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The impact of climate change and economic development on the catches of small pelagic fisheries

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ABSTRACT

Small pelagic fishes play a crucial role in marine food webs, providing significant ecological support services. They are the largest target group in global commercial fisheries, accounting for 30 % of the total catch. However, their population status and spatial distribution are highly susceptible to environmental changes and economic development. This study is based on fishing data for 11 small pelagic fisheries in a long-term time series from 1963 to 2021. By integrating various machine learning methods and generalized additive models, we quantitatively assess the impacts and differences of typical climate change events (ENSO and AMO) as well as economic development on the catches of different small pelagic fisheries. Our findings reveal the complex nonlinear and asymmetrical effects of ENSO, AMO, and economic development on the catches, with varying degrees of influence. Economic factors predominantly drive changes in the exploitation of small pelagic fisheries. ENSO, AMO, and their lagged effects significantly influence regional fisheries through teleconnections, with ENSO exerting a particularly pronounced impact on the southeastern Pacific area. While most species are adversely affected by the positive phases of climate change, extreme negative phases do not always benefit. This research provides a systematic understanding of the impacts of climate change and economic expansion on small pelagic fisheries, offering valuable insights for government policymakers and stakeholders to formulate scientific fishing strategies and mitigate the risks of fishery resource depletion.

1. Introduction

Marine capture fisheries are indispensable to the livelihoods of hundreds of millions of fishers and the nutrition of billions of people, playing an essential role in global socio-economic development and food security [1]. More than 3 billion people in the world get at least 20 percent of their daily animal protein from fish, with some countries consuming 50 percent or more [2]. The annual global commercial catch is approximately 80 million tons, with one-third used for fishmeal and fish oil production, and about 75 % of the fishmeal is derived from small pelagic fish [3]. Small pelagic fisheries represent the largest segment of global commercial catches, accounting for 30 % of the total catch [4]. Typical small pelagic fishes, such as anchovies, sardines, and herrings, are rich in protein, lipids, minerals, and vitamins. Besides being consumed by humans, they are a crucial source of animal food production systems, including animal feed, fish oil, and pet food [5]. The rapidly growing aquaculture industry has increased the fishing pressure on small pelagic fish. Small pelagic fisheries directly or indirectly provide employment for millions of fishers, workers, and related service industries. Although often considered as low-value commodities, small pelagic fisheries contribute increasingly to regional food security and employment in some developing countries, generating significant foreign exchange earnings [6,7].

Socio-economic factors have long dominated fishing practices, human demand for marine resources continues to expand, and the scope, scale and footprint of human activities persistently affect marine ecosystems. Fisheries, shipping, and energy extraction activities pose increasing challenges and threats to global marine ecosystems, leading to degradation and even collapse [8,9]. However, global fishery development remains unsustainable, with 33 % of fish populations classified as ‘overfished’ [10]. The overfishing limits the marginal returns of fishing activities, slowing fish growth rates, reducing the quality of mature individuals, and diminishing economic value. These effects further decrease the future harvesting potential of fisheries, severely harming the well-being and long-term stability of fishing communities [11,12]. In response to the current overexploitation of marine capture

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fisheries, stakeholders are increasingly focusing on making fishing decisions based on sustainable yield and advocating for ecosystem-based management strategies to restore marine ecosystems, thereby endowing fishery production with sustainable development capabilities [8,13,14]. To enhance the economic performance of fisheries while increasing the resilience and recovery capacity of marine ecosystems, countries implement dynamic fishing regulation strategies under different biomass conditions. By adopting conservative or exoteric flexible fishing efforts, these strategies aim to balance economic and ecological interests, ensuring comprehensive benefits for both the present and the future [15]. For example, the Peruvian anchovy, the largest commercially harvested fish species in the world, has been subjected to severe exploitation. It reached a record maximum annual catch of 13.06 million tons in 1970, but only 90,000 tons in 1984. Both overfishing and climate change have significantly undermined its sustainability [16]. In response, Peru enacted the Maximum Catch Limit per Vessel Law in 2008. This legislation explicitly charges for fishing rights, generating economical resource rent to prevent anchovy catches from exceeding sustainable levels [17].

Small pelagic fishes are species characterized by short life cycles, rapid growth, small body size, and apparent schooling behavior. They typically inhabit the upper tens to hundreds of meters of the ocean water column, feeding on phytoplankton and zooplankton [6]. These fishes provide crucial ecological support services within the marine food web. They convert energy from primary producers and transfer it to higher trophic levels, including larger fishes, mammals, and seabirds [18,19]. Consequently, the population size and health of small pelagic fishes directly impact the survival and reproduction of these predators. On average, small pelagic fishes support 22 % of seabird biomass, 15 % of mammal biomass, and 34 % of total fishery catches [20]. Additionally, their feeding behavior exerts top-down control on plankton abundance, influencing the overall productivity and carbon cycling of marine ecosystems [21]. The community status and spatial distribution are highly susceptible to environmental changes. Climate events such as ENSO (El Niño-Southern Oscillation) and AMO (Atlantic Multidecadal Oscillation) impact the physiological activities and predation processes of small pelagic fishes, leading to fluctuations in their biomass and subsequently affecting fishing activities [18]. These changes include short-term variations based on habitat shifts and alterations in physiological activities, mid-term changes in breeding, hatching, and juvenile survival rates, and long-term shifts in community structure [22,23]. At the same time, extreme events such as heatwaves, cold spells, heavy rainfall, and hurricanes induced by climate change impact fishing activities [24,25]. ENSO, as a powerful interannual climate variability mode, exerts significant influences on global weather patterns through mechanisms such as sea surface temperature anomalies and atmospheric circulation changes, causing extreme events like droughts and heavy rainfall [24,26]. These events disrupt marine food webs, alter species distributions, and significantly affect fishery yields. In contrast, AMO operates on a decadal scale and drives long-term climatic changes in the Northern Hemisphere through feedback mechanisms such as thermohaline circulation and atmospheric teleconnections. Its multidecadal nature allows for the assessment of sustained ecosystem responses and fisheries dynamics [27–30]. These two modes occur in the Pacific and Atlantic Oceans respectively, but affect the globe through teleconnection, integrate both short-term and long-term climate processes, which are critical for understanding the impacts of climate change. Selecting ENSO and AMO as representative modes allows for a more comprehensive understanding of the complex interactions between oceanic and atmospheric phenomena and their effects on global ecosystems. Furthermore, other decadal climate models such as IPO are significantly associated with both ENSO and AMO. IPO are included in the decadal signal portion of ENSO, and the positive phase of AMO tends to trigger negative phase IPO. Therefore, this study mainly discusses ENSO and AMO, two climate phenomena with far-reaching effects. Additionally, ENSO and AMO have delayed effects on marine ecosystems, often persisting for months to years after their occurrence. Climate events experienced by small pelagic fishes at different life stages have impacts throughout the life cycle. Furthermore, the delayed responses of their food resources and predators contribute to the lagged effects of ENSO and AMO [26].

Understanding the impact of climate change and economic development on small pelagic fisheries is crucial for promoting sustainable management of these fisheries. Small pelagic fish production is highly sensitive to climate change, and through scientifically managing fishery resources and reducing overfishing, the sustainable utilization of these resources can be ensured. However, existing research mostly focuses on the impact of climate change on small pelagic fishes in specific regions or explores ecosystem-based fishery management practices. There is a significant gap in understanding the combined effects and contribution ratio of climate change and economic development on global small pelagic fisheries. This study, based on a long-term time series of catch data for 11 small pelagic fish species from 1963 to 2021, employs various machine learning methods and generalized additive models (GAMs) to address the following key questions：(1) To what extent are the fluctuations of ENSO and AMO and their lagging stages synchronized with catches of different small pelagic fisheries? (2) How do climate change and economic development differentially affect the catches of various small pelagic fisheries? (3) What are the relative contributions of climate phenomena such as ENSO and AMO compared to economic factors in determining small pelagic fishery catch levels?

