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Research Article

Seasonal Stratification and Depth Effects on Chub Mackerel Fishery Yields

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Abstract: Assessing how environmental and anthropogenic factors jointly influence fishery yields is crucial for targeted fishery management under climate change. By integrating Gray Relational Analysis (GRA) with Bayesian Generalized Linear Mixed Models (GLMM) to quantify how sea surface temperature (SST) and sea surface salinity (SSS) affect the yields of chub mackerel *(Scomber japonicus)* and Japanese Spanish Mackerel *(Scomberomorus niphonius)* in the Bohai Sea. Through the combination, key environmental drivers are identified and ranked using GRA, and their effects are estimated while accounting for uncertainty by Bayesian GLMM. The analyses revealed a strong association between water temperature at 50 m depth and mackerel catch yields, with interaction terms involving the engine power of fishing vessels further strengthening this correlation. By incorporating lagged catch, fishing vessel count, SST at 50 m, surface SSS, and seasonal factors into a Bayesian GLMM framework, the analysis reveals that chub mackerel yields are predominantly influenced by environmental changes, particularly through interactions between SST and fishing vessels ($p < 0.1$). For Japanese Spanish mackerel, the interaction between SST at 50m and fishing vessel count is significant ($p<0.01$). Seasonal analyses indicate that summer and winter conditions notably affect catch yields. These findings underscore the complex interplay between environmental drivers and anthropogenic factors in influencing fishery productivity under climate change. The combined GRA–Bayesian GLMM approach enhances variable prioritization and statistical inference, offering a practical framework for disentangling environmental and human influences on fishery productivity.

Keywords: Climate change; Chub mackerel; Fishery yields; Japanese Spanish mackerel; SST and SSS

1. Introduction

Chub mackerel and Japanese Spanish mackerel, two principal pelagic species harvested in the Yellow Sea and Bohai Sea, are highly sensitive to rising sea temperatures. Chub mackerel is a smaller, schooling planktivorous species, whereas Japanese Spanish mackerel is a larger, fast-growing coastal predator; both support important commercial fisheries but occupy different trophic niches and have distinct growth and reproductive strategies, which motivates separate modeling of their population and fishery responses to environmental change. Recent studies indicate that these species are shifting toward higher latitudes, with spawning grounds contracting in traditional areas such as the Yellow Sea and East China Sea (Kunimatsu et al., 2023). Projections for Korean waters suggest that chub mackerel habitat may expand by approximately 13%–42% in the East Sea but decline by 5%–21% in the Yellow Sea by the 2050s due to changes in temperature and sea surface salinity (Bang et al., 2024). Northward shifts in mackerel distribution disrupt traditional fishing grounds, increasing costs and reducing catch quality (L. Wang

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et al., 2021; Holsman et al., 2019). In the Bohai Sea, chub mackerel capture has undergone three distinct phases: initial growth (1981-1994), fluctuating increase (1994-2013), and recent decline (2013-2022) (Bureau of Fisheries, Ministry of Agriculture and Rural Affairs, 2023), prompting the need for quantitative models that link environmental forcing to fishery outcomes.

In this study, environmental effects on chub mackerel are characterized using habitat and distribution-based models (incorporating temperature, stratification, and depth) and then coupled to a bioeconomic framework that relates the resulting habitat suitability and biomass indices to fishery yields and economic performance, thereby extending previous work that has focused mainly on biological or physical habitat responses. Model validation studies of related species distribution and habitat suitability applications report high predictive skill (AUC > 0.95) for projected spatial shifts and indicate that the semi-enclosed Bohai Sea may emerge as a future hotspot for cold temperate species because of its unique bathymetry and relatively slower warming compared with adjacent waters (Chen et al., 2023). This regional heterogeneity, together with the importance of the Bohai Sea for marine biodiversity and coastal economies (Zhang, Yang, et al., 2022; Cao et al., 2017), underpins the Bohai Sea as the study area and justifies the combined use of environmental and bioeconomic models to assess the implications of climate-driven changes in mackerel fisheries.

