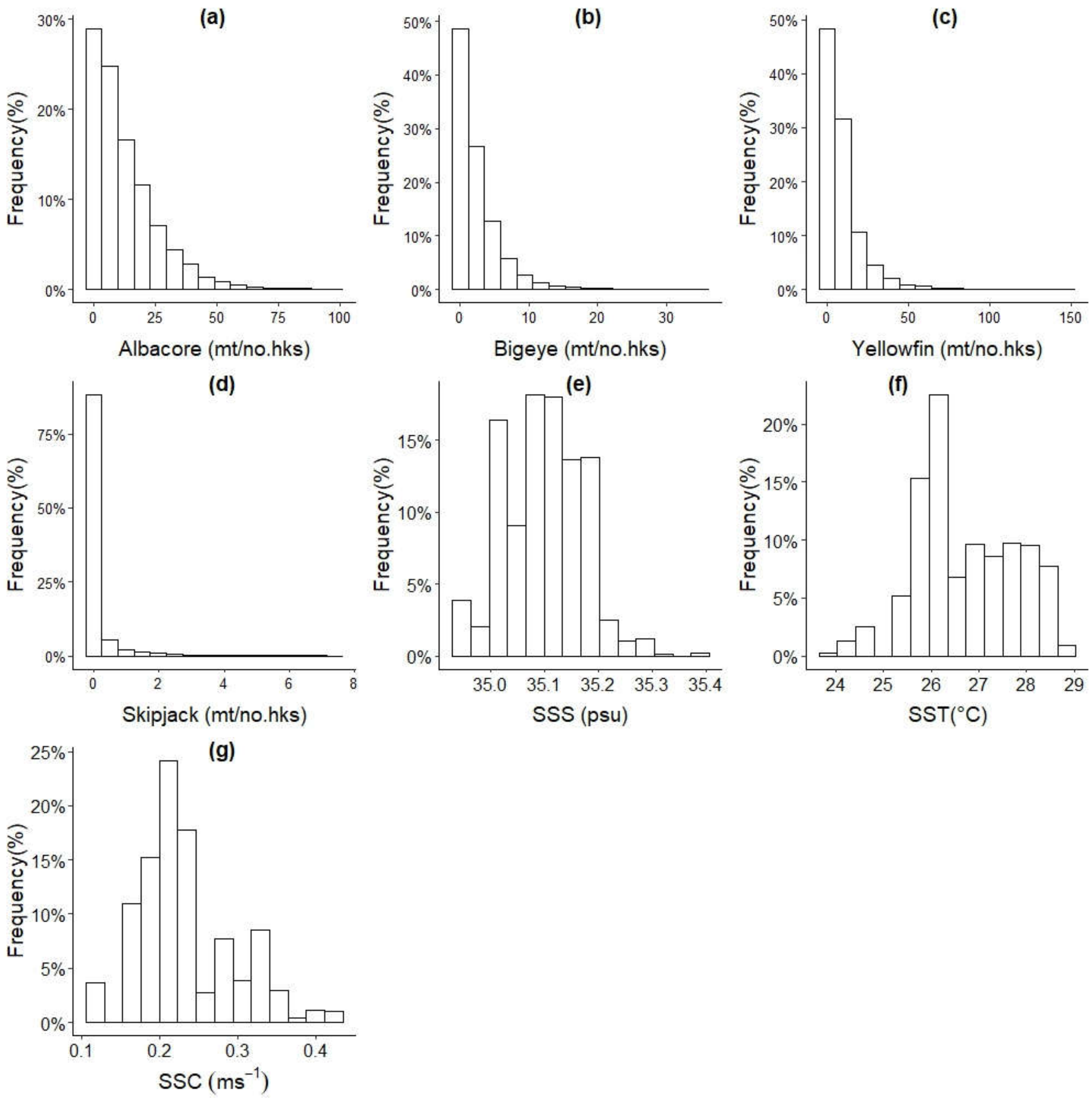

Figure 2. Histograms of the distribution of CPUE (million tons per number of hooks) of tuna ((**a**) albacore, (**b**) bigeye, (**c**) yellowfin, (**d**) and skipjack) and environmental data ((**e**) SSS, (**f**) SST, and (**g**) SSC) for the duration of the study period of this study, 2002–2018, of the Tonga tuna fisheries and the Bio–ORACLE version 2.0 dataset [44], respectively, taken within the EEZ (Figure 1) of Tonga. SSC = sea surface current, SSS = sea surface salinity, and SST = sea surface temperature.