2. Data and methods

2.1. Data source and preprocessing

The fishery catch data used in this study were sourced from FAO Fishery Catch Database. Using Python's 'pandas' library, we extracted the catch data for 11 small pelagic fish species, resulting in a long-term time series dataset spanning 59 years from 1963 to 2021. The small pelagic fish species (and their corresponding FAO 3-alpha codes) are as follows: Peruvian anchovy (VET), Chilean jack mackerel (CJM), Indian oil sardine (IOS), South African anchovy (ANC), Pacific saury (SAP), Arctic capelin (CAP), European anchovy (ANE), European pilchard (PIL), Atlantic herring (HER), Atlantic mackerel (MHA), and Gulf menhaden (MHG). These small pelagic fisheries are distributed across all major oceans, accounting for 16 % of the annual global commercial fish catch [31]. Before conducting further analysis, we performed a logarithmic transformation on the catch data. This transformation helps to reduce the magnitude differences between catch data and climate indices, effectively normalizing the data and improving the accuracy of model estimates [32]. The economic development data, represented by global per capita GDP values, were sourced from the World Bank's open database and were similarly subjected to logarithmic transformation.

The ENSO and AMO climate indices used in this study were obtained from NOAA. The ENSO index was derived from the three-month moving average of sea surface temperature anomalies in the NINO3.4 region (5°S-5°N, 120°-170°W). It was measured using the average anomalies from December to February (DJF), during which ENSO events typically peak (Liu, Y. et al., 2023[33]). ENSO events are categorized as weak (0.5–0.9°C), moderate (1–1.4°C), strong (1.5–1.9°C), and very strong El Niño events (≥2°C). La Niña events are similarly classified according to temperature anomalies below 0.5°C. The annual AMO index was calculated based on sea surface temperature anomalies in the North Atlantic region (0°-60°N, 80°W–0°). The AMO phase fluctuates by approximately 0.5°C, with values above 0°C indicating a warm phase and values below indicating a cold phase. Small pelagic fishes typically respond quickly to climate changes within their short life cycles and breeding periods. However, the full impact of climate change on the entire ecosystem may exhibit delayed effects. Consequently, short-term habitat shifts may not accurately reflect actual biomass fluctuations [26]. Therefore, considering the delayed and cumulative effects of climate change, this study analyzed the impact of climate change on global small pelagic fisheries based on the five-period lag effects of ENSO and AMO indices. This approach allowed us to explore the short- to medium-term impacts of climate change on small pelagic fisheries while capturing the delayed effects of climate change on fisheries without overly complicating the model. The current and preceding five years' ENSO or AMO indices are represented as ENSO, AMO, and ENSO1 to ENSO5 and AMO1 to AMO5, respectively.

2.2. Methods

2.2.1. Machine learning methods

Machine learning method represent a crucial application of artificial intelligence across various scientific research domains. These methods are capable of capturing complex patterns and regularities within data, aiding researchers in identifying characteristic relationships present in the data [34]. Feature selection is an important dimensionality reduction technique in machine learning, aimed at determining a subset of features from the original dataset that have varying degrees of relevance to the target variable, thereby eliminating redundant or irrelevant feature information [35]. In this study, we employed a self-learning feature selection method assisted by SHAP values. SHAP values quantify the contribution of each feature to the prediction outcome and have been demonstrated to be more effective in feature selection compared to variance analysis, mutual information, and recursive feature elimination [36–38]. In this study, we utilized five algorithms (RF, XGB, LGBM, GBR, and CatBoost) to construct machine learning models. Subsequently, the SHAP analysis was conducted using the optimal model to ascertain the contribution of different features.

RF is a regression model based on the random forest algorithm. It constructs an ensemble model by building multiple decision trees, each of which relies on independently sampled random vector values. The final estimation is obtained by averaging the results generated by these individual trees [39,40]. XGB, LGBM, GBR, and CatBoost leverage decision tree algorithms based on gradient boosting. These models minimize the loss function by iteratively building tree models [41,42]. Each tree is trained based on the residuals from the previous iteration, thereby gradually optimizing the performance [43,44]. The aforementioned five machine learning algorithms are capable of rapidly and accurately handling feature relationships within models, thereby quickly resolving numerous data science problems. They are widely applied in various research fields, such as data mining and bioinformatics. However, the application of machine learning methods in fisheries research remains relatively underdeveloped. In this study, we utilized Python libraries 'scikit-learn', 'xgboost', 'lightgbm', and 'CatBoost' to perform feature analysis on ENSO, AMO, and their lags.

2.2.2. Generalized Additive Models

Generalized Additive Models (GAM) leverage link functions to allow the relationship between response and predictor variables to be nonlinear, enabling the flexible handling of complex inter-variable relationships. By adding multiple smooth functions to the predictor variables, GAM can capture nonlinear relationships and are widely used in fisheries research [18,26]. The deviance explained (DE) of the GAM model output reflects the proportion of variability in the dependent variable data that the model accounts for. A higher DE value indicates a stronger fitting ability of the model to the data. The final setting of the GAM model also needs to consider the Akaike Information Criterion (AIC) and Generalized Cross-Validation (GCV) values. AIC and GCV are primarily used to balance model fit and complexity. Smaller values of AIC and GCV suggest that the model achieves a good fit to the data without the risk of overfitting and unnecessarily complicating the model. Ultimately, this study selected the optimal model based on the principles of maximizing DE and minimizing AIC and GCV (Table 1) for further analysis. The analysis process was conducted in R using the smooth functions from the 'mgcv' package. The GAM model is as follows：

Table 1
Optimal response models of small pelagic fisheries to climate change and economic impacts.

VET	s(GDP)+s(ENSO)+s(ENSO1)+s(AMO3)	R^2	DE %	GCV	AIC
VIF P	1.045 1.029 1.021 1.053 < 2e^{-16} *** 0.004** 0.076· 0.019*	0.847	90.5	0.2480	74.819
CJM	s(GDP)+s(AMO3)+s(ENSO1)+s(ENSO4)	R^2	DE	GCV	AIC
VIF P	1.045 1.050 1.003 1.009 < 2e^{-16} *** 0.003** 0.019* 0.005**	0.974	98	0.0977	27.388
IOS	s(GDP)+s(ENSO5)+s(AMO1)+s(ENSO4)+s(ENSO3)+s(AMO3)	R^2	DE	GCV	AIC
VIF P	1.058 1.118 1.675 1.059 1.149 1.659 < 2e^{-16} *** 0.084· 0.034* 0.022* 0.049* 0.034*	0.854	90.4	0.0464	−21.545
ANC	s(GDP)+s(AMO1)+s(AMO3)+s(ENSO3)+s(ENSO4)	R^2	DE	GCV	AIC
VIF P	1.057 1.656 1.653 1.048 1.030 3.47e^{-07}*** 0.025* 0.047* 0.010* 0.039*	0.741	82.6	0.1689	55.693
CAP	s(GDP)+s(AMO3)+s(AMO2)+s(ENSO4)+s(ENSO3)	R^2	DE	GCV	AIC
VIF P	1.059 1.806 1.817 1.048 1.021 < 2e^{-16}*** 0.004** 0.017* 0.003** 0.018*	0.875	92.1	0.2531	76.785
ANE	s(GDP)+s(AMO4)+s(AMO3)+s(ENSO)+s(ENSO1)+s(AMO5)	R^2	DE	GCV	AIC
VIF P	1.059 2.080 2.019 1.061 1.032 2.046 < 2e^{-16}*** 0.002** 0.011* 0.004** 0.046* 0.009**	0.837	91.6	0.0256	−69.075
PIL	s(GDP) + s(AMO3) + s(ENSO5)+ s(AMO2)	R^2	DE	GCV	AIC
VIF P	1.060 1.768 1.007 1.782 < 2e^{-16}*** 0.170 0.146 0.291	0.896	92.4	0.0130	−92.735
HER	s(GDP)+s(AMO1)+s(ENSO5)+s(AMO3)+s(ENSO4)	R^2	DE	GCV	AIC
VIF P	1.058 1.618 1.019 1.620 1.023 < 2e^{-16}*** 0.057· 0.0001*** 0.159155 0.0006***	0.942	96.6	0.0128	−101.75
MHA	s(GDP) + s(AMO5)+ s(AMO) + s(ENSO2) + s(ENSO4)+ s(ENSO1)	R^2	DE	GCV	AIC
VIF P	1.068 1.503 1.272 1.107 1.298 1.025 5.8e^{-06}*** 0.003** 0.017* 0.008** 0.043* 0.001**	0.954	98.8	0.0175	−142.48
SAP	s(GDP)+s(AMO2)+s(AMO1)+s(AMO)+s(ENSO4)+s(ENSO5)+s(ENSO3)+s(ENSO1)	R^2	DE	GCV	AIC
VIF P	1.066 3.482 2.463 2.168 1.057 1.133 1.216 1.918 0.025* 0.0005*** 0.007** 0.0004*** 0.0009*** 2.05e^{-06}*** 0.0006*** 0.009**	0.823	92.2	0.0606	−27.771
MHG	s(GDP)+s(AMO1)+s(AMO2)+s(ENSO1)+s(ENSO2)+s(ENSO3)	R^2	DE	GCV	AIC
VIF P	1.063 2.285 2.815 1.777 1.072 1.128 2.35e^{-07}*** 0.06716· 0.003** 0.061· 0.009** 0.002**	0.847	93.4	0.0223	−87.661

