Int. J. Aquat. Biol. (2025) 13(1): 49-57
ISSN: 2322-5270; P-ISSN: 2383-0956
Journal homepage: www.ij-aquaticbiology.com

Original Article

Predicting the distribution of yellowfin tuna (*Thunnus albacares*) in the Indian Ocean using Bayesian probability: a species distribution modelling approach

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Abstract: The present study attempted to use Bayesian probability for predicting yellowfin tuna, *Thunnus albacares*, distribution in the FAO's 51 fishing grounds of the Indian Ocean based on mixed layer depth. Satellite remotely sensed mixed layer depth data from 2010-2017 were utilized. Bayesian probability was used to predict tuna fish distribution in the ocean, with the mixed layer depth serving as the prior probability. The northern Indian Ocean area was found to have minimal temporal change in mixed layer depth and therefore affects the *T. albacares* presence probability that is predicted. Variability in the predicted probability of *T. albacares* distribution was observed in Somali coastal waters and Madagascar western waters. The Bayesian probability method was not computationally intensive, largely because a single environmental variable was utilized in the study. Therefore, studies with limited environmental variables are recommended. Conversely, the application of numerous environmental factors has the potential to increase computational intensity and complexity of interpretation of the findings. In conclusion, the use of Bayesian probability can be another approach in modeling the distribution of marine fishes, particularly if presence data only is obtainable.

Article history:
Received 27 December 2024
Accepted 21 February 2025
Available online 25 February 2025

Keywords:
Bayesian probability
Indian Ocean
Species distribution modeling
Mixed layer depth

Introduction

Species distribution modeling (SDM), which is known as habitat suitability modeling or ecological niche modeling, is a computational technique used to predict the spatial distribution of species based on environmental variables. It is a valuable tool in various fields such as ecology, conservation biology, biogeography, and epidemiology (Miller, 2010). SDM is thus meant to understand the ecological requirements of a species, map suitable habitats, and predict potential species distribution under different scenarios that may inform conservation and management. The species distribution modeling workflow usually entails the following: acquiring species occurrence information (presence-absence or abundance data) (Liu et al., 2011) and environmental predictor data from diverse sources such as field surveys (Newbold et al., 2010), citizen science (Hutchinson et al., 2017), remote sensing (Randin et al., 2020) and climate datasets (Booth, 2018). Data preprocessing and model choice are then done, and the selection of a successful modeling strategy is based on the nature of the data and the research objectives. The models are then calibrated from data describing the species occurrences and environmental conditions with a model parameter estimation to optimize predictive performance. Finally, the performance of the calibrated model is tested using measures such as area under the receiver operating characteristic curve (AUC-ROC), true skill statistic (TSS), or kappa statistic (Kuhn and Johnson, 2013). The model is validated against independent data or by cross-validation methods to identify its predictive accuracy and the ability to generalize (Hijmans, 2012). Lastly, in the final step, the calibrated model is projected to predict the likely distribution of the species over the study region, based on the prevailing environmental conditions. Maps or spatial depictions of predicted

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DOI: https://doi.org/10.22034/ijab.v13i1.2486

distribution are drawn to depict suitable habitats, species hotspots, or areas of high conservation priority (Miller, 2010).

SDM can loosely be divided into correlative (Jarnevich et al., 2015) and mechanistic approaches (Evans et al., 2015), each with its own strengths, limitations, and applications. Some of the different SDM methods are correlative models, machine learning algorithms, species distribution models with spatial structure, mechanistic models, and ensemble modeling. Each of the SDM approaches has its particular assumptions, requirements of computation, and suitability with respect to data types and research questions. Choices between methods should be based on the characteristics of the species, environmental data, the extent of available training data, the desired level of model complexity, and the specific objectives of the study. Comparison and evaluation of alternative modelling techniques are often useful, by quantifying the performance and uncertainty of species distribution predictions.