SST and SSS are the key environmental factors affecting the distribution and abundance of marine ecosystems and fishery resources. SST changes can directly affect the metabolism, growth, reproduction, and distribution range of fish (Pörtner and Peck, 2010), whereas SSS changes have a significant effect on fish physiological and organismal adaptation and population structure (Wanta et al., 2023; Neuenfeldt et al., 2009). Considering the availability of data in the Bohai Sea area, the long-term high-resolution observation data of dissolved oxygen and acidity are limited, making it difficult to support large-scale and long-time series empirical research (Han et al., 2013). Therefore, SST and SSS are selected as representative climate variables.

This study examines how climate change has affected fishery catches in the Bohai Sea from 1981 to 2010 by relating chub mackerel and Japanese Spanish mackerel yields to sea surface temperature (SST) and sea surface salinity (SSS) at multiple depths (0, 20, and 50 m). Building on previous work that has largely focused on surface conditions, the analysis explicitly considers vertical structure to identify seasonal patterns and depth layers that most strongly influence catch yields, thereby improving understanding of climate–fishery interactions in a stratified, semi-enclosed sea. To achieve these aims, GRA is first used to rank the relative importance of SST and SSS at different depths and seasons under limited and noisy data conditions. Bayesian GLMMs are then applied to quantify the effects of key environmental drivers on the two mackerel species while accounting for temporal and spatial random effects. This integrated approach allows surface and subsurface environmental variability to be linked to fishery yields in a probabilistic way, providing a structured, modeling-based risk assessment of climate impacts in the Bohai Sea. By highlighting which depth-specific temperature and salinity changes are most closely associated with changes in mackerel catches, the results offer evidence to support regionally tailored management measures, critical habitat protection, and climate adaptation policies. However, as with any model-based analysis, the reliability of these findings depends on data completeness and quality; the method requires accurate input variables for both surface and subsurface parameters, and results should be interpreted within these limitations.

2. Methods

2.1 Data Collection

Figure 2 presents a flowchart of the analytical method used. The climate data used in this study were sourced from the National Marine Center. The specific dataset is observation data from Chinese oceanic stations, including ZhiFuDao, XiaoChangShan, and LaoHuTan in the Bohai Sea. The dataset consists of long-term monthly climatological averages for 1981–2010. For each calendar month (January to December), the values represent the mean conditions over the 30-year period. The dataset provides standardized measures for SST and SSS, with a spatial resolution of 0.25° × 0.25°, covering the geographic extent from 100°E to 170°E longitude and 0°N to 50°N latitude across multiple marine depths. For the purposes of this analysis, three depth strata were selected: 0, 20, and 50 m as shown in Figure 1, there are three depth contours in the Bohai Sea.

For the Bohai Sea region, the raw gridded data were spatially subset using Python-based data processing tools, such as X array, to match Bohai Sea geographic boundaries (117°E–121°E, 37°N–41°N). The data processing workflow involved reading the original NetCDF files, extracting grid cells corresponding to the target longitude and latitude range, selectively retrieving data at the specified depths, and saving the resulting Bohai Sea subset as a new NetCDF file for subsequent analysis.

