Role of environmental conditions in structuring the stock trajectory of *Thunnus albacares*, *Th. alalunga* and *Th. obesus* in the South Pacific Region

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The lifestyle and culture of South Pacific Island countries have been long intertwined with oceanic resources. These countries are heavily dependent on tuna resources for their economies and socioeconomic livelihoods. Despite their importance, the mechanisms behind tuna stock trajectory patterns need to be better understood. With changing climatic and environmental conditions, it has become vital to understand the impact of these changes on tuna resources and if possible include them in long-term tuna harvest and management plans. A significant portion of the stock dynamics of yellowfin tuna (*Thunnus albacares*), albacore tuna (*Th. alalunga*) and bigeye tuna (*Th. obesus*) in the South Pacific Region may possibly be explained only by the environmental factors of sea surface temperature (SST) and Atlantic Multidecadal Oscillation AMO. The relationship of monthly SST and AMO was investigated with time series stock patterns of *Th. albacares*, *Th. alalunga* and *Th. obesus* in the Eastern and Western Pacific Ocean for the years 1972 to 2019. Monthly variables that exhibited significant correlation with CPUE variables were used in the Generalised Linear Model and Generalized Additive Model to reproduce the CPUE trajectory of the three tuna species from 1972 to 2019. Results showed that a significant portion of stock dynamics of *Th. albacares*, *Th. alalunga* and *Th. obesus* can be explained well by two environmental conditions of SST and AMO. This shows that a large portion of tuna variation in the Eastern and Southern Pacific is related to environmental conditions. Models with single variables are evidence of the significant individual effect of SST and AMO on stock time series of each tuna species. Models with two variables had a better fit in comparison to models with a single variable for all tuna stocks. Possibilities of two significantly different patterns in the trajectory of the three tuna species and environmental conditions used in the models were also observed. The trajectory patterns seemed to change around the 1990s and had significantly different means, indicating possible regime shifts. Environmental conditions play a highly significant role in structuring tuna stock trajectory in the South Pacific and need to be included in tuna management / harvest plans to ensure sustainability of this important resource. The importance of regime shifts should be recognised and further investigated for possible inclusion in tuna sustainability plans due to their influence on long-term tuna trajectory patterns.

Keywords: albacore tuna; bigeye tuna; yellowfin tuna; Atlantic Multidecadal Oscillation; sea surface temperature; regime shift.

Introduction

The population and economies of a number of South Pacific Island Countries (PICs) are heavily dependent on the harvest of tuna resources (Bell et al., 2015; Bell et al., 2021). Tuna is harvested for sustenance of the socioeconomic livelihood and makes vital contribution towards food security of a significant population of PICs (Pilling et al., 2015; Johnson et al., 2020). Due to the limited capacity for tuna harvest, licences are issued to foreign nations for harvest of tuna resource in exchange for a licence fee. Some PICs economies are so heavily dependent on these fees that they are classified as tuna dependent (Bell et al., 2021). Overall, tuna fisheries from the Western and Central Pacific (WCP) contribute >50% of total global tuna supplies worth around USD$5.3 billion/year with a record catch of 2.9 million metric tonnes of tuna harvest in 2019 (World Bank, 2016; Seto & Hanich, 2018; Post & Squires, 2020). Tuna resources in the Eastern and Western South Pacific have seen a general decline over time and needs to be better understood in order to make effective and informed long-term management plans. Yellowfin tuna (*Thunnus albacares*) and bigeye tuna (*Th. obesus*) in WCP had already been assumed to have already reached the Maximum Sustainable Yield (MSY) limit and been overfished in early 2000s (Reid, 2006; Ovando et al., 2021).

Globally, tuna harvests have increased more than 1000 fold in the past six decades and account for around 61% of total offshore harvests (Fromentin & Powers, 2005; Coulter et al., 2020). These estimates do not include illegal and unregulated harvests, which may indicate that actual estimates may be much higher. Overharvesting and unsustainable practices of fishing have been claimed to be a major factor in depletion of oceanic tuna resources globally (Öztürk, 2015; Christensen, 2016). A stronger management of tuna harvesting and better planning may help recover tuna stocks. This, however, must be done with caution as tuna stocks may be affected by numerous other factors at varying levels including pollution, biological interactions and the changing climate.

Environmental variation impacts on tuna resources can studied and quantified using models that incorporate environmental variables (Sambah et al., 2023; Taboada et al., 2023; Wang et al., 2023). These models normally require environmental data over decadal timescales, which are not always readily available and may not be always of reliable quality. If reliable data is used, modelling approaches can provide reliable information that can be used by fishery managers to develop or improve their stock management plans for their important but limited tuna resources. Effective management approaches to tuna stocks impacted through environmental and climatic conditions would require cross country, regional and perhaps global management coordination across different sectors (Gianelli et al., 2023).