Table 1. Pre-selection environmental variables and tuna fisheries data used to build the species models. Both the tuna fisheries and the environmental data were taken within the EEZ (exclusive economic zone, latitude 14.15°S–20.22°S, longitude 171.31°W–179.10°W) of Tonga.

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

2.3. Predictor Variables

We used the R packages *sdmpredictors* and *leaflet* to access potential predictor variables. We chose the Bio–ORACLE version 2.0 dataset [44], which provided the most complete set of variables for the study area both in the current and future projections. The variables selected (Table 1) were temperature, salinity, and current velocity, among other factors at the sea surface. Secondly, we performed a statistical selection by employing the variance inflation factor (VIF) method, utilising the *sdm* package in the R environment [45,46]. We included all selected variables due to their low *VIF* (<3) and Pearson correlation coefficients ($r < 0.7$). This ensures reduced dependence among the variables and enhanced predictability. The present values refer to the period between 2010 and 2022 and the future projections refer to the periods 2040–2050 and 2090–2100 under different greenhouse gas concentration scenarios based on different representative concentration pathways (RCPs). 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) to forecast the future distribution of the four tuna species across the range of climate change predictions, respectively. The variables were available at a spatial resolution of 5 arc-minutes (~0.083°).

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 three algorithms of the *sdm* R package version 1.0–67 [47]. These algorithms were: generalised additive models (GAM, a nonparametric regression approach), generalised linear models (GLM, a flexible generalisation 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 four 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 minimise the error for each model and created a weighted ensemble model by aggregating those with an optimal TSS. True skill statistic is threshold dependent, and we used the sensitivity–specificity sum maximisation approach which selects the best thresholds (Table 2) for correct classification rates of presences and absences [48]. For the purpose of this study, we included in our analysis algorithms with a mean test TSS under 0.5 (Table 2) considering that it has a larger range (between -1 and 1) of variation than the AUC (between 0 and 1). We then used the selected algorithms and the complete modelling 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, and RCP 8.5 [49] 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 representing the presence of the species and pixels lower than the threshold indicating 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.

Table 2. Predictive models from machine learning (FDA), regression (GAM and GLM), and their performance evaluation of *sdms* using different statistical parameters for albacore, bigeye, skipjack, and yellowfin within the EEZ (exclusive economic zone, latitude 14.15°S–20.22°S, longitude 171.31°W–179.10°W) of Tonga. Sensitivity and specificity describe the rate of true positive and negative, respectively.

Model	AUC	TSS	Deviance	Sensitivity	Specificity	Threshold	Prevalence
Albacore							
GAM	0.48	0.40	0.21	0.66	0.54	0.24	0.71
GLM	0.48	0.41	0.19	0.60	0.63	0.22	0.62
FDA	0.48	0.42	0.19	0.60	0.62	0.22	0.63
Bigeye							
GAM	0.47	0.43	5.47	0.55	0.69	0.25	0.56
GLM	0.48	0.42	0.40	0.55	0.70	0.24	0.55
FDA	0.48	0.41	0.40	0.55	0.71	0.24	0.54
Skipjack							
GAM	0.43	0.42	0.25	0.55	0.68	0.26	0.55
GLM	0.44	0.42	0.25	0.53	0.73	0.26	0.52
FDA	0.44	0.42	0.25	0.52	0.72	0.24	0.52
Yellowfin							
GAM	0.46	0.42	0.24	0.50	0.77	0.24	0.48
GLM	0.45	0.44	0.25	0.46	0.80	0.26	0.45
FDA	0.44	0.43	0.25	0.45	0.81	0.25	0.44

2.5. Climatic Suitable Areas

We obtained climatically suitable areas using a weighted method, where the presence probability (obtained using the *ensemble* function in the *sdm*) of each current and future scenario is multiplied by the cell's area, then subsequently summing all raster values [50]. 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 a 0.1 value, that is a 10% chance of the species occurring in the cell, we calculated 10% of the cell area and added 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 2. The accuracy of our models was not very high (TSS range 0.40 to 0.44, deviance range 0.19 to 0.47). 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. 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 the species presence and absence cells were well identified, and the proportion of correctly classified samples was maximised.

3.2. Relative Contribution of the Predictor Variables

In terms of variable importance, our results show that 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 3). In addition to the observed trends, the likelihood of encountering these species is strongly influenced by the selected 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 3) 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 3).