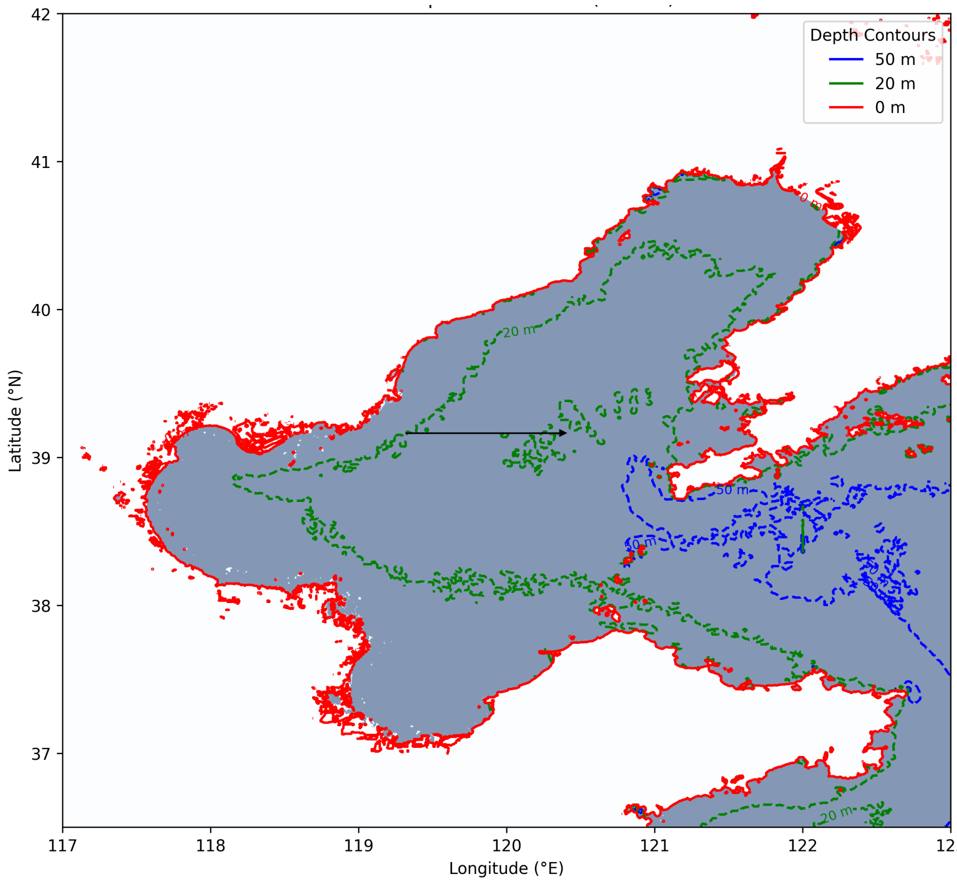

Figure 1 Water depth in the Bohai Sea, China

Note: This figure is based on the GEBCO 2024 dataset (https://download.gebco.net/). The red line represents the 0-m depth contour, the green line indicates the 20-m depth contour, and the blue line marks the 50-m depth contour.

Data from the China Fishery Yearbook for Japanese Spanish mackerel and chub mackerel compiled for 1981–2010 and 2020, respectively. These data aim to analyze both one-year and ten-year lagged trends in capture. Furthermore, we partitioned the annual catch data into four seasons: spring (March–May), summer (June–August), autumn (September–November), and winter (December–February). Given the distribution characteristics and primary catch species in the Bohai Sea, the spatial range for Japanese Spanish mackerel encompasses the Bohai Sea, Yellow Sea, and East China Sea, extending to waters south of Hokkaido, Japan, and including areas near the Korean Peninsula and the warm currents of the Northwest Pacific (Zhang, Yu, et al., 2022; Piccinetti et al., 2020). Chub mackerel, a warm-water pelagic species, is distributed in the Northwest Pacific, including the coastal waters of China, Japan, and Korea. During spring and summer, chub mackerel inhabits the upper and middle water layers, and as the spawning season approaches, they aggregate in large schools and migrate to coastal areas for reproduction

(Zhao et al., 2025; Guo et al., 2022).

In addition, fishing vessel power data from the China Fishery Yearbook were collected for the Bohai Sea to assess the interactive effects of fishing efforts in the region. This multi-source approach aligns with established practices in agricultural and fisheries data collection, emphasizing the integration of environmental, biological, and socioeconomic variables to support empirical analysis and minimize measurement errors.