Yellowfin tuna (*Thunnus albacares*) holds cultural, ecological, and economic value worldwide (Nikolic et al., 2017). Yellowfin tuna is among the most valuable and largest tuna species, with commercial significance and highly valued fisheries, as well as being an easily accessible source of nutrition for coastal communities and global markets. Its streamlined shape, yellow finlets, and migratory habits render it a desirable species for recreational anglers, hence bringing in tourism. Ecologically, the yellowfin tuna is an important apex predator in ocean food webs, regulating prey populations and ecosystem processes (Olson et al., 2014). Its population is, however, threatened by overfishing, habitat loss, and climate change (Hutubessy et al., 2021) and therefore underscores the need for an effective sustainable management response to ensure long-term sustainability of this iconic fish species.

The habitats of *T. albacares* are affected by pollution in the form of oil spills, heavy metals, and industrial effluents (Lazim and Al Naqeeb, 2021; Aziz et al., 2024), which can be mitigated successfully through microbial processes, thereby restoring ecological balance. Aquatic processes, such as aquatic plants, have been extensively studied for their potential application as bioindicators of heavy metal and hydrocarbon contaminations in ecosystems, aiming to understand the sources of environmental pressure on fisheries and marine sustainability (Hameed Khudhair et al., 2021; Lazim et al., 2022; Khadher et al., 2022). With increasing environmental issues of ocean pollution and its impacts on ecosystems, such as plastic contamination, it has become a growing environmental issue, and there is a need for an adequate treatment process to reduce its impacts on ecosystems (Saleh et al., 2024). Aquatic animals such as *T. albacares* are highly vulnerable to plastic debris, affecting the quality of water and food chains. Several strategies can be important in minimizing water pollution that affects species (e.g., *T. albacares*). For example, diatomaceous earth is an efficient and economical alternative to conventional chemicals to eliminate impurities, decreasing marine pollution (Benouis et al., 2022).

Yellowfin tuna, *Thunnus albacares*, is an important tuna species because of its ecological, economic, and cultural value to humans worldwide (Nikolic et al., 2017). This particular tuna species among the different species that exist happens to be one of the largest; hence, the fish has significant value, considering its support for many valued fisheries in food supply with respect to communities and international markets. With an elongated body shape and bright yellow finlets, their migratory behaviors also make them a prime target among sportfishers, hence also benefiting the tourism industry. Ecologically, yellowfin tuna plays a vital role as a top predator in marine food webs, regulating prey populations and influencing ecosystem dynamics (Olson et al., 2014). However, according to Hutubessy et al. (2021), the populations are threatened by overfishing, habitat degradation, and climate change. It also wants to draw attention to sustainable management practices that could make this iconic species last even longer.

Bayesian probability is a statistical concept that refers to a way in which people revise beliefs about the occurrence of something with increased evidence or information (Ellison, 2004). Unlike the classical or frequentist probability, which views probabilities as static and objective-Bayesian probability allows for the introduction of prior knowledge or belief in the analysis (Doll and Jacquemin, 2018). The Bayesian probability signifies the distribution of probability regarding the occurrence of any particular event with regard to certain fish species in the Indian Ocean. Indeed, these are powerful methods for drawing inferences from observed data, considering prior knowledge about the species' preference for certain habitat conditions and how such a distribution can be affected by environmental factors.

However, despite its flexibility and wide applicability, the use of Bayesian probability in SDM for marine ecosystems has been relatively limited. Conditional probability-based SDM offers broad potential benefits under conditions of poor data, mainly in the case of data availability, specifically presence data. Given the rare application of Bayesian probability in SDM in the marine context, we used it here to predict the distribution of *T. albacares*, yellowfin tuna, in the Indian Ocean concerning mixed layer depth. The depth of the 20°C isotherm (D20), an appropriate index of thermocline variability, is a proxy for the pycnocline layer (Yu, 2003). Such a depth less than 150 m has already been found to have immense influence on the presence of tuna species and hence the catch of tuna species, as mentioned in Lan et al. (2018). For tuna fish, the mixed layer depth in an ocean plays an important role, which affects distribution and presence. This is one of the key factors in the highly migratory species' ability to feed on nutrients or prey, which is essential for its survival.