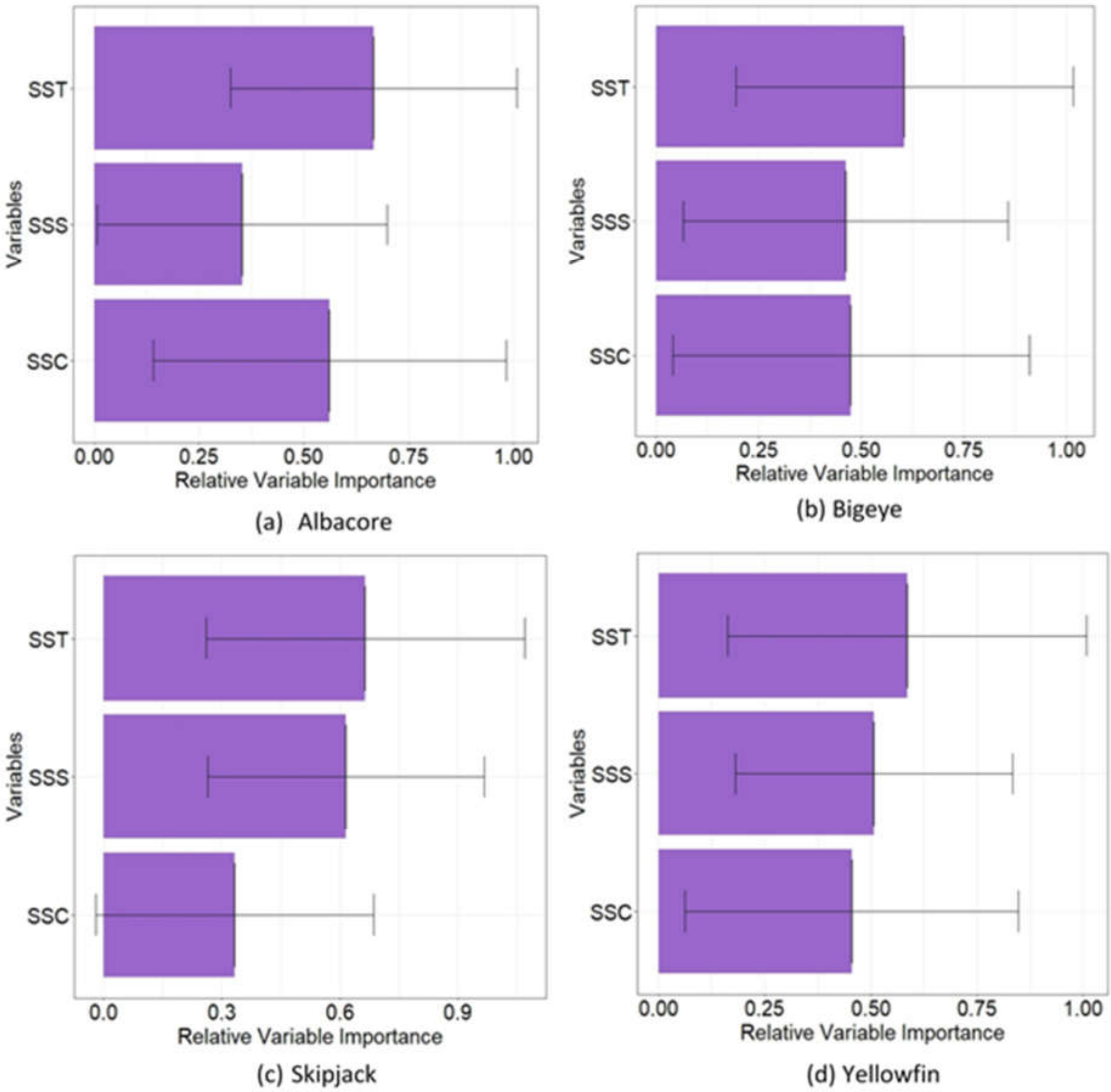

Figure 3. Variable importance for three less correlated environmental variables of the ensemble species distribution model for albacore, bigeye, skipjack, and yellowfin in panels (**a**–**d**), respectively. SSC = sea surface current, SSS = sea surface salinity, and SST = sea surface temperature in the EEZ (exclusive economic zone, latitude 14.15°S–20.22°S, longitude 171.31°W–179.10°W) of Tonga.