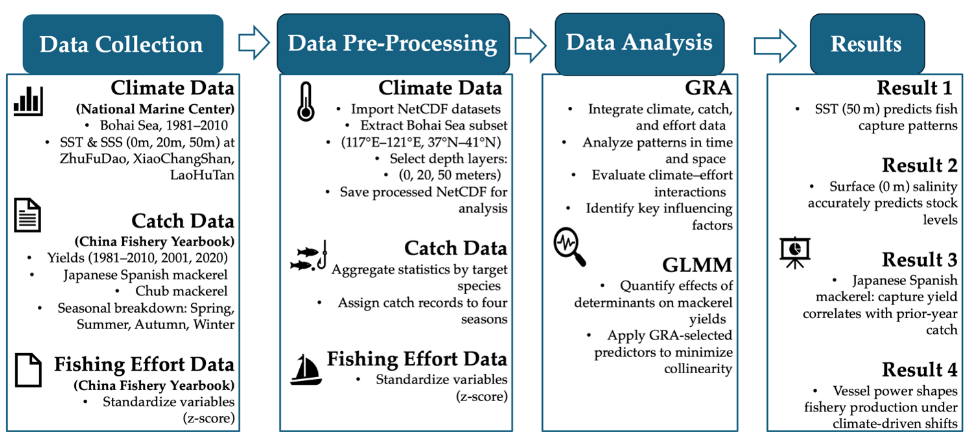

Figure 2 Flowchart of the analytical method used

2.2 Method Introduction

GRA, originally developed by Deng (Wei, 2010), is a nonparametric analytical framework designed to evaluate the relationships between variables in systems characterized by data scarcity, uncertainty, or noise. GRA is used in agriculture, industry, economy, management, and other disciplines, and has achieved remarkable results. The GRA method involves the following five steps. First, the reference and comparison series are determined. The reference sequence X_0 *(k)* is annual capture yields of Japanese Spanish mackerel and Chub mackerel. Comparison sequences $X_i(k)$ by climate drivers include SST and SSS (0–50m depth stratified). The amount of horsepower of fishing vessels measures fishing effort. Interaction terms are SST $\times$ Vessel and SSS $\times$ Vessel.

To address unit disparities among variables, min–max normalization was applied, as shown in Equation (1). $X_i(k)$ is normalized value of variables SST and SSS defined by i at observation year k after min–max normalization, used to make variables with different units comparable, $X_i'(k)$ is unnormalized value of variables SST and SSS i at observation year k. The minimum and maximum of the variable SST and SSS across all observation's year k, used in the normalization bounds.

$$X_i(k) = \frac{X_i'(k) - \min X_i'}{\max X_i' - \min X_i'}, \quad (i = 0, 1, \ldots, m;\ k = 1, 2, \ldots, n) \tag{1}$$

Absolute deviations are computed with time-varying weights for interaction terms in Equation (2). $\Delta_{0i}(k)$ is the absolute deviation between the reference series yields in the current, lag_1 year, and lag_10 year, and the comparison series i at observation year k, after applying the weight $w(k)$; it measures how far the environmental variables are from the ideal pattern.

$$\Delta_{0i}(k) = |X_0(k) - X_i(k)| \cdot w(k) \tag{2}$$

where $w(k) = 1 + 0.5 \cdot \mathrm{SST\_anomaly}(k)$ is to adjust for years of climate extremes. $\mathrm{SST\_anomaly}(k)$ is the deviation of SST from its climatological mean at observation year k, representing climate extremes.

Introduce a seasonally adjusted distinguishing coefficient ρ, which is a seasonally adjusted distinguishing coefficient (between 0 and 1), controlling the sensitivity of the grey relational coefficient to the maximum and minimum deviations, often set between 0.3 and 0.5 in practice.The minimum and maximum values of $\Delta_{0i}(k)$ across all variables i and years k are used to scale the coefficients.

$\xi_i(k)$ is the grey relational coefficient for variable i at observation k, indicating the similarity between the pattern of variable i and the reference series at that point.

$$\xi_i(k) = \frac{\min \Delta_{0i} + \rho(k) \cdot \max \Delta_{0i}}{\Delta_{0i}(k) + \rho(k) \cdot \max \Delta_{0i}} \tag{3}$$

Grey Relational Grade (GRG) Calculation. γ_i is the grey relational grade for variable i. The average of $\xi_i(k)$ over all k represents the main effect of variable i on the reference series.