Amongst the multitude of factors impacting tuna resources in the Pacific, changes in climatic and environmental conditions are expected to be having a vital impact on the resources affecting the livelihood and economies of PICs (Johnson et al., 2020). The impact of environmental and climatic factors may have a more profound impact than is perhaps realised by fishery managers in the PICs and needs to be studied extensively and accounted for in tuna harvest plans. Wu et al. (2022) investigated the effect Pacific Decadal Oscillation (PDO), Atlantic Multidecadal Oscillation

(AMO) and sea surface temperature (SST) on Indo-Pacific *Th. albacares* stock CPUE from 1971–2018. The results showed a strong link between *Th. albacares* and environmental factors of SST and AMO phases. Similarly, a study on the East Pacific Ocean tuna catch with reference to effort between 1970–2018 and SST revealed a strong non-linear relation between tuna (*Th. albacares* and *Katsuwonus pelamis* (skipjack tuna)) and SST trajectory (Mediodia et al., 2020). Relationship of North Pacific and South Atlantic albacore tuna (*Th. alalunga*) populations to SST has been shown in different works (Singh et al., 2017; Singh et al., 2018; Vayghan et al., 2020). Indian Ocean and Atlantic Ocean *Th. obesus* stocks have been shown to be related to SST variation in different studies (Lee et al., 2005; Syamsuddin et al., 2016; Lan et al., 2018). Despite the importance of tuna in the South Pacific region, limited studies have been done on establishing the roles of long-term variations in climatic and environmental conditions on the stock trajectory patterns. The objective of this work was to determine whether the stock dynamics of *Th. albacares*, *Th. alalunga* and *Th. obesus* in the South Pacific Region can be explained significantly only by the environmental factors of SST and AMO.

Materials and methods

Stock data. Fish stock distribution data used in this study was obtained from the Western and Central Pacific Fisheries Commission (WCPFC). The WCPFC compiles annual, aggregate and operational tuna catch and effort estimates and makes these available through their public domain version available online (www.wcpfc.int). Historical longline catch and effort data for *Th. albacares*, *Th. alalunga* and *Th. obesus* in the South Pacific Region was obtained from the WCPFC public domain data for the years 1972–2019. Figure 1 shows the stock distribution zone for the three tuna species used in this study. The stock abundance index of standardized catch per unit effort (CPUE) data for all three tuna species is represented in Figure 2. *Th. alalunga* CPUE shows two visually distinct trends of CPUE means, with a lower average pattern between 1972 and 1991 and a higher average between 1992 and 2019. *Th. obesus* CPUE has a reducing trend from 1972 to 1981 with stock recovery between 1982 and 1986 followed by gradual stock reduction from 1987 to 2019. *Th. albacares* CPUE shows an increasing pattern between 1972 to 1978 followed by a gradual stock reduction between 1979 and 2019.
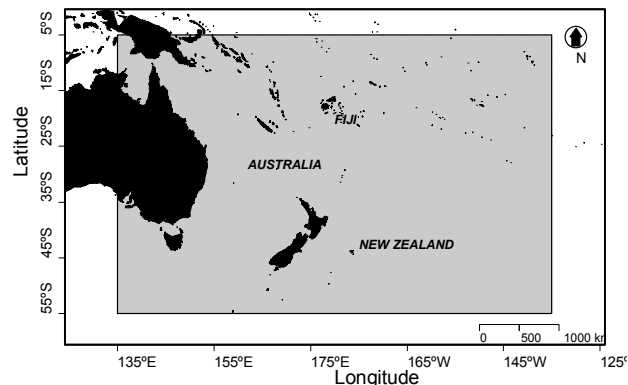

Fig. 1. Map showing the geographical region (shaded) for *Th. albacares*, *Th. alalunga* and *Th. obesus* in the Eastern and Western South Pacific Region between the coordinates of 55° S to 5° S and 135° E to 135° W where longline fishing data within the shaded region for the years 1972 to 2019 was used for study
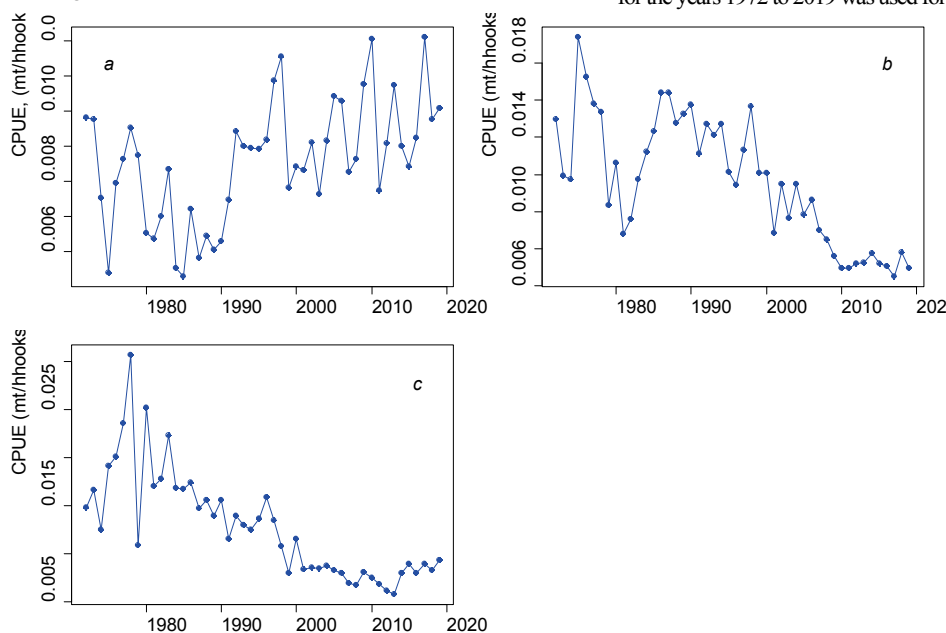