Note: VIF represents the Variance Inflation Factor, and P-value indicates the significance level, where"***"denotes 99.9 % confidence, "**"denotes 99 % confidence, "*"denotes 95 % confidence, "."denotes 90 % confidence. R^2 represents the goodness of fit, DE represents the deviance explained by the model, GCV represents the Generalized Cross-Validation, and AIC represents the Akaike Information Criterion. The small pelagic fish species (and their corresponding FAO 3-alpha codes) are as follows: Peruvian anchovy (VET), Chilean jack mackerel (CJM), Indian oil sardine (IOS), South African anchovy (ANC), Pacific saury (SAP), Arctic capelin (CAP), European anchovy (ANE), European pilchard (PIL), Atlantic herring (HER), Atlantic mackerel (MHA), and Gulf menhaden (MHG). The current and preceding five years' ENSO or AMO indices are represented as ENSO, AMO, and ENSO1 to ENSO5 and AMO1 to AMO5, respectively. GDP represents the global per capita GDP values.

$$\text{GAM:g(LNCapture)} \sim \text{s(ClimateVariables}_1) + \ldots\ldots \text{s(ClimateVariables}_n) + \text{s(EconomicVariable)}$$

In this equation, g represents the link function, and s denotes the smooth function. LNCapture represents the logarithmic values of the catches of different small pelagic fisheries over the years. ClimateVariables$_{(1\ldots\ldots N)}$ represent climatic factors(ENSO, AMO, and their lagged terms). EconomicVariable represents the economic factor(GDP).

2.2.3. Evaluation of the approach

Our study compared the predictive performance of the RF, XGB, LGBM, GBR, and CatBoost models across different tasks. Each algorithm

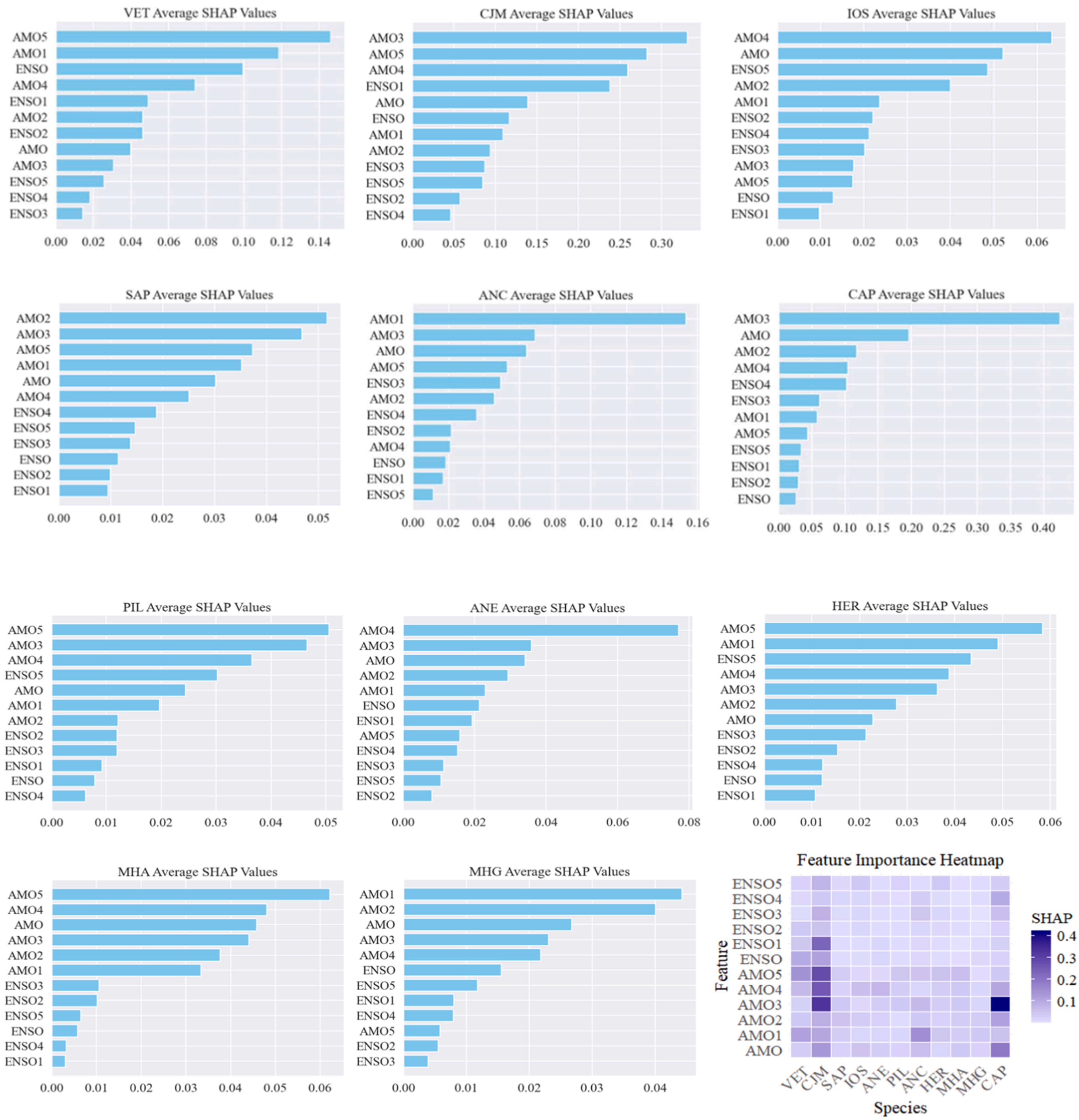

Fig. 1. Ranking of feature importance of ENSO, AMO, and their lag terms to catch variations in small pelagic fisheries. The horizontal axis represents the average SHAP feature importance values. The longer the bar, the greater the impact on the corresponding small pelagic fisheries catches. In the SHAP value heatmap, darker colors indicate larger average feature importance values. The small pelagic fish species (and their corresponding FAO 3-alpha codes) are as follows: Peruvian anchovy (VET), Chilean jack mackerel (CJM), Indian oil sardine (IOS), South African anchovy (ANC), Pacific saury (SAP), Arctic capelin (CAP), European anchovy (ANE), European pilchard (PIL), Atlantic herring (HER), Atlantic mackerel (MHA), and Gulf menhaden (MHG). The current and preceding five years' ENSO or AMO indices are represented as ENSO, AMO, and ENSO1 to ENSO5 and AMO1 to AMO5, respectively.

was evaluated using 1000 bootstrap samples, with RMSE serving as the performance metric. The results show that the CatBoost model outperforms all other models in terms of the lowest average RMSE and best stability (see Appendix for detailed results). Based on its superior performance in prediction accuracy and stability, CatBoost was selected as the optimal model for calculating SHAP values.