3.3. Predicted Suitability Habitat

The results of the predicted suitability habitats for both current and future projections are presented in Tables 3 and 4. 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 a total of 78,951 km^2 (Table 3). The future scenarios showed a general increase in suitable habitats 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, for bigeye, it is 54,537 km^2 for RCP 6.0 in the year 2050, for skipjack, it is 56,682 km^2 for RCP 8.5 in the year 2100, and it is 20,139 km^2 for yellowfin in the year 2050 for RCP 8.5 (Table 3). The percentage increase of the future scenarios relative to the current scenario is presented in Table 4. The high percentage increase corresponds 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, from 33,558 km^2 for RCP 4.5 in the year 2100 to 48,053 km^2 for RCP 8.5 in the year 2100 for bigeye, from 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 for yellowfin, and from 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 3. Total summed area in current and future scenarios taken within the EEZ (exclusive economic zone, latitude 14.15° S–20.22° S, longitude 171.31° W–179.10° W) of Tonga using a weighted method described in Section 2.5.

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 4. The percentage increase of the future scenarios relative to the current scenario based on the assumption in maintaining present fishing efforts within the EEZ (exclusive economic zone, latitude 14.15° S–20.22° S, longitude 171.31° W–179.10° W) of Tonga. The percentage values are in terms of the area presented in Table 3.

Scenario	% Increase Relative to the 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 4) showing the suitability areas or presence (invaded area, coloured 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, and 0.26, respectively (Table 2). Pixels below the threshold were considered not suitable (uninvaded, coloured red) for the species. Future projections indicate a general expansion of suitability areas for all species (Table 3, Figure 4). Furthermore, our future projections also indicated a shift trend in suability areas to the south of the EEZ for albacore and yellowfin (Figure 4a,c) and towards the north for bigeye (Figure 4b). Skipjack suitability areas increase (Figure 4d) in the northern, 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 the southern part of the EEZ. Our projection shows that skipjack has the highest suitability habitat areas and then bigeye and yellowfin (Table 3 and Figure 4). Hence, we identified three main climatic stable areas from our future projection: the southern part (more pronounced for albacore and yellowfin), the northern part (more pronounce for bigeye), and 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 the tuna predicted suitability habitats areas (Table 3) for the species.