Fig. 2. Stock trajectories as catch per unit effort (CPUE) for *Th. alalunga* (*a*), *Th. obesus* (*b*) and *Th. albacares* (*c*) in the Eastern and Western South Pacific region for the years 1972 to 2019 where CPUE is in metric tonnes per hundreds of hooks (mt/hhooks); the years are indicated in the abscissa

Environmental data. Environmental factors used for this work included monthly sea surface temperature (SST) and monthly index of Atlantic Multidecadal Oscillation (unsmoothed version) (AMO). Monthly SST for the South Pacific Region was obtained on a 1° by 1° resolution for the years 1967 to 2019 from the public domain data available from the link www.metoffice.gov.uk/hadobs/hadisst. The data is compiled by the Meteorological Office Hadley Center, UK as Hadley Centre Sea Ice and Sea Surface Temperature data set (HadISST) and described in (Rayner et al., 2003). AMO is an index of North Atlantic sea temperature oscillation and described in (Enfield et al., 2001). The monthly AMO index was obtained from the Physical Sciences Division of National Oceanic and Atmospheric Administration (NOAA).

Correlation exploration of variables. The correlation between independent variables of tuna CPUE in the year t ($C_{a,t}$) and dependent variables of SST in the month m for the year $t–i$ ($T_{m,t-i}$) were calculated. Here t denotes the year and m denotes the month, a represents the tuna species and i denotes the time lag in years where $i = (0,1,…,5)$. Correlations between tuna CPUE in year t ($C_{a,t}$) and AMO for the month m and year $t–i$ ($A_{m,t-i}$) were also determined. Data exploration protocols were followed to avoid assumption violation of statistical methods used as outlined by Zuur et al. (2010).

Model formulation. The environmental variables that exhibited significant correlation ($P < 0.05$) with CPUE variables were used as candidates independent variables to reproduce the natural logarithm of tuna CPUE [$\ln(C_t)$] in year t ranging from 1972 to 2019. Model fitness with actual stock trajectory was determined using R^2 value, Akaike Information Criterion (AIC) (Akaike, 1981), t-tests, F-tests and significance level based on the P-value of $P < 0.05$ for each model. Similar modelling techniques

have been used in previous works (Singh et al., 2015a, 2015b, 2017; Sakuramoto, 2021). Model formulation was restricted to two independent environmental variables to reduce complexity of the final models and ease their comprehensiveness. The interaction component of independent variables was also included for possibility of interaction impact on tuna stocks. The Generalised Linear Model was used to reproduce all three tuna CPUE trajectories shown in Equation 1.

$$\log(C_{a,t}) = \log(\alpha_{0,m,i}) + \alpha_{1,m,i} \times T_{m,t-i} + \alpha_{2,m,i} \times A_{m,t-i} + \alpha_{3,m,i} \times$$
$$(T_{m,t-i} \times A_{m,t-i}) + \varepsilon \qquad \text{(Eq. 1)}$$

where C_a is the CPUE of tuna species a, α_0 is the intercept parameter, α_1, α_2, α_3 represent the parameter estimates and ε represents an unsolved normally distributed random variable.

The Generalized Additive Model (GAM) was also used to model the CPUE of all three tuna species as shown below. GAM allowed testing of non-linear responses of independent environmental variables on tuna CPUE of each species. Polynomial functions of second and third order was inserted in Equation 1 to investigate whether GAM resulted in better fit of models. The resulting GAM is shown as Equation 2.

$$\log(C_{a,t}) = \log(\beta_{0,m,x,i}) + \beta_{1,m,x,i} \times T^x_{m,t-i} + \beta_{2,m,x,i} \times A^x_{m,t-i} +$$
$$\beta_{3,m,i} \times (T_{m,t-i} \times A_{m,t-i}) + \varepsilon \qquad \text{(Eq. 2)}$$

where β_0 is the intercept parameter, β_1, β_2, β_3 represent the parameter estimates and $x = (1,2,3)$. Natural logarithmic transformation of the dependent variable and intercept parameter in Equation 1 and Equation 2 was essential to reduce outlier and skewness effects. All possible combinations of independent variables in Equation 1 and Equation 2 were tested. This enabled testing of both individual and combined effects of the two independent environmental variables. This also allowed testing of both linear and non-linear effects of the independent variables. Variance homogeneity tests were also done to ensure all variance values are <4.00 to ensure stability of least square estimators (Fox, 2015) to avoid selection of false models. Estimated tuna trajectories resulting from both one and two independent environmental variables were investigated and graphed against referred tuna trajectories. "R", version 4.0.1 (R Core Team, 2020) was used for all statistical and modelling analysis in this study.