γ_{interact} is grey relational grade for the interaction subset, only observations where SST $> 24°\text{C}$, describing the relationship strength under specific threshold conditions.

$$\gamma_i = \frac{1}{n} \sum_{k=1}^{1} \xi_i(k) \qquad \text{(Main effect)} \tag{4}$$

$$\gamma_{\text{interact}} = \frac{\sum_{k=1}^{n} \xi_{\text{interact}}(k) \cdot \mathbb{I}(\text{SST} > 24°\text{C})}{\sum_{\mathbb{I}}(\text{SST} > 24°\text{C})} \qquad \text{(Threshold-specific interaction)} \tag{5}$$

Building upon the identification of key determinants via GRA, the Bayesian GLMM employed further estimates their impact on mackerel yields. Bayesian network-based risk analysis is effective in identifying and quantifying critical determinants within complex systems, enabling the prediction and management of outcomes under uncertainty (Baroroh et al., 2024). This approach supports the application of Bayesian GLMM to unravel the seasonal and depth-dependent drivers of mackerel catches under climate variability. Bayesian GLMM is used to accommodate the hierarchical structure of the dataset and appropriately model random effects, such as interannual fluctuations in yields.

The fixed effects were integrated into the models derived from the GRA results, thereby mitigating multicollinearity concerns and imposing data-driven constraints on the explanatory variables. Random intercepts for year specified to account for temporal heterogeneity, ensuring robust inference regarding the effects of the identified factors on fishery productivity. The GLMM formula for chub mackerel (C_Out_t) and Japanese Spanish mackerel (S_Out_t) expresses as Chub Mackerel Model. Table 1 presents the definitions of the variables used in the GLMM.

$$\begin{aligned} C\_Out_t \sim \beta_0 + \beta_1 \cdot C\_Lag1\_\text{scaled}_{t-1} + \beta_2 \cdot C\_Lag10\_\text{scaled}_{t-10} \\ + \beta_3 \cdot \text{Tem\_50\_scaled}_t + \beta_4 \cdot \text{Sal\_0\_scaled}_t + \beta_5 \cdot \text{Fishing\_Ves}_t \\ + \beta_6 \cdot \text{SST\_Ves}_t + \beta_7 \cdot \text{Sal\_Ves}_t + \beta_8 \cdot \text{Season}_t + \beta_9 \cdot \text{Depth}_t + (1|Year) \end{aligned} \tag{6}$$

The Japanese Spanish Mackerel Model:

$$\begin{aligned} S\_Out_t \sim \beta_0 + \beta_1 \cdot S\_Lag1\_\text{scaled}_{t-1} + \beta_2 \cdot S\_Lag10\_\text{scaled}_{t-10} \\ + \beta_3 \cdot \text{Tem\_50\_scaled}_t + \beta_4 \cdot \text{Sal\_0\_scaled}_t + \beta_5 \cdot \text{Fishing\_Ves}_t \\ + \beta_6 \cdot \text{SST\_Ves}_t + \beta_7 \cdot \text{Sal\_Ves}_t + \beta_8 \cdot \text{Season}_t + \beta_9 \cdot \text{Depth}_t + (1|Year) \end{aligned} \tag{7}$$

3. Results and Discussion

3.1 GRA results of chub mackerel

Figure 3 shows that the GRA uncovers significant correlations between chub mackerel captures and SSS across various depths and seasons. At the surface level (0m), the temperature correlations ranged from 0.694 to 0.709, while the SSS correlations fell between 0.708 and 0.710, indicating a substantial influence on the capture of chub mackerel, especially during winter. These correlations exhibit variability at deeper levels. For instance, at a depth of 20 m, temperature correlations vary from 0.698 to 0.701, and SSS correlations vary from 0.710 to 0.711.