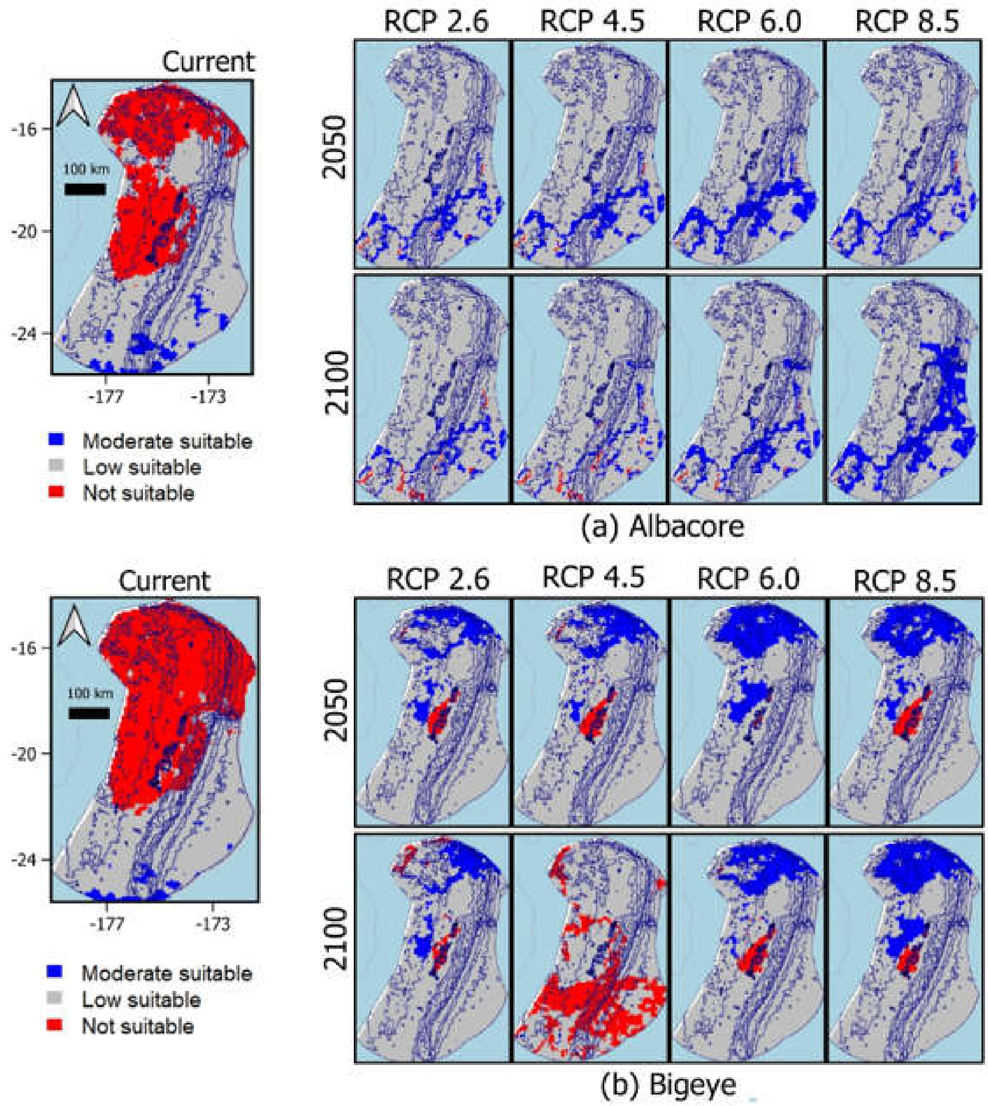

Figure 4. *Cont.*

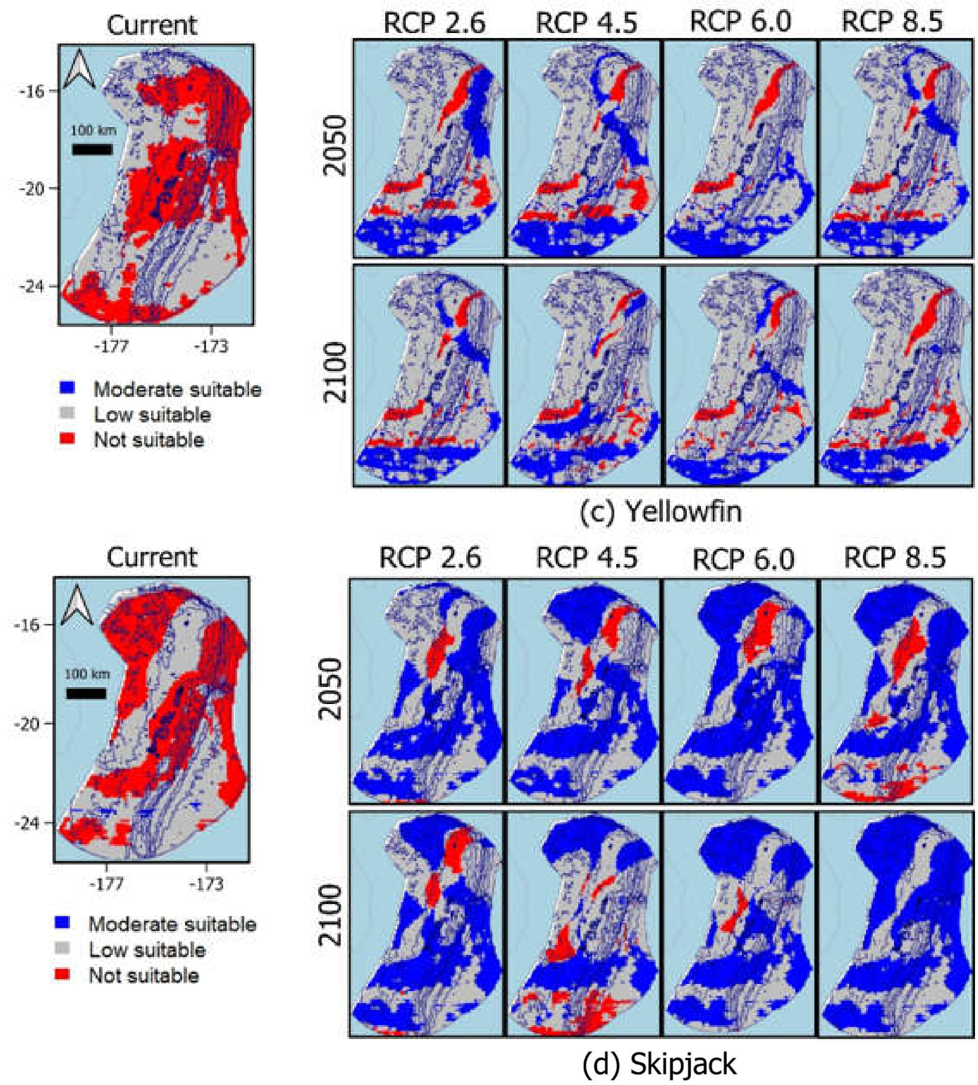

Figure 4. Projection distribution of suitability areas (invaded, indicated by blue and grey colours) and unsuitable areas (uninvaded, indicated by the red color) for the current and future times for (**a**) albacore, (**b**) bigeye, (**c**) yellowfin, and (**d**) skipjack yielded by our ensemble niche models of each diagnostic species (see Table 1) taken within the EEZ (exclusive economic zone, latitude 14.15° S–20.22° S, longitude 171.31° W–179.10° W) of Tonga. Also shown are the bathymetry contours (indicated by soft coloured blue lines) from the National Oceanic and Atmospheric Administration [51] 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 conducted in other areas [8,39,52] including the South Pacific [8] and the WCPO [53] on different tuna species. Our selected predictor variables have been used in previous studies [8,54] but these studies were not conducted in countries' local EEZs. Furthermore, when conducted, these studies were limited to a single species [55]. In our study, we used a common dataset (both in the current and future scenarios) and consistent approaches (using GAM, GLM, and FDA in the *sdm* package) to provide a comprehensive view of suitable 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 conducted on tuna suitability habitats nor on our selected predictor variables in Tonga [19,56]. 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 a strong indication of stable suitability areas both in our current and future projections (see Sections 3.3 and 3.4, Figure 4). Similar studies have been conducted elsewhere, employing comparable methodologies on marine and land species [54,57–59]. Our selected environmental variables indicated that the four tuna species' occurrences can either increase or decrease at certain predictor variable ranges (Figure 3). This might be due to the fact that tuna species prefer certain environmental conditions for feeding [60,61], migration [62], and spawning [63]. Hence, changes in environmental conditions can significantly alter the presence of tuna. From our variable response curves (Figure 3), the tuna species were caught in the temperature range of 23 °C to 30 °C, the salinity range of 34.6 PSU to 35.6 PSU, and the ocean current range of 0.08 ms^{-1} to 0.48 ms^{-1}. These correspond to the world's tropical–subtropical and temperate tuna preferences range of 20 °C to 30 °C and $\leq$25 °C [64], respectively. Bigeye and yellowfin have less clearly defined salinity preferences and tolerate water salinity as low as 33 PSU [64,65].