Results

Correlation of variables. Comparison of tuna CPUE with environmental variables of SST and AMO showed highly significant correlation for different months and lag periods (Fig. 3). South Pacific *Th. alalunga* stock had strongest correlation with SST July in year t–3 and AMO November in year t–0 while South Pacific *Th. obesus* stock had strongest correlation with SST June in year t–5 and AMO October in year t–2 and South Pacific *Th. albacares* stock had strongest correlation with SST July in year t–1 and AMO October in year t–4.
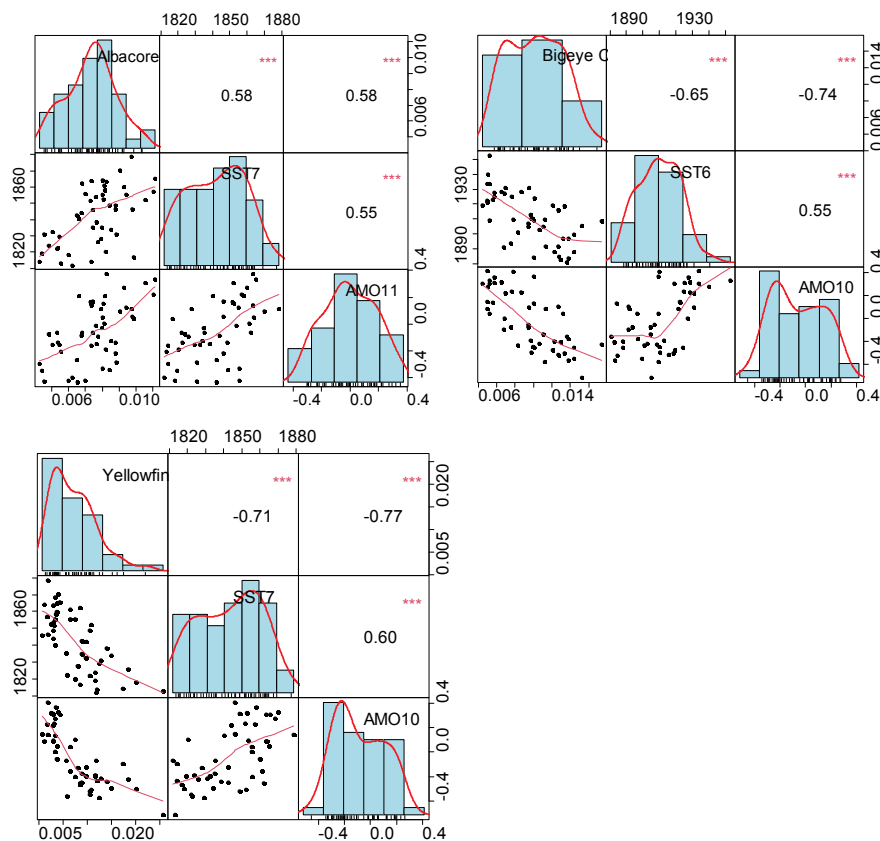

Fig. 3. Correlation scatterplot matrix for CPUE of *Th. albacares*, *Th. alalunga* and *Th. obesus* in the South Pacific Region against independent environmental variables of sea surface temperature (SST) and Atlantic Multidecadal Oscillation (AMO): numbers represents different months (1–12); matrix also shows kernel density overlays, distribution, histograms and absolute correlations at different significance levels; * P < 0.05, ** P < 0.01, *** P < 0.001

Figure 4 shows the time series dynamics of environmental variables over time with respective lags that resulted in the strongest correlation with tuna CPUE. The variable dynamics in all cases seemingly follow two different trend patterns over time. Tuna stock time series in Figure 2 also seems to have two different trend dynamics. To test this, tuna and environmental variables were divided into two regimes from the points where stock patterns seemingly changed. Boxplots of regimes (Fig. 5) shows a clear representation of the regime differences. T-tests showed significant difference (P < 0.05) in means for all variables used for stock reproduction models from Figure 5.

Results from the correlation study (Fig. 3) were used for reconstructing the CPUE stock dynamics of the three South Pacific tuna species. Models showing strongest relationship with tuna CPUE with reference to R^2 values, AIC and p-values are shown in Table 1. Models with two variable and single variables are shown to determine the impact of combined and individual variables on each of the three South Pacific tuna CPUE dynamics. From Figure 6 and Table 1, models with two variables have a better fit in comparison to models with single variable for all tuna stocks. When single environmental variable models are compared (Table 1), *Th. alalunga*, the single model with SST performs better than AMO.

For *Th. obesus* and *Th. albacares*, the single model with AMO performs better that SST. When the observed CPUE is compared with CPUE forecast from the models presented in Table 1 using linear regression, it is indeed observed that two different linear relationships or regimes may actually exist (Fig. 7).