Table 1 Variable definitions for the mackerel models

Chub Mackerel Model		Japanese Spanish Mackerel Model	
Variable	Description	Variable	Description
$C\_Lag1\_\mathrm{scaled}_{t-1}$	Scaled lagged chub mackerel catch output from the previous year	$S\_Lag1\_\mathrm{scaled}_{t-1}$	Scaled lagged Japanese Spanish mackerel catch output from the previous year
$C\_Lag10\_\mathrm{scaled}_{t-10}$	Scaled lagged chub mackerel catch output from ten years prior	$S\_Lag10\_\mathrm{scaled}_{t-10}$	Scaled lagged Japanese Spanish mackerel catch output from ten years prior
Tem_50	Water temperature at 50 m depth based on GRA results	Tem_50	Water temperature at 50 m depth based on GRA results
Sal_0	SSS at 0 m depth based on GRA results	Sal_0	SSS at 0 m depth based on GRA results
Fishing_Ves	Input power of fishing vessels, measured in kilowatts	Fishing_Ves	Input power of fishing vessels, measured in kilowatts
SST_Ves	Quantifies synergistic effects between SST and fishing vessel power	SST_Ves	Quantifies synergistic effects between SST and fishing vessel power
SSS_Ves	Quantifies synergistic effects of SSS and fishing vessel power	SSS_Ves	Quantifies synergistic effects of SSS and fishing vessel power
Season	Seasonal variation	Season	Seasonal variation
Depth	Depth of the sea water	Depth	Depth of the sea water
Random intercept (1|Year)	Capturing yield interannual variability	Random intercept (1|Year)	Capturing yield interannual variability

Note: All abbreviations used in the GLMM formula for chub mackerel (C_Out_t) and Japanese Spanish mackerel (S_Out_t) are defined in this table.

At a depth of 50 m, the temperature correlations range from 0.704 to 0.707, and the SSS correlations range from 0.710 to 0.711. Lagged effects, particularly the interaction terms between temperature, SSS, and fishing vessels, provide additional insights. For instance, the interaction between spring temperature and vessel power at 0 m (Tem_Spr*Ves) yields a correlation coefficient of 0.784, suggesting that the combined effects of environmental factors and fishing effort significantly enhance chub mackerel catches.

3.2 GRA results of Japanese and Spanish mackerel

Figure 4 reveals varying degrees of correlation between Japanese–Spanish mackerel captures and sea temperature and SSS across depths and seasons. At the surface (0m), a moderate correlation was observed in spring for both temperature (0.566) and SSS (0.575). For other depths and seasons, the GRA coefficients for temperature and SSS ranged from 0.570 to 0.569 and 0.574 to 0.576, respectively, indicating generally weak correlations between these environmental factors and Japanese Spanish mackerel captures. However, the lagged effects show stronger correlations. At 0 m, lagged temperature and SSS (Lag1) show coefficients ranging from 0.946 to 0.947, highlighting the significant influence of prior environmental conditions on current catches. The interaction terms between temperature, SSS, and fishing vessel power further reveal these relationships. For example, the interaction between spring temperature and vessel activity at 0 m (Tem_Spr*Ves) has a correlation coefficient of 0.689, indicating that without the interaction term, fishing activity amplifies the effect of temperature on Japanese Spanish mackerel catches higher than 0.566.