To determine the optimal model of GAM, we retained variables that significantly increased DE and reduced AIC and GCV scores. This process continued until the introduction of additional parameters no longer produced significant changes in these metrics. Additionally, all variables were subjected to significance testing. The VIF values were all below 5, indicating that the retained features in the model did not suffer from multicollinearity, thereby ensuring the model's reliability and accuracy. By comprehensively considering these factors, we identified the best model configuration. As shown in Table 1, the features constituting the optimal GAM did not entirely align with the feature importance rankings derived from machine learning algorithms. This discrepancy primarily arose from the need to mitigate the risks of overfitting and multicollinearity associated with introducing too many variables into the model. The GAM constructed in this study did not include interactions between variables. Additionally, as a semi-parametric model, the GAM uses smoothing functions to capture the nonlinear effects between independent and dependent variables. This makes the GAM more sensitive to nonlinear causal relationships among variables, allowing it to flexibly capture nonlinear trends. The feature importance obtained by the machine learning algorithm not only helped us to identify the synchronized fluctuations of catch changes and ENSO, AMO, but also provided a valuable reference for the construction of the subsequent GAM model. The important features selected by machine learning were used to optimize the model structure, avoiding the time-consuming search process among all possible feature combinations.

3. Result

3.1. The relative importance of ENSO and AMO and their lagging terms on changes in small pelagic fisheries

Fig. 1 shows the feature importance ranking of ENSO and AMO indices, along with their five-period lags. It was evident that climate indices and their lags had varying levels of importance for different small pelagic fishery catches, reflecting the fluctuations in catches to different extents. There was a significant correlation between the catches of small pelagic fisheries and the AMO and its lag effects. The ENSO index and its lag effects notably influenced the catches of Peruvian anchovy, Indian oil sardine, and Chilean jack mackerel, with these features ranking high in importance.

Consequently, we used the feature importance analysis results to introduce GAMs according to their importance order, proceeding with a more detailed analysis of the estimated effects of climate indices and economic development on the catches of various small pelagic fisheries based on the results from the optimal GAM models.。

3.2. Response of small pelagic fishery catch volume changes to climate change and economic development

3.2.1. The impact of ENSO on changes in small pelagic fishery catches

Table 1 presents the optimal models for the variations in catches of different small pelagic fisheries. Specifically, as shown in Fig. 2, ENSO, AMO, their lag periods, and economic development significantly influenced the catches of various small pelagic fisheries (calculated using Eqs. (1) and (2)).

For Peruvian anchovy (VET), the optimal model affecting its catch volume comprised ENSO, ENSO lagged by one period (ENSO1), and AMO lagged by three periods (AMO3). During the transition from La Niña to El Niño, the impact of ENSO and ENSO1 on anchovy catches shifted from positive to negative. Extreme El Niño events (ENSO at 2.5) resulted in a cumulative 117 % decline in anchovy catches. For Chilean jack mackerel (CJM), the significant influencing factors included AMO3, ENSO1 and ENSO4. During the period when ENSO increased from −2, ENSO1 and ENSO4 initially caused a decline in the catches of Chilean jack mackerel, followed by an increase, and then another decline during El Niño events. Extreme El Niño events resulted in a 24 % reduction in the catches of Chilean jack mackerel. For Indian oil sardine (IOS), the optimal model included AMO1, AMO3 and ENSO3, ENSO4, ENSO5. During the transition of ENSO from negative to positive, the catches of Indian oil sardine gradually declined. When ENSO shifted from 0.5 to an extreme El Niño event, the catches experienced a 49 % reduction. For South African anchovy (ANC), the significant influencing factors included ENSO3, ENSO4 and AMO1, AMO3. As the ENSO index transitioned from negative to positive, its positive impact on South African anchovy catches gradually weakened, while the negative impact strengthened. When the ENSO index increased from 0 to 2.5, the catches of South African anchovy decreased by 38 %. For Arctic capelin (CAP), the significant influencing factors included AMO2, AMO3 and ENSO3, ENSO4. During the transition from La Niña to El Niño events, ENSO3 had a significant negative impact on capelin catches. The response of capelin catches to ENSO4 was more complex, exhibiting an "M-shaped" distribution. As ENSO reached extreme states, the cumulative effect of El Niño and its lag periods led to a 102 % loss in capelin catches.

For European anchovy (ANE), the significant influencing factors included AMO3, AMO4, AMO5 and ENSO, ENSO1. During the transition from La Niña to El Niño events, the catches of European anchovy gradually decreased. When the ENSO index increased from 1 to extreme El Niño events, the catches of European anchovy experienced a 22 % reduction. For European pilchard (PIL), the optimal model included AMO2, AMO3 and ENSO5. When ENSO transitioned from 0 to an extreme El Niño event, the catches of European pilchard decreased by 5 %. For Atlantic herring (HER), the significant influencing factors included AMO1, AMO3 and ENSO4, ENSO5. As the ENSO index gradually increased from −2, the effects of ENSO4 and ENSO5 on Atlantic herring catches exhibited a "mountain-shaped" distribution. Both indices reached their peak positive impact when the ENSO index was at 0. As the ENSO index continued to increase to 2.5, the catches of Atlantic herring experienced a 23 % reduction. For Atlantic mackerel (MHA), the significant influencing factors included AMO, AMO5, and ENSO1, ENSO2, and ENSO4. These factors exhibited complex nonlinear effects on catches. Overall, the impact of ENSO on Atlantic mackerel catches followed a pattern of initial decline, subsequent rise, and another decline. The catches reached a first trough when the ENSO index was around −1, followed by a peak between 0 and 0.5. When the ENSO index continued to increase and entered an extreme El Niño event, Atlantic mackerel catches experienced a 28 % reduction. For Pacific saury (SAP), the optimal model included AMO, AMO1 and AMO2, as well as ENSO lagged by one and three to five periods. The impact of ENSO on Pacific saury catches exhibited a complex nonlinear effect, generally showing a fluctuating downward trend. For Gulf menhaden (MHG), the optimal model included AMO1, AMO2 and ENSO1, ENSO2, and ENSO3. During ENSO neutral and weak La Niña events, Gulf menhaden catches reached an initial peak. The catches reached a trough during moderate El Niño events, after which the positive impact on Gulf menhaden catches continued to increase.