Materials and Methods

Data preparation: The environmental data parameters are obtained from the MODIS NASA project (NASA Goddard Space Flight Center, Ocean Ecology Laboratory, 2021). In this, the mixed layer depth was available in NetCDF format (.nc) with a resolution of 0.5° × 0.5°, covering all ocean areas. Monthly presence data for *T. albacares* from the years 2010 to 2017 were sourced from OBIS (2024). In addition, Bayesian probability calculations were done to predict the presence of T. albacares in all 51 FAO fishing areas. For every presence point in each year from this species, the mixed layer depth was extracted from the mixed layer depth raster layers. The result was a data frame that included year, month, longitude, latitude, and mixed layer depth of the presence points.

Data analysis: The mixed layer depth data were categorized into 10 classes (C_i, $i = 1, 2, 3, \ldots, 10$) using the cut function in R 4.1.0. For each class, the ratio of presence (p) points at each category were determined as the prior probability ($P(C_i)$) to calculate conditional probabilities, i.e., $P(p \mid C_i)$. The joint probability ($P(p \cap C_i)$) was obtained by multiplying $P(C_i = i)$ by $P(p \mid C_i)$. The joint probability of presence, based on mixed layer depth, was illustrated using the raster R package (Hijmans, 2021).

Results

Error! Reference source not found. shows the distribution of the annually averaged mixed layer depth of the 51 fishing areas. In the northern part of the fishing area, the mixed layer depth had little change, whereas in the northeastern part, significant annual fluctuations always showed latitudes from 0° to 10°N, representing low values, and values between 30°S ~ 50°S showing high values.

The frequency distribution of mixed layer depth for each year has been presented in **Error! Reference source not found.**. In most of the studied years, the distributions are left-skewed. However, in 2011, the distribution of the data pertaining to the mixed layer depth did not provide any specific pattern. The minimum values of the data are in 2010 and 2014, with a maximum of about 80 m, while in 2011 and 2017, the data reached their highest values at around 120 and 140 m, respectively.

The predicted probability of *T. albacares* presence from 2010 to 2017 for 51 fishing areas is given in Figure 3. According to mixed layer depth, the highest probability of presence, around 0.4, was predicted for the northern areas. It is clear from this map that the northwestern part of the Red Sea had a low probability of *T. albacares* presence, while the southeastern part