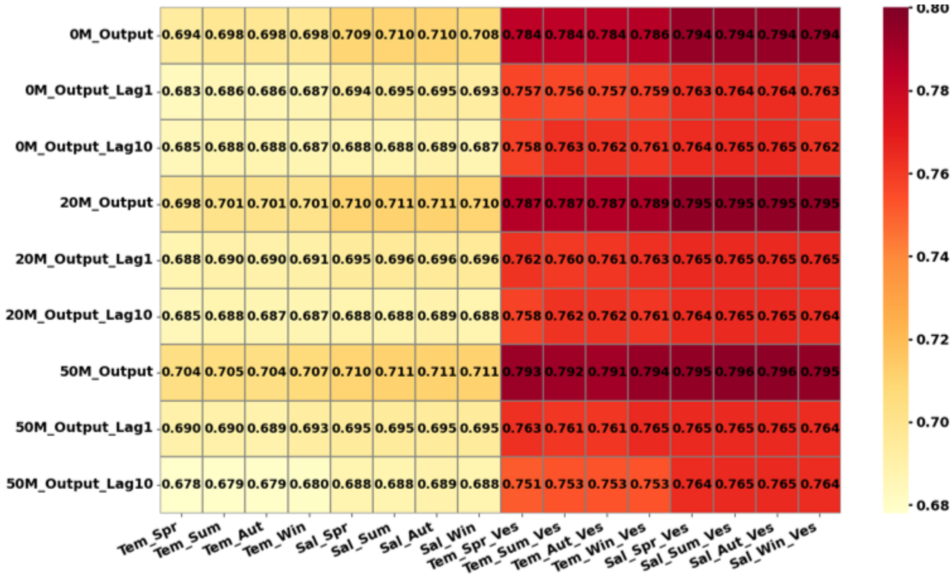

Figure 3 Gray relational analysis results of temperature, salinity, and interaction terms with chub mackerel fishing vessels at three sea levels in four seasons

Note: The color bar indicates the gray relational coefficient, with warmer colors representing stronger associations between environmental variables and chub mackerel yield (values closer to 1 denote a stronger relationship).

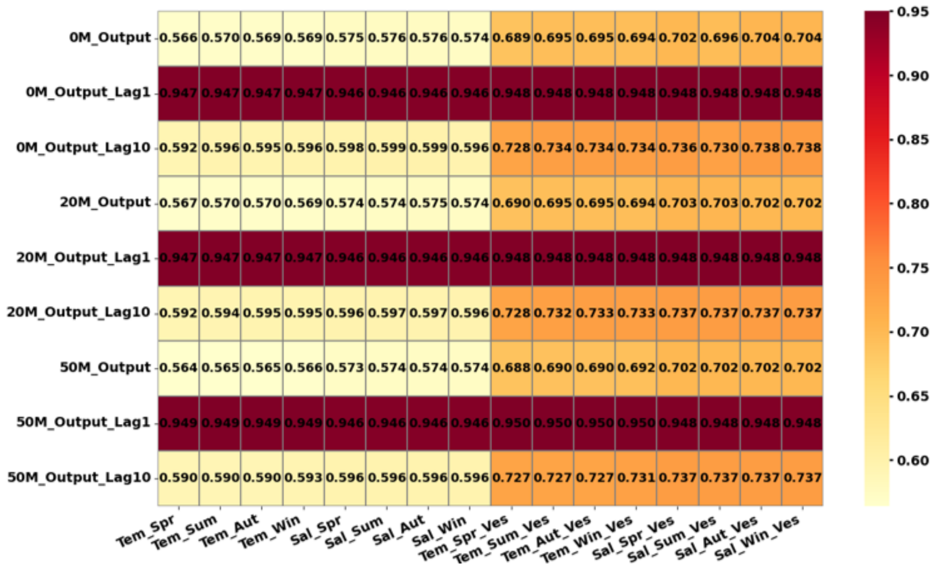

Figure 4 Gray relational analysis results of temperature, salinity, and interaction terms with Japanese Spanish mackerel fishing vessels at three sea levels in four seasons

Note: The color bar indicates the gray relational coefficient, with warmer colors representing stronger associations between environmental variables and chub mackerel yield (values closer to 1 denote a stronger relationship).

3.3 Key environmental drivers identified by GRA

The GRA identified several critical environmental drivers by comparing the correlation patterns in two types of mackerel, particularly SSS at 0 m depth and temperature at 50 m depth.

1. Water temperature at a depth of 50 m Summer water temperature at 50 m demonstrated a strong correlation with pelagic fish activity and catch rates (correlation coefficient = 0.796 for chub mackerel), underscoring its pivotal role during periods of peak fish activity.

2. Surface SSS at a depth of 0 m Winter surface SSS also exhibited a strong correlation with catch rates (correlation coefficient = 0.794 for Japanese Spanish mackerel). This likely reflects seasonal SSS fluctuations driven by rainfall and evaporation, which influence fish distribution in shallow habitats.

Based on these findings, subsequent