$$\Delta LNCapture_{l(E/A)} = s(ClimateVariables_l)_{E/A}|(E_i / A_i) \tag{1}$$

$$\Delta Capture_{\frac{E}{A}} = \left\{ \sum_{l=0}^{n} [\exp(LNCapture_{l\left(\frac{E}{A}\right)}) - 1]|(E_i / A_i) \right\} 100\% \tag{2}$$

$$\Delta LNCapture_{lt(E/A)} = s(ClimateVariables_l)_{t(E/A)} \tag{3}$$

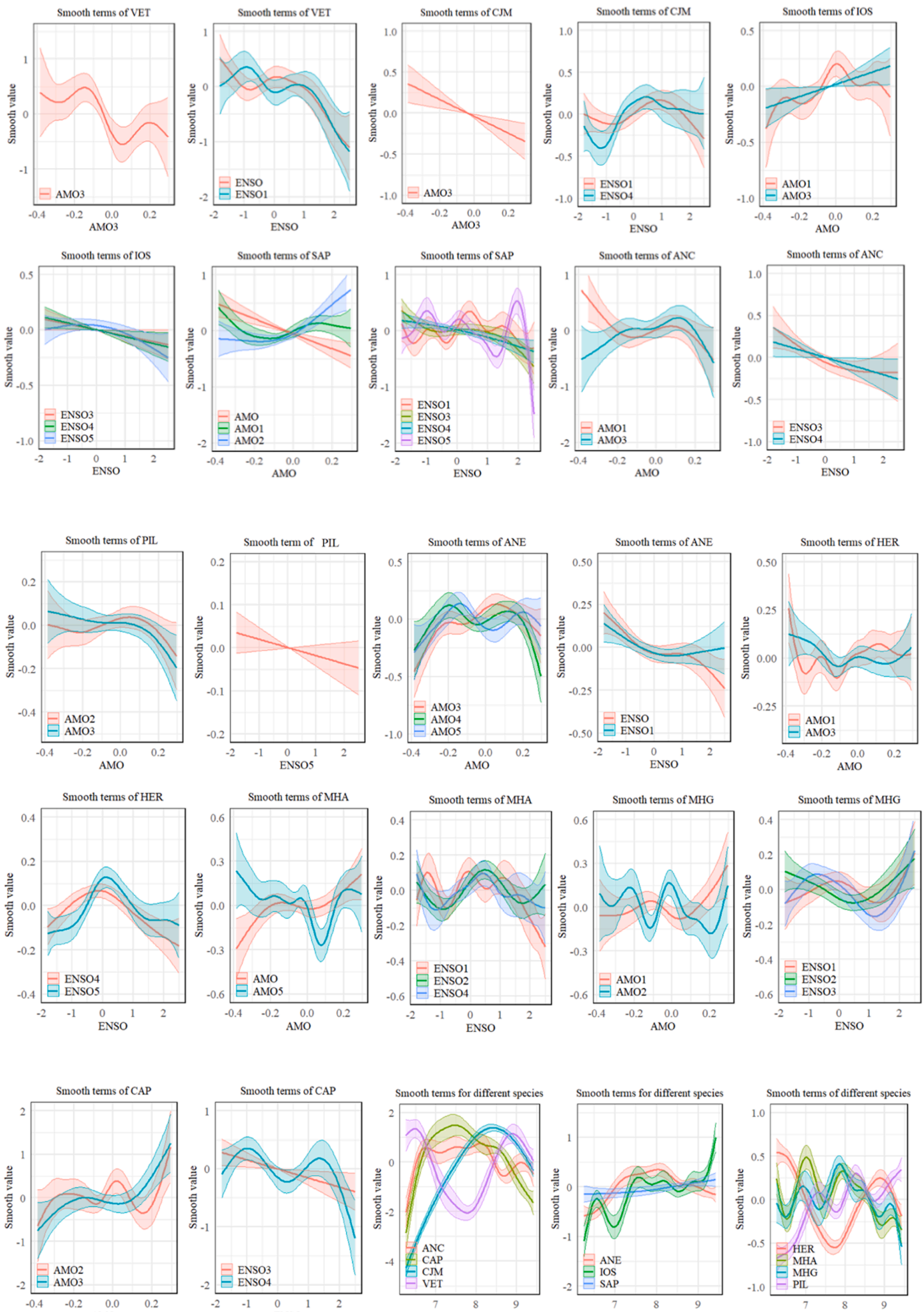

Fig. 2. The impact of ENSO, AMO, and economic development on the variability of catches of small pelagic fisheries. The x-axis of each subplot represents the range of values for climate indices (ENSO and AMO, including their lagged variables) and the level of economic development (log-transformed). The y-axis represents the extent of change in catches (log-transformed).

$$\Delta Capture_{t(E/A)} = \{\sum_{l=0}^{n} \exp(LNCapture_{lt(E/A)}) - 1\}100\% \tag{4}$$

Note: Among them, l represents n-period lags(0−5). E/A represent the corresponding ENSO or AMO indices. E_i/A_i represent the specific values of the ENSO (or AMO) indices at a given level. t represents specific years from 1963 to 2021. s is the smooth function, representing the impact of ENSO or AMO on the logarithmic changes in catches in the optimal model. Eq. (1) represents the changes in the dependent variable (logarithmic catches) caused by ENSO (or AMO) at a specific index level in the optimal model. Eq. (2) represents the changes in catches (%) caused by all ENSO (or AMO) lagged terms included in the optimal model.(1) and (2) measures the cumulative change in catches resulting from the occurrence of ENSO (or AMO) in the optimal model. Eqs. (3) and (4) represent the changes in catches caused by ENSO (or AMO) and related lagged terms for a specified year. They measure the comprehensive impact of climatic changes in that particular year, along with the delayed effects of previous climatic changes on catches (%).

3.2.2. The Impact of AMO on Changes in Small Pelagic Fishery Catches

During the transition of AMO from its cold phase to warm phase, the effect of AMO3 on Peruvian anchovy shifted from positive to negative and exhibited a nonlinear trend during this transition. For Chilean jack mackerel (CJM), the warm phase of the AMO resulted in a 29 % reduction in catches. For Indian oil sardine (IOS), AMO3 exhibited a linear positive effect on catches. The influence of AMO1 showed a "mountain-shaped" distribution. During the transition from the cold phase (-0.4) to neutral (0), the catches of Indian oil sardine fluctuated and increased, peaking at 0. After reaching this peak, as AMO continued to warm, the catches gradually declined. For South African anchovy (ANC), as the AMO index transitioned from −0.4 to −0.2, the positive effect of AMO1 gradually weakened to zero, while the negative effect of AMO3 similarly weakened to zero. As the AMO index continued to increase to 0.3, the catches of South African anchovy decreased by 87 %. For Arctic capelin (CAP), the warm phase of AMO had a notably different impact, showing a nonlinear positive effect on the catches.

For European anchovy (ANE), the effects of AMO lagged by three to five periods (AMO3 to AMO5) on catches exhibited an "M-shaped" impact. The positive influence of these three lags reached its first peak when the AMO index increased to approximately −0.2, occurring sequentially for lags of 3, 4, and 5 periods, with the magnitude of the positive effect being inversely related to the lag period. This pattern indicated that the positive impact of AMO cold phase on European anchovy accumulated and manifested over time. As the AMO index increased further, the positive influence weakened and then strengthened again, reaching a second peak at around 0.1. It was evident that both extreme cold and warm phases of AMO were detrimental to anchovy catches. For European pilchard (PIL), as the AMO transitioned from the cold phase to the warm phase, the catches of European pilchard initially declined slowly. However, as the AMO index exceeded 0.1 and continued to rise, the catches experienced a sharp decline, resulting in a 32 % loss. For Atlantic herring (HER), the effects of AMO1 and AMO3 on catches displayed "W-shaped" and "V-shaped" patterns, respectively. As the AMO index increased to −0.1, the positive stimulation on Atlantic herring catches gradually weakened. Following this initial decrease, the catches began to slowly increase, with the influence of AMO3 being relatively smaller compared to AMO1. For Atlantic mackerel (MHA), the influence of AMO on catches was characterized by a nonlinear positive effect. However, the impact of AMO5 on catches followed a trend of initial decline followed by an increase. For Pacific saury (SAP), the response of catches to AMO and its lagged periods shifted from negative to positive. As the lag period extended, the positive stimulation of AMO on catches became more pronounced. For Gulf menhaden (MHG), the effects of AMO1 and AMO2 on catches exhibited significant nonlinear trends. The positive impact of AMO1 was amplified as the AMO index entered the warm phase, while the response of catches to AMO2 was more variable.