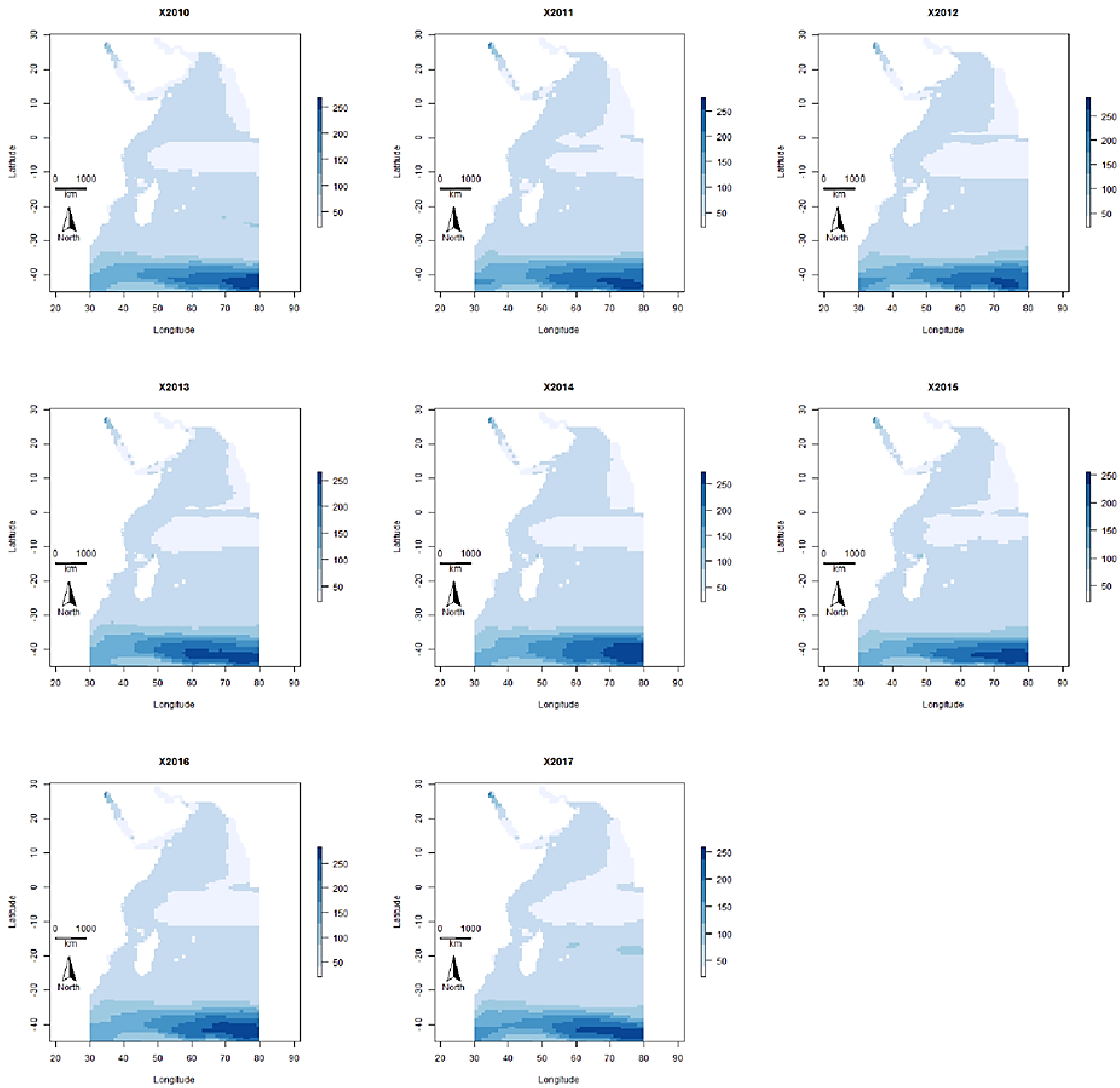

Figure 1. The annually-averaged mixed layer depth of the 51 fishing areas.

of the Red Sea showed a higher probability of its presence.

Off Somalia, the waters had annual variability in the probability of presence for *T. albacares*. Similarly, the eastern waters around Madagascar were also predicted to have a marked annual variation in presence probability. On the western side of Madagascar, however, the presence probability was predicted to remain consistent throughout the year. Generally, the waters south of -10°S latitude were predicted to have a low presence probability, but this area did show annual variations.

Discussions

In the study, the mixed layer depth was considered one of the main variables for analyzing the distribution of *T. albacares* in the Indian Ocean. The mixed layer depth is crucial in defining the yellowfin tuna's habitat preferences by determining temperature and light availability, which are essential for its nutrition and behavior. This has also been described by Torres et al.