However, albacore and skipjack were still caught in Tonga in the salinity range of 35 PSU–37 PSU (Figure 3) even when the previous finding stated that their salinity preference is much more well defined [66–68]. Our results showed that SST has the highest contribution in predicting suitability habitats followed by SSS for all species (Figure 3). Furthermore, the probability of tuna occurrence is higher with a lower sea surface temperature and sea surface salinity but in a higher sea surface current (Figure 3). 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 are well known as a migratory species, little is known about their local distribution such as the EEZ of small Pacific Island Countries like Tonga [69,70]. Distribution modelling studies are thus essential for optimising the necessary information on potential productive sites and their environmental traits to enable the 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 a regression algorithm (FDA). Our current predictions show mostly areas of low and unsuitable 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 in suitable fisheries areas for the future relative to the current conditions for all species mainly in the year 2050 (see Sections 3.3 and 3.4). This presents an opportunity for effective management strategies for tuna fisheries in Tonga. The information could be used to ensure successful stewardship of these growing areas through conducting regular monitoring and assessment of the tuna population in order to validate the current analysis. This will help ensure the accuracy and reliability of the data used for management decisions. Also, through this evaluation, adjustments could be made to resource allocation, fishing techniques, and gear in order to maintain sustainable practices. There is an opportunity to understand the ecological interactions within the newly suitable habitat which allows for a comprehensive approach that considers behavioural changes, competition, and predation. This allows greater engagement by stakeholders, including fishing communities, scientists, environmental organisations, and policymakers, in decision-making processes which fosters inclusivity and effective management strategies that align with the changing habitat conditions.