3.2.3. The impact of economic development on changes in small pelagic fishery catches

In terms of the impact of economic development on the catches of various small pelagic fisheries, Fig. 2 shows that different small pelagic fisheries have largely experienced cycles of development-underdevelopment or recovery-redevelopment. The positive stimulation of GDP on the catches of Peruvian anchovy(VET) reached a first peak in the earlier period and then rapidly declined. After reaching a trough at 7.8(the GDP level), the catches gradually rose to a second peak at 9, and then continued to decline. For South African anchovy(ANC), the catches increased as GDP initially grew to 6.7, after which they entered a stable fluctuating state. However, when GDP reached 8.3, the catches began to decline. Although another peak occurred at 9, it was far below the earlier growth levels. For Arctic capelin (CAP) and Chilean jack mackerel (CJM), both exhibited a pattern of initial increase followed by a decrease in catches. Arctic capelin reached its peak exploitation level earlier. The catches of Arctic capelin started to decline after reaching a peak at 7.5. For European anchovy (ANE), GDP growth up to 8.1 consistently promoted the exploitation activities of this species, after which the catches gradually declined. The response of Indian oil sardine (IOS) catches to GDP was more complex. Although it reached a trough at 7, the overall trend showed an increasing pattern. In contrast, the catches of Pacific saury (SAP) were positively influenced by GDP in a relatively smooth manner. For European pilchard (PIL), the response to GDP exhibited a notable nonlinear growth pattern, with two peaks at 7.3 and 8.3, and two troughs at 7.7 and 8.6. In contrast, Atlantic herring (HER) catches responded to GDP with a trough at 7.7, followed by a peak at 8.8, after which the volumes declined again. However, this latter peak was significantly lower than the earlier development levels. For Atlantic mackerel (MHA) and Gulf menhaden (MHG), the catches exhibited similar response patterns to GDP. Both species experienced two peaks around GDP levels of 7 and 8, and two troughs around 6.5 and 7.5. In the later stages, the trend primarily showed a decline.

3.2.4. Differences in the contribution of climate change and economic development to changes in small pelagic fishery catches

Additionally, drawing on the research by Lai et al. [45,46], we evaluated the contribution differences of each variable in causing fluctuations in the catches of various small pelagic fisheries based on the optimal GAM model. As shown in Fig. 3, with the exception of the best model for Pacific saury (SAP) catches, GDP accounted for the largest contribution proportion in all other models. Specifically, for Peruvian anchovy (VET), Chilean jack mackerel (CJM), Indian oil sardine (IOS), Atlantic herring (HER), and European anchovy (ANE), the influence of GDP fluctuations on these fishery resources exceeded 50 %. It was evident that economic factors play a dominant role in fishery catches. On the other hand, AMO and its lagged effects held a more significant influence on catches compared to ENSO, which aligned with the results from the machine learning analysis. Therefore, regional governments must consider resource conservation and climate change factors comprehensively when making fishery management decisions aimed at achieving economic performance, to ensure sustainable development.

3.2.5. Annual changes in catches of various small pelagic fisheries induced by ENSO and AMO

Next, we further explored the data fluctuations in catches of various small pelagic fisheries caused by AMO and ENSO and their lag periods (specific calculations are given by Eqs. (3) and (4)). As shown in Fig. 4, these climatic indices and their lag effects significantly influenced the catches of small pelagic fishes. It can be observed that the catches of Peruvian anchovy(VET), Pacific saury(SAP), and Arctic capelin(CAP) exhibited significant fluctuations. The boxplot boundary lines for these species exceeded 0.5, indicating that the annual variations in catches due to climate changes reached over 50 %. This demonstrated that these

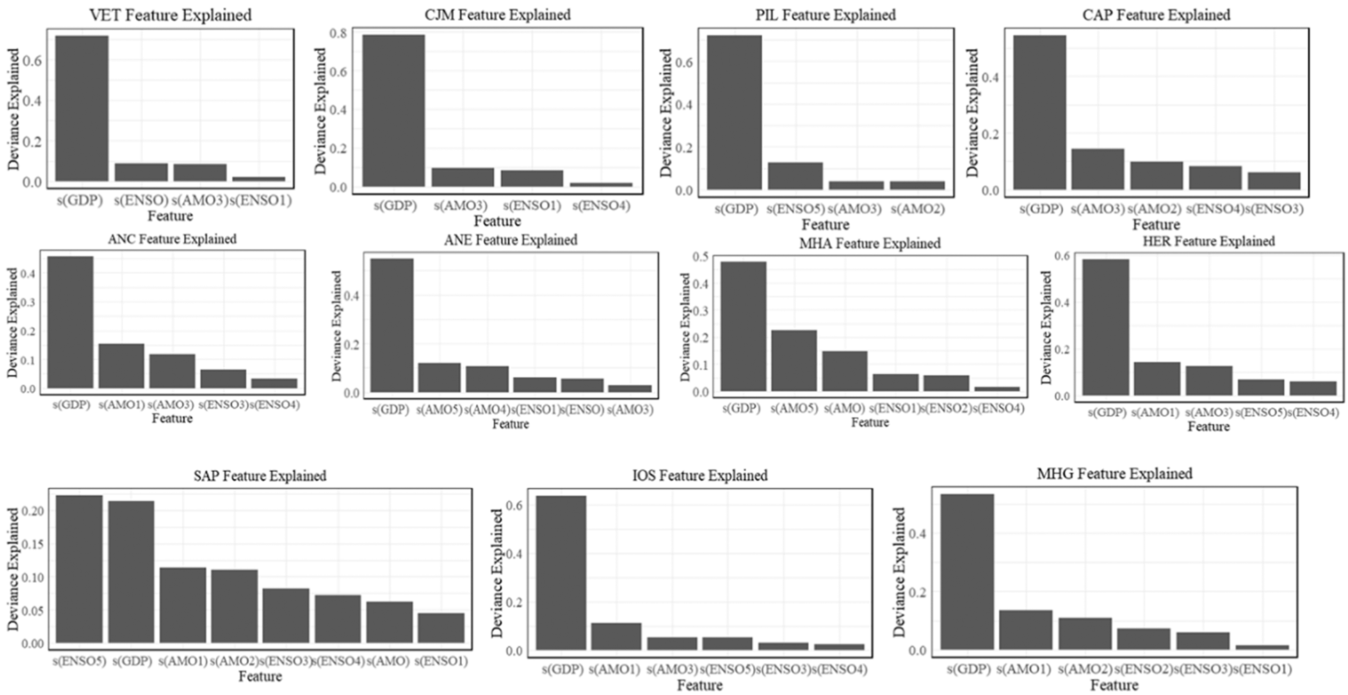

Fig. 3. Explanatory power of climate change and economic development on changes in small pelagic fishery catches. The horizontal axis represents the explanatory variables included in each optimal model. The vertical axis represents the proportion of the variation in catches explained by different explanatory variables in the optimal model. The taller the bar, the greater the explanatory power of that factor, indicating a higher impact on changes in catches within the optimal model.