Discussion

Marine ecosystems are difficult to understand and the health of any given species is determined via interaction of various biotic and abiotic factors interacting in a complex relationship. Environmental factors have an important influence on marine life over time and need to be seriously considered in harvesting plans for marine resources. Population dynamics of commercial fish species such as tuna are affected by a multitude of factors including interspecies relationships, habitat degradation, ocean acidification, climatic and environmental factors alterations over time and anthropogenic influences including pollution and harvesting levels, to name a few (Johnson et al., 2020). This is further compounded by the highly migratory nature of tuna species.
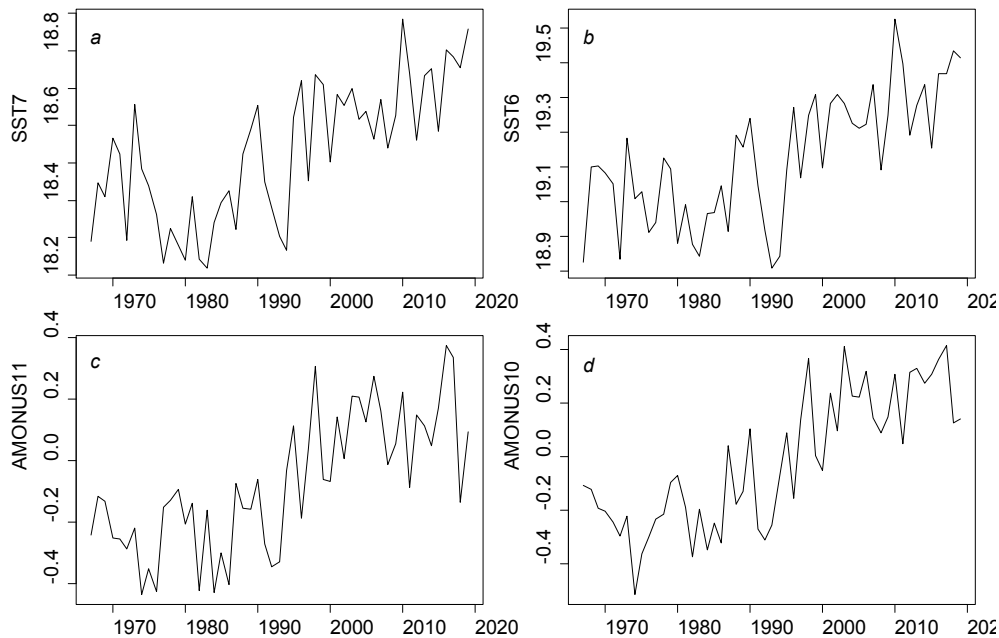

Fig. 4. Time series trends for selected independent environmental variables of sea surface temperature (SST) and Atlantic multidecadal oscillation (AMO): these variables showed highest correlation with the dependent variables and numbers represents different months (1–12); the years are indicated in the abscissa; all plots (a–d) seem to show a change in pattern and mean value occurring around the mid-1990s
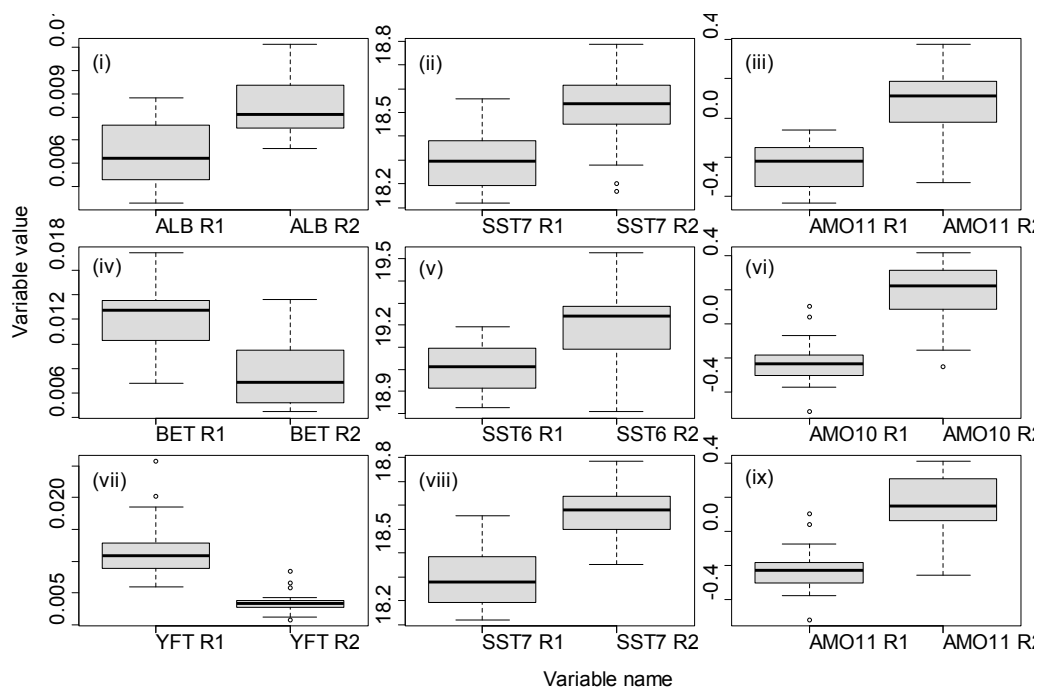

Fig. 5. Boxplots of individual variables divided into different regimes (R1, R2) for comparison: R1 and R2 means are significantly different ($P < 0.05$) in all cases; numbers next to variables represent months (1–12); SST – sea surface temperature and AMO – Atlantic multidecadal oscillation: (i) *Th. alalunga* (ALB) R1 = 1972–1992, R2 = 1993–2019; (ii) SST7 R1 = 1969–1989, R2 = 1990–2016; (iii) AMO11 R1 = 1972–1992, R2 = 1993–2019; (iv) *Th. obesus* (BET) R1 = 1972–1994, R2 = 1995–2019; (v) SST6 R1 = 1967–1989, R2 = 1990–2014; (vi) AMO10 R1 = 1970–1992, R2 = 1993–2017; (vii) *Th. albacares* (YFT) R1 = 1972–1996, R2 = 1997–2019; (viii) SST7 R1 = 1969–1993, R2 = 1994–2016; (ix) AMO11 R1 = 1968–1992, R2 = 1993–2015

Table 1

CPUE stock reproduction models using SST and AMO variable for South Pacific *Th. alalunga*, *Th. obesus* and *Th. albacares*

	Th. alalunga CPUE				
	Model and parameters (two variables)				
i.	$log(C_t) = -13.546 + 4.744 \times 10^{-3} \times SST_{j,t-3} + 0.330 \times AMO_{n,t}$	t-value	5.957	*p*-value	3.36×10^{-7}
		F statistic	35.48	R^2 AIC	0.436
		CC	0.660		−36.55
	Models and parameters (single variables)				
ii.	$log(C_t) = -4.748 + 0.535 \times AMO_{n,t}$	t-value	4.696	*p*-value	2.42×10^{-5}
		F statistic	22.05	R^2 AIC	0.324
		CC	0.582		−27.91
iii.	$log(C_t) = -17.80 + 0.579 \times SST_{j,t-3}$	t-value	4.965	*p*-value	9.89×10^{-6}
		F statistic	24.65	R^2 AIC	0.349
		CC	0.579		−29.71
	Th. obesus CPUE				
	Model and parameters (two variables)				
i.	$log(C_t) = 7.803 - 6.412 \times 10^{-3} \times SST_{u,t-5} - 3.363 \times 10^{-4} \times$ $(SST_{u,t-5} \times AMO_{o,t-2})$	t-value	9.134	*p*-value	6.70×10^{-12}
		F statistic	83.42	R^2 AIC	0.645
		CC	0.792		−22.32
	Models and parameters (single variables)				
ii.	$log(C_t) = -4.516 - 0.884 \times AMO_{o,t-2}$	t-value	7.539	*p*-value	1.42×10^{-9}
		F statistic	56.84	R^2 AIC	0.553
		CC	0.739		−11.28
iii.	$log(C_t) = 6.782 - 3.059 \times 10^{-6} \times SST_{u,t-5}^2$	t-value	6.007	*p*-value	2.83×10^{-7}
		F statistic	36.08	R^2 AIC	0.440
		CC	0.647		−0.460
	T. albacares CPUE				
	Model and parameters (two variables)				
i.	$log(C_t) = 10.858 - 8.278 \times 10^{-3} \times SST_{j,t-1} - 0.996 \times AMO_{o,t-4}$	t-value	11.809	*p*-value	1.59×10^{-15}
		F statistic	139.40	R^2 AIC	0.752
		CC	0.831		−11.67
	Models and parameters (single variables)				
ii.	$log(C_t) = -4.496 - 0.771 \times AMO_{o,t-4}$	t-value	9.57	*p*-value	1.61×10^{-12}
		F statistic	91.59	R^2 AIC	0.665
		CC	0.771		2.660
iii.	$log(C_t) = 25.812 - 1.633 \times 10^{-2} \times SST_{j,t-1}$	t-value	7.182	*p*-value	4.86×10^{-9}
		F statistic	51.58	R^2 AIC	0.529
		CC	0.715		19.153

Notes: different model parameters are also shown; model uses independent variable from Figure 3 and 4; two variable and single variable models are included; models shown have highest significance with reference to P-value, Akaike information criterion (AIC), regression coefficient (R2) values, correlation coefficient (CC), t-value and F statistic; model subscripts refer to the respective months and lag period; j – July, n – November, u – June, o – October; Ct – CPUE for year t; SST – sea surface temperature; AMO – Atlantic multidecadal oscillation.
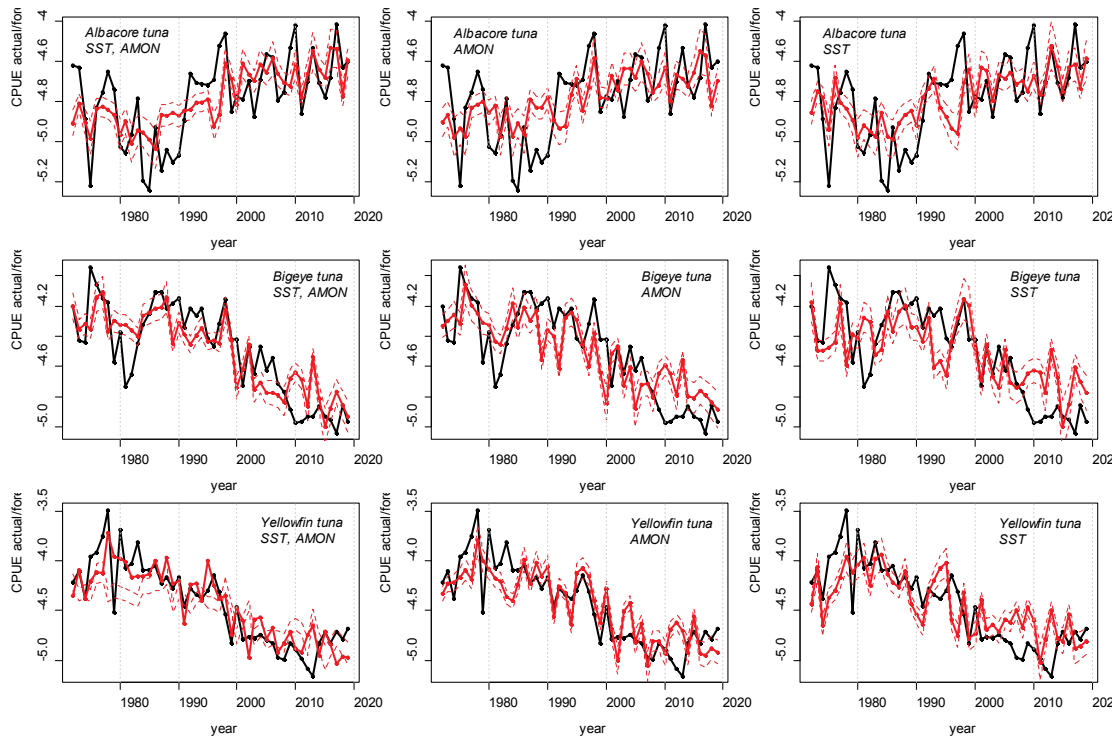