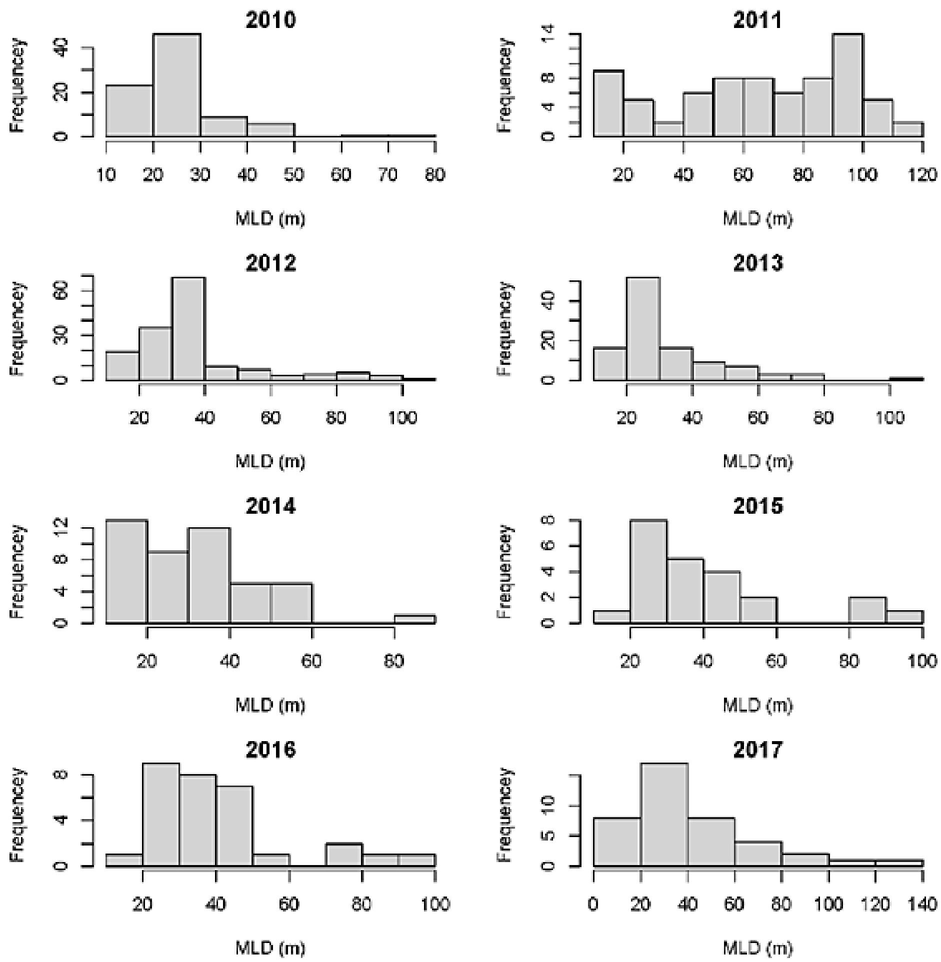

Figure 2. The frequency distribution of mixed layer depth over the years 2010-2017 in 51 fishing area.

(2011). Although these findings have contributed significantly to the understanding of the distribution of *T. albacares* in the Indian Ocean, several limitations remain. Further studies might therefore focus their efforts on the model improvement with other environmental variables that could help increase the predictive capacity of the model (Knudby et al., 2011). Similarly, studies investigating freshwater biodiversity, such as Merza (2021), contribute to understanding species distribution patterns and ecological interactions, thereby reinforcing the importance of comprehensive environmental monitoring in both marine and freshwater systems. The integration of various environmental factors would yield a better understanding of the ecological drivers for the distribution of *T. albacares* in the Indian Ocean, as indicated by Song et al. (2008), which in turn would enhance the predictive power of the method applied in mapping yellowfin tuna distribution. Moreover, including several environmental variables permits an integral assessment of the ecological processes affecting the distribution pattern of a species. This would enable researchers to understand how various environmental factors interact with and influence the spatial distribution of *T. albacares*, hence providing a detailed understanding of the habitat requirements and ecological niche that the species inhabits. Although there is merit in combining several environmental factors, the main goal of this study was to test a Bayesian probability framework for species distribution. Thus, a single environmental factor would clarify the methodology.