These predicted highly stable areas could be attributed to: (i) the environmental preferences of the species; (ii) the geologically bathypelagic features of the fishing ground; and (iii) the presence of pelagic prey species in the fisheries area. As previously stated (see Section 2.1), the EEZ of Tonga partly envelops the famous Tonga Trench, the Tonga Ridge, the Tofua Arce Volcanic Front, the 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 the 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 influences the vulnerability of albacore tuna [71]. At tropical latitudes, albacore tuna showed a distinct diel pattern in vertical habitat, occupying shallower, cooler waters above the mixed layer depth [72]. These features can create areas of upwelling and nutrient-rich waters, which can attract tuna and other pelagic species [73]. In addition, the physical characteristics of the seafloor, such as the depth and substrate type, can also play a role in tuna habitat selection and movement [74].

Furthermore, the presence of pelagic prey species can have a significant influence on the abundance and distribution of tuna [75]. 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 [76]. Environmental factors such as temperature and salinity affect the distribution and abundance of both tuna and their prey [77]. 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 fish and squid that make up their diet [78,79]. A better understanding of the dynamics between tuna and their prey species is essential for effective fisheries management and conservation.

An increase in the stable habitat area for skipjack happens along the west in the north–south direction which is an occupied by the Tonga Ridge and the famous Tonga Trench and the northern end of the Louisville Seamount Chain (Figures 1 and 2). These oceanic features may influence environmental conditions such as surface water temperature, nutrients, salt content, upwelling, and mixed layer depth, which are preferred habitats for pelagic species such as tuna [69,71,72]. Furthermore, studies have shown that large offshore fish are well known to inhabit these areas principally due to foraging advantages [69] and possibly for reproductive and navigational benefits [69,80,81]. This may also be the reason for the persistent presence of the four tuna species in their current conditions and their expansion in future projections (Figure 4).

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 [82]. Additionally, statistical analyses may be limited in their ability to detect significant effects or relationships due to insufficient data points [82]. 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 [83], such as fuel prices, the distance to fishing grounds [84], and vessel efficiency [85], which is information not available to our study. This can make it challenging to isolate the true effect of travel costs on tuna catch [86] and to generalise the 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 [87], 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 [88,89]. Tuna species, in particular, are widely exploited for commercial purposes, making it imperative to understand their population dynamics [90,91]. However, obtaining accurate information on their population trends has proven to be challenging due to the species' migratory behaviour and high mobility [91–93]. To address this issue, it is important to conduct studies on species population genetics and isotopic trophic food and investigations on the ocean current variability and chemistry of our study area. Population genetics provide information on genetic diversity, gene flow, and population structure [64]. 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 [94,95]. Ocean current variability and chemistry are important in providing information on the distribution and migration patterns of the species, as well as their physiological responses to changes in ocean conditions [96,97]. 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 [98,99]. Therefore, we recommend further studies to be conducted in light of the above stated areas, which could provide valuable insights on the goals of this study.

5. Conclusions

We have predicted 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 four tuna species. It was also shown that tropical–subtropical tuna (bigeye, skipjack, and yellowfin) have more future occurrences and stable areas than temperate tuna (Albacore) due to their ability to tolerate the 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 the 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 the 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 the 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 [100–102]. The application of species distribution modelling can be limited, for example, by model performance and the reliability of climatic future predictions [103] and by assuming that there is a balance between environmental changes and the spatial distribution of the species [104]. Nevertheless, our study provides a solid foundation for the future development of conservation measures aimed at the 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: https://www.mdpi.com/article/10.3390/d15070844/s1. Figure S1. Receiver operator characteristic (ROC) curve using bootstrap and subsampling replication methods for different *sdms* for (a) albacore, (b) bigeye, (c) skipjack, and (d) yellowfin taken within the EEZ of Tonga. The sensitivity (true positive rate) of the vertical line and 1-specificity (false positive rate) of the horizontal line describe the proportion of correctly and incorrectly classified samples. The red and blue curves represent the mean of the AUC using the training and test data, respectively. Figure S2. Response curves from the ensemble models to the three selected environmental variables for albacore, bigeye, skipjack, and yellowfin in panels (a), (b), (c), and (d), respectively, taken within the EEZ of Tonga. The response curves were fitted through locally estimated scatterplot smoothing (LOESS). SSC = sea surface current, SSS = sea surface salinity, and SST = sea surface temperature.

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