Fig. 6. Model fit showing observed CPUE in black and model reconstructed CPUE in red for South Pacific *Th. alalunga*, *Th. obesus* and *Th. albacores*: models with highest correlation are shown for single and combined variables from Table 1; tuna species and independent variable(s) are shown for each graph; dashed lines represent 95% confidence interval for the models in red; the years are indicated in the abscissa
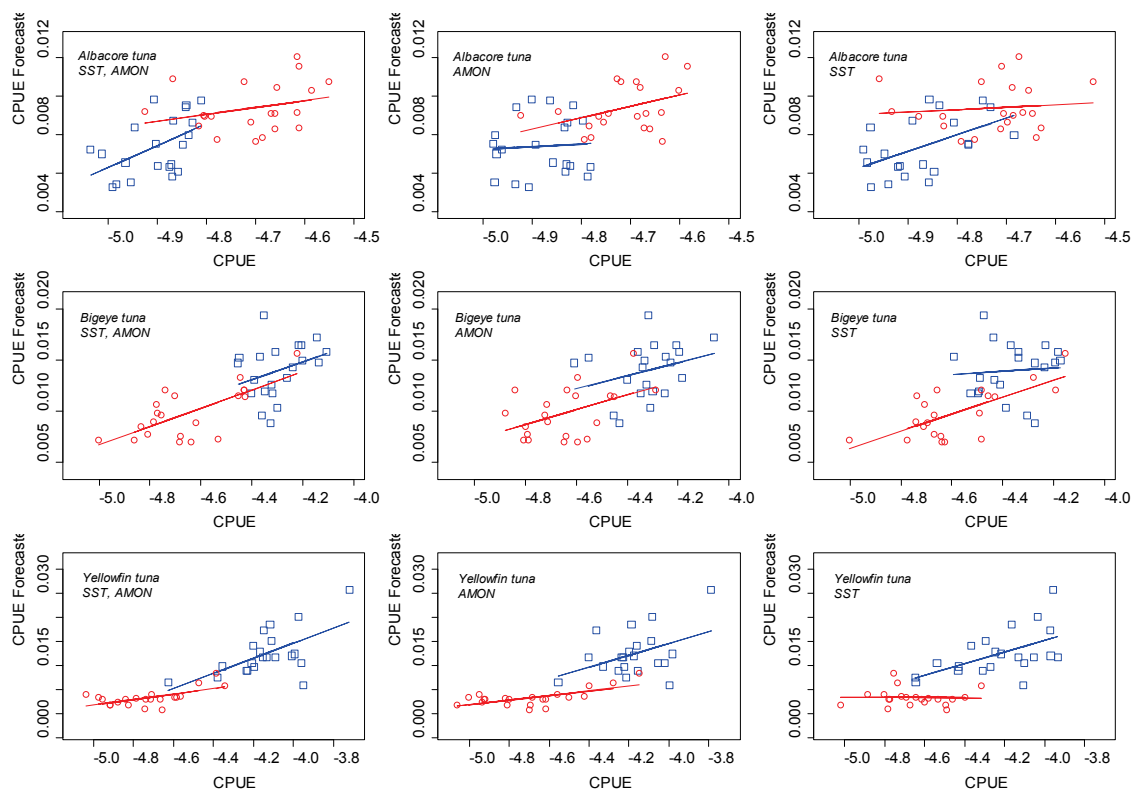
Fig. 7. Regression graphs for CPUE against CPUE forecast from Table 1: data points are divided in two regime periods with regime 1 in blue and regime 2 in red; tuna species and independent variable(s) are shown for each graph; the regression lines for the regimes differ significantly from each other in all cases at P < 0.05