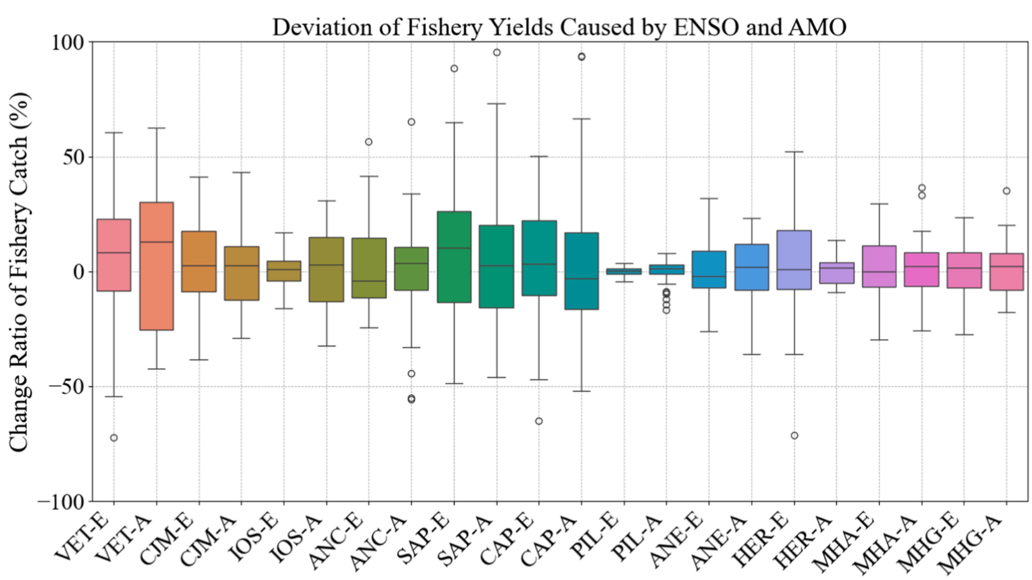

Fig. 4. Annual changes in catches of various small pelagic fisheries induced by ENSO and AMO (%). The vertical axis represents the percentage change in catches (in their original scale) of different small pelagic fisheries due to climate variations. The lower boundary of the box indicates the first quartile (25th percentile, Q1), meaning 25 % of the values are below this number. The upper boundary of the box indicates the third quartile (75th percentile, Q3), meaning 75 % of the values are below this number. The height of the box represents the interquartile range (IQR), which is the difference between the third quartile and the first quartile (IQR = Q3 - Q1), reflecting the range of the middle 50 % of the data values. From the lower boundary of the box extending to the lower whisker end, it represents the minimum value within Q1 minus 1.5 times the interquartile range (Q1 - 1.5IQR). From the upper boundary of the box extending to the upper whisker end, it represents the maximum value within Q3 plus 1.5 times the interquartile range (Q3 + 1.5IQR). The independent points (dots) beyond the whiskers indicate outliers, referring to data points that exceed the range of Q1 - 1.5IQR or Q3 + 1.5IQR, representing extreme values.

fish species were more sensitive to ENSO and AMO. Additionally, the catches of Chilean jack mackerel(CJM), South African anchovy(ANC), and Atlantic herring(HER) also exhibited significant variations. In contrast, other fish species showed relatively smaller ranges of fluctuation. The presence of multiple outliers further revealed the potential for extreme climate events to cause abnormal variations. Specifically, except for Arctic capelin (CAP), the median of boxplots depicting the impact of AMO deviations on the catches of other fish species was above 0. This indicated that from 1963 to 2021, the annual catches of most fish species had been influenced by AMO above the average level. This was primarily because the period since 1963 had seen more instances of AMO in its negative phase than in its positive phase. As previously mentioned, the positive phase of AMO tended to negatively impact the catches of most small pelagic fishes, while the negative phase generally supported increased catches. Consequently, the prevalence of the negative phase had resulted in more years with catches above the average level. However, the results from the GAM indicated that Arctic capelin (CAP) responded positively to the positive phase of AMO. This explained why its catches were below the average in most years. The positive phase of AMO likely benefited its habitat and food supply, leading to higher catches during these periods. Regarding the influence of ENSO, the medians of Peruvian anchovy (VET), Chilean jack mackerel (CJM), Pacific saury (SAP), and Arctic capelin (CAP) were above 0. A closer analysis of the GAM model results revealed that the catches of Peruvian anchovy significantly declined when the El Niño index exceeded 1. Since 1963, above moderate El Niño events (index greater than 1) had accounted for one-sixth of all years. Similarly, the catches of the other three species also showed noticeable negative growth trends during moderate or stronger El Niño events, following periods of positive growth. Despite this, we cannot overlook the significant impact of El Niño events on these fish species. The boxplots revealed that the catches of these four species—Peruvian anchovy (VET), Chilean jack mackerel (CJM), Pacific saury (SAP), and Arctic capelin (CAP)—experienced losses close to 50 % due to El Niño events. In particular, Peruvian anchovy showed losses exceeding 50 % in several years. This phenomenon underscored the critical impact of extreme El Niño events on fishery resources, necessitating effective management and conservation measures to address the severe challenges posed by climate change.

4. Discussion

4.1. The dominant driving role of economic development on small pelagic fisheries

Small pelagic fisheries are vital to global socio-economic development, supporting millions of livelihoods through an industry chain that spans from fishing and processing to sales. However, demand expansion and overfishing have led to interdecadal fluctuations in catches, with some fisheries experiencing collapses. This study highlights that economic factors are key drivers of these fluctuations, influencing fishing intensity, resource management, and long-term sustainability. For example, the Peruvian anchovy fishery peaked at over 12 million tons in 1970 (GDP at 6.5) before collapsing due to overfishing. Recovery efforts during the 1980s and 1990s (GDP at 7.8) remained limited, stabilizing only after the implementation of the Maximum Catch Limit per Vessel Law in 2008 (GDP at 9). Our findings align with Iwamoto and Pauly, who noted similar patterns in the fishery, but with a clearer focus on the role of economic factors as key drivers[16,47]. For South African anchovy, faced fluctuations due to growing fishmeal demand and technological advances. By the 1990s (GDP at 8.3), South Africa adopted an ecosystem-based joint fishing strategy with total allowable catches and individual quotas to curb overfishing [48,49]. The Arctic capelin fishery grew from the 1960s to the late 1970s (GDP at 7.5) but declined sharply thereafter, reflecting the regulatory framework introduced by the bilateral fisheries agreement between Russia and Norway [50]. Chilean jack mackerel catches increased until the 1990s (GDP at 8.4) before declining due to overexploitation, consistent with studies emphasizing the role of commercial fishing in stock depletion [51,52].

European anchovy catches surged during the 1960s, driven by technological advances and market value, peaking in the mid-1980s (GDP at 8.1). However, overfishing led to resource depletion, consistent with the findings of Palomera and Oguz [53,54]. This study underscores that while technological progress initially boosted catches, long-term sustainability was compromised by overexploitation. Pacific saury also saw steady growth in catches, prompting the establishment of the Pacific Saury Working Group in 2015 to ensure sustainable fishing practices [55,56]. Indian oil sardine catches declined in the late 1960s and early 1970s (GDP between 6.5 and 7), but gradually increased due to improvements in vessel size and gear [57]. European pilchard exhibited cyclical fluctuations, peaking in the mid-1970s and early 1990s (GDP at 7.3 and 8.3, respectively), reflecting challenges in managing fisheries under overexploitation pressures. For Atlantic herring, catches peaked in the mid-1960s but collapsed by the 1980s (GDP at 7.7), later recovering due to reduced fishing effort and efficient methods [65]. However, by the early 2000s(GDP at 8.8), another crisis emerged, and the cumulative effects of fishing mortality have led to a gradual decline in catches, despite a regional management organization established in 2005. Similar fluctuations were observed in Atlantic mackerel and Gulf menhaden fisheries, with notable peaks in the mid-1970s and mid-1980s (GDP at 7.5), but overfishing ultimately compromised sustainability [58].

Furthermore, catches of most small pelagic species declined after the 1980s (GDP at 8), coinciding with the implementation of sustainable fisheries management policies by the United Nations. This period marked the beginning of increased awareness about the need for balancing resource utilization with conservation. While advancements in fishing technology and modernized equipment improved fishing efficiency, the expansion of fishing activities driven by heightened market demand and international trade contributed to increased fishing pressure. The result was a growing threat to the resilience and regenerative capacity of marine ecosystems, pushing fishery resources closer to collapse. These findings highlight that effective fishery management measures can help balance fishing pressure with resource conservation. Our analysis shows that stricter catch quotas and the establishment of marine protected areas can mitigate overfishing risks. While these measures may limit short-term profits, they are essential for maintaining fishery stocks and ensuring long-term resource availability. We recommend that regional governments implement comprehensive monitoring systems to track fishery resource changes. These systems should be based on scientific research and data-driven assessments to allow for timely adjustments to catch quotas. Additionally, seasonal fishing bans, aligned with the reproductive and growth cycles of species, could help reduce pressure on fish populations during critical periods. Incorporating innovation into sustainable fishing technologies, such as the development of eco-friendly fishing gear, is also crucial. Encouraging fishers to adopt alternative livelihoods can reduce overreliance on fishing, thus supporting community resilience.