Although the Bayesian probability method allows flexibility in the inclusion of several environmental variables, there is a need to consider computational

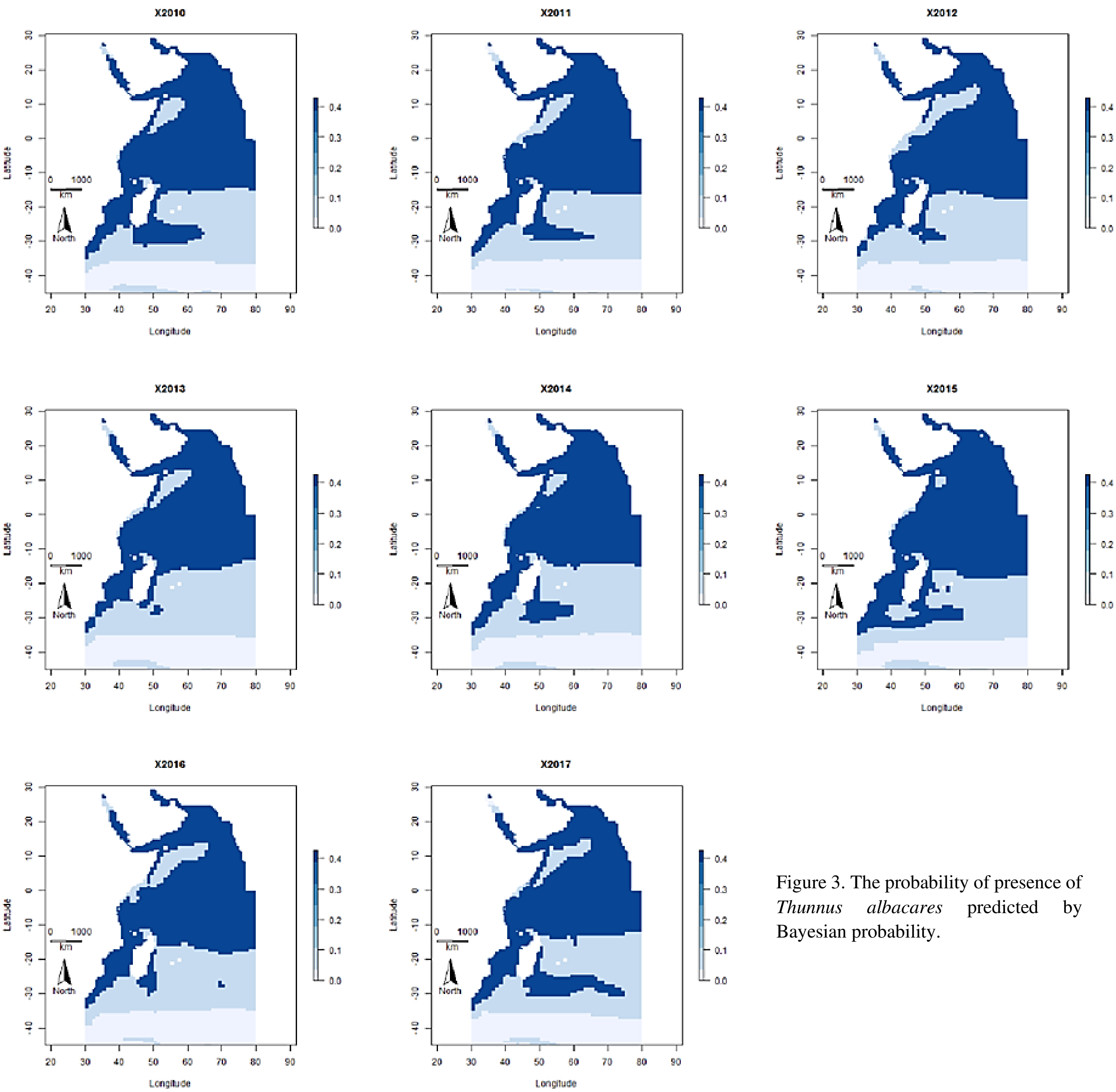

Figure 3. The probability of presence of *Thunnus albacares* predicted by Bayesian probability.

challenges related to complex models (Green *et al.*, 2005). Increasing the number of variables increases the computational intensity and time required for processing the model. The categorized environmental factors ought to have been nested within each other, which may be practically challenging to process and analyze the data. Therefore, considering the increased environmental variables in this model, an increase in complexity also occurs simultaneously. This may affect how the results, especially which particular factors are identified as most influential in driving distribution, can easily be interpreted using *T. albacares*. It should be a reasonable balance between these two aspects.