This work shows that a significant portion of stock dynamics of South Pacific *Th. alalunga*, *Th. obesus* and *Th. albacares* can be explained well by two environmental conditions of SST and AMO. This shows that a large portion of tuna variation in the Eastern and Southern Pacific is related to environmental conditions. Only two variables were sufficient to create good models. However it should be noted that this does not mean that these models are the best possible. If a larger number of long term environmental, ecological and biological variables are made available, then far more reasonable models can be constructed to explain even larger proportions of the stock patterns of the three tuna species studies here. Most developing island countries in the South Pacific do not have reliable long term data, which makes it very difficult to understand multivariate impacts on tuna resources over long time series (Chambers et al., 2017; Varea et al., 2020; Mori et al., 2023). This work shows that it is possible to construct sufficiently acceptable models with limited environmental variables. The models show that the stock pattern of *Th. alalunga*, *Th. obesus* and *Th. albacares* in the South Pacific can be mostly explained by the two environmental conditions. The stock dynamics can be said to be not density-dependent. This indicates that biological interactions, pollution and harvesting have much lower possible impacts on these tuna resources. Tuna management approaches and planning in the South Pacific Island Countries need to move away from systems that mostly include fishing intensity and density-dependent effects such as maximum sustainable yield (MSY) towards more modern approaches that are density-independent and more inclusive of environmental factors.

Models with single variables are evidence of significant individual effect of SST and AMO on stock time series of each tuna species. Although models with a single variable resulted in significant fitness, models with two variables had a better fit in comparison to models with a single variable for all tuna stocks. Adding more environmental variables may likely lead to models with higher statistical significance, however models with more than two variables will be difficult to explain biologically. Due to this, models with two variables are better suited to explain the stock trajectory of the three tuna species in this work. Lag periods of environmental variables indicate their impact at different life stages of the respective tuna stock. The lag period depends on the tuna species and stock studied and the respective environmental variable. The relationship of environmental variables with tuna in Eastern and Western Pacific can be represented by equation 3 shown below,

$$\log(C_t) = \log(l) + f(y_{i,t-n}) + \varepsilon \qquad (3)$$

where l is a parameter estimate and $f(y_{i,t-n})$ is a function that incorporates the influence of environmental variables in with lag period of $t-n$. y_i is various variables that impact the stock trajectory of the three species of tuna. Since the models presented here do not fully explain tuna variability over time and tuna, like most marine organisms, are influenced by multiple variables with complex interactions, y_i represents all variables affecting tuna time series variability with $i = (1,2,...,k)$, where k represents environmental, biotic, ecological and anthropogenic variables. Due to its complexity, factors and interactions affecting tuna stock may never be completely understood. To account for this, the term ε is included to represent a normally distributed random variable(s).

A recent work similarly showed a strong relationship between long-term *Th. albacares* CPUE in the Indo-Pacific region with SST and AMO (Wu et al., 2022). Wu et al. (2020) showed significant negative correlation of Eastern and Western Pacific *Th. albacares* and AMO with lag periods of 1–5 years, which is similar to the results presented in this work. Mediodia et al. (2020) also established a strong non-linear relationship between the *Th. albacares* catch with reference to effort and SST in East Pacific Ocean. Singh et al. (2017) used SST to develop stock reproduction models which explained a significant portion of stock variation of North Pacific *Th. alalunga*. *Th. alalunga* distribution from 2000 to 2016 has been shown to be affected by SST in the Indian Ocean (Mondal et al., 2022). *Th. obesus* distribution and stock pattern in the Indian Ocean area off Java and Atlantic Ocean *Th. obesus* stocks has been shown to be related to SST variation in different studies (Lee et al., 2005; Syamsuddin et al., 2016; Lan et al., 2018). A recent work on long-term variability of *K. pelamis* CPUE in the North West Pacific showed this to be significantly related to AMO and SST (Hou et al., 2022).

There seem to be two significantly different patterns in the trajectory of the three tuna species and environmental conditions used to model them. Both tuna and environmental conditions show significantly different regimes differing around the 1990s. When actual CPUE and forecast CPUE were separated into two regimes and compared, two significantly different linear relationships were observed. This indicates a good chance

for regime shifts to exist in tuna stock related to or driven via environmental variables or SST and AMO in the Eastern and Western South Pacific. Regimes shifts in fish stock dynamics and environmental conditions were shown in Singh et al. 2018 for *Th. alalunga* and other species in different works (Oh et al., 2005; Sakuramoto, 2005; Sakuramoto, 2012; Singh et al., 2014). Hou et al. (2022) studied the long-term trajectory pattern of Skipjack tuna variability in the North West Pacific from 1972–2019 and determined the non-stationarity pattern in the dynamics affected by AMO transitioning in the early 1990s. This is similar to the findings of the present study. These mentioned works have established regime shifts in fish stock time series related to environmental conditions. Regime shifts for South Pacific tuna stock need to be further studied and included in long term tuna sustainability plans as they have a significant influence on structuring the stock trajectory patterns of these important commercial species.

Conclusion

The results presented here show that environmental conditions play a highly significant role in structuring tuna stock trajectory in the South Pacific and need to be included in tuna management/harvest plans to ensure sustainability of this important resource. A likely regime shift in tuna population may exist in the South Pacific region related to environmental conditions. The importance of regime shifts should be recognised and further investigated to be possibly included in tuna sustainability plans due to their influence on long term tuna trajectory patterns.

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