4.2. Effects of ENSO on Small Pelagic Fisheries

The feature importance reveals that while ENSO significantly impacts global fishery resources, its influence is more pronounced in fisheries systems located near the equator and in the Southern Hemisphere. This study reveals that El Niño events suppress the catches of most small pelagic species, while La Niña events generally have positive effects, except for species like Chilean jack mackerel and Atlantic herring. The transition to neutral conditions often coincides with recovery and peak catches for these species, illustrating the variable impacts of ENSO phases across different fisheries. Additionally, The "M-shaped" or "mountain-shaped" response curves observed in catches highlight that extreme La Niña events are not universally beneficial. Strong La Niña events disrupt fish reproduction by displacing fish eggs from habitats and damaging juvenile fish, reducing survival rates. Similarly, while nutrient-rich upwelling zones during La Niña support fish survival, they also increase the risk of eutrophication. El Niño events reduce the equatorial undercurrent, disrupting fish migration patterns, leading to changes in fishing areas and times, and ultimately affecting the efficiency of fishing operations [24]. These changes are driven by reduced nutrient supply, warmer sea surface temperature, and altered rainfall and storm patterns, which collectively impact primary productivity and fishery yields [59]. Species-specific responses further illustrate the diverse impacts. For example, Peruvian anchovy populations decline significantly during El Niño due to reduced upwelling and lower ocean productivity, which affect survival across life stages [60,61]. Similarly, Indian oil sardine experience disrupted reproductive behavior and reduced metabolic efficiency during El Niño due to weakened upwelling [62]. Additionally, ENSO impacts regional marine ecosystems through changes in ocean-atmosphere circulation patterns such as the Walker and Hadley circulations. For example, in the Gulf of California, El Niño reduces winter upwelling and chlorophyll concentrations, diminishing productivity in dependent fisheries [63]. However, in some cases, increased storm activity during El Niño enhances productivity through deep-water mixing, boosting phytoplankton concentrations in regions like the Gulf of Mexico. Gulf menhaden benefit from El Niño events, as warmer temperature and reduced predator populations support their growth, while nutrient-rich runoff from the Mississippi River ensures ample food supply [64].

4.3. Effects of AMO on small pelagic fisheries

The results of the machine learning analysis indicate that, compared to ENSO, AMO has a larger-scale impact on global small pelagic fish catches. It influences the distribution of heat and salinity in the global oceans, wind fields, ocean circulation, and the thermocline through the Atlantic Meridional Overturning Circulation (AMOC), exerting a cumulative effect across different oceans, thereby influencing fishing activities and decision-making. Our study reveals that the warm phase of AMO generally exerts negative effects on catches due to increased ocean temperature and stronger vertical stratification, which weaken coastal upwelling systems and primary productivity. However, certain species, such as Arctic capelin, Atlantic herring, Atlantic mackerel, and Gulf menhaden, benefit from the warm phase, indicating the heterogeneous nature of the impacts. The warm phase of AMO also amplifies cyclone and hurricane activity, resulting in increased precipitation and storm events. These climatic shifts influence the distribution and abundance of key fishery species, prompting fishing communities to adapt their target species and fishing areas. For instance, anchovy, sardine, and herring populations in the central and eastern Atlantic ocean tend to shift northward during the warm phase, as documented by Alheit [66]. Additionally, AMOC-driven changes propagate Rossby and Kelvin waves, which affect temperature and nutrient availability in distant marine regions. For example, a stronger AMOC suppresses upwelling off the Peruvian coast, reducing primary productivity and fishery yields [22]. The distribution of heat during the warm phase increases the metabolic costs for fish species. Additionally, higher ocean temperature and stronger vertical stratification weaken coastal upwelling systems. These directly impact the primary productivity of important upwelling systems, such as the Humboldt, Benguela, California, and Canary systems, affecting the survival of small pelagic fish species [67,68]. However, excessive upwelling can also lead to hypoxic conditions, light limitation and displacement of juvenile fishes and plankton from suitable habitats, exacerbating declines in fishery productivity [69]. Hypoxia-tolerant species, such as jellyfish, expand during these conditions, intensifying predation pressure on small pelagic fishes and heightening competition for limited resources [70]. Interestingly, Arctic capelin exhibit a positive response during the AMO warm phase, attributed to moderate temperature increases that reduce ice cover and enhance light penetration, boosting phytoplankton productivity. Combined with reduced predation pressure from species like cod and improved reproduction conditions, these factors collectively expand the distribution and population of Arctic capelin, leading to increased catches [71].

Meteorological events triggered by ENSO and AMO, such as severe flooding, droughts, and wildfires, can lead to socio-economic disruptions, including famine, epidemics, and conflicts, causing substantial economic losses [72–74]. This study highlights the significant impact of ENSO and AMO-driven climate fluctuations on small pelagic fisheries. Both the positive and negative phases of these events have asymmetric, nonlinear effects on fish catches. While most species are adversely affected by the positive phases, extreme negative phases do not always benefit fisheries. Additionally, the delayed effects can result in fishery losses years later. To mitigate these impacts, regions should establish robust monitoring and early warning systems for ENSO and AMO phases. Fishing efforts should be adjusted accordingly, and habitat protection should be prioritized during extreme events. Ecosystem restoration projects can enhance the resilience of marine ecosystems to climate fluctuations.

5. Conclusion

In summary, the impacts of climate change and economic development on the catches of small pelagic fisheries exhibit significant species-specific and complex nonlinear characteristics. This variability reflects the socio-economic conditions of specific regions as well as the different adaptive capacities and ecological requirements of various fish species. The level of economic development plays a key role in the utilization and conservation of fishery resources. While advanced infrastructure and technological advancements improve extraction efficiency, they also necessitate the establishment of a robust fishery management system to tackle the challenges posed by overfishing. Reasonable catch quotas and ecosystem-based fishery management plans are crucial for ensuring the long-term sustainability of fish stocks. Moreover, different fish species show specific response patterns to environmental changes, with their varying adaptive capacities influencing the extent of catch fluctuations in response to ENSO and AMO. Disastrous events induced by climate change, such as heavy rainfall and hurricanes, further exacerbate these fluctuations by impacting fishing activities. Therefore, the effects of climate change and economic development on fish catches are complex and multifaceted, requiring a comprehensive approach that integrates both socio-economic and ecological perspectives.

This study provides valuable insights for developing effective fishery management and resource conservation strategies. By understanding the varying mechanisms, we can better formulate adaptive management strategies with dynamic regulation, ensuring the effective protection and rational utilization of fishery resources in different regions, thus maintaining the sustainability of global fisheries. However, this study has certain limitations. Firstly, FAO data rely on reports from national governments, which may vary in reporting standards and accuracy. Secondly, the accuracy of historical data may be affected by changes in data collection methods and technologies, with earlier data potentially being less accurate than more recent data. Thirdly, illegal, unreported, and unregulated (IUU) fishing activities are not fully reflected in FAO data, which may result in underestimation of actual catch volumes. Additionally, the analysis was conducted at a global level and did not sufficiently account for regional differences. Future research could focus on identifying regional variations, investigate the migration patterns in the context of climate change, and address issues related to cross-regional cooperation and benefit distribution. Moreover, this study focused only on 11 species. The population fluctuations of other small pelagic fish species, as well as larger fish species, in response to climate change and economic development remain to be explored. The mechanisms through which climate change affect catches can be further investigated from multiple perspectives, including physical, chemical, biological, and economic aspects, to develop more refined fishery management strategies.

CRediT authorship contribution statement

Zhang Ying: Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Fang Xiaohan:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.marpol.2025.106631.

Data availability

Data will be made available on request.

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