When MLD is used as an explanatory variable, *T. albacares* has the highest probability in the northern part of the Indian Ocean, indicating that it has the optimum environmental conditions for the species. Machine learning has proven to be a powerful tool for environmental monitoring, particularly in predicting sources of water pollution in major river systems, a recent study demonstrated how advanced models can analyze pollution patterns, enabling more effective water quality management to improve pollution control strategies and marine biodiversity protection (Rashid et al., 2024). According to Cayré and Marsac (1993) and Hartoko (2010), *T. albacares* is largely affected by water temperature. It is defined as the depth of a layer beyond which temperature can be uniform in a homogenous vertical distribution. The depth of the mixed layer, therefore, which is determined by temperature, among other aspects, determines the distribution patterns that tuna fish assume. In addition, this research now explains that a little temporal change in the predicted probability within the distribution area of the species is situated in the northern part of the Indian Ocean. Arrizabalaga et al. (2015) comment that the possible use of mixed layer depth in species distribution modeling may have value to fisheries and management conservation policies. Resource managers may apply the identification of regions with optimal mixed layer depth for yellowfin tuna in implementing targeted conservation measures to protect critical habitats and ensure the sustainability of tuna populations. Understanding the environmental preferences of *T. albacares* will also help inform spatial management strategies that reduce the impact of fishing activities on tuna populations (Song et al., 2008).

Since foodborne microorganisms can enter aquatic ecosystems through wastewater runoff, they can cause severe contamination of water and irrigated plants, posing a significant risk to marine biodiversity. Such contamination, alongside other environmental stressors, may impact species distribution, including *Thunnus albacares*. Addressing these issues through better sanitation practices and water quality management is essential for both public health and environmental conservation (Al-Abboodi, 2023). Additionally, the strong temporal fluctuation of the probability of yellowfin tuna presence in waters off Somalia and east of Madagascar within this prediction may be due to several factors such as climate change (Dueri, Bopp and Maury, 2014) and prey availability (Sardenne *et al.*, 2016). Being able to understand these fluctuations becomes of paramount importance for the purpose of addressing specific and targeted conservation measures and sustainable fisheries practices in both regions. Future research may try to address the explicit environmental drivers of yellowfin tuna distribution patterns, climate change impacts on their habitats, and refining the predictive models with more relevant variables to yield insight into any shifts that would impact the fisheries community (Rubio et al., 2020).

Also, the strong temporal variability of the yellowfin tuna presence probability off Somalia and to the east of Madagascar in this prediction may be due to several reasons such as climate change (Dueri, Bopp and Maury, 2014) and prey availability (Sardenne et al., 2016). The capacity to understand these changes becomes of critical importance for the purpose of addressing targeted and focused conservation measures and sustainable fishery activities in both regions. Further research may try to fill the gap between the current known explicit environmental drivers of yellowfin tuna distribution patterns, how climate change is affecting their habitat, and improving the predictive models using other relevant variables to get insight into whether there would be any changes affecting the fisheries community (Rubbio et al., 2020).

Hence, Bayesian probability contributed to obtaining very important information regarding the preferred habitat of *T. albacares*. Bayesian probability application, in this case, is an approach toward more accurate predictions about yellowfin tuna distribution within the Indian Ocean. The research outcome has proven that Bayesian probability provides a framework for species distribution modeling, where prior knowledge can be integrated with the belief update through observed data. It has made possible the understanding of how the mixed layer depth affects the distribution of *T. albacares* in the Indian Ocean and has gone ahead to further predict suitable habitats for the species using a simple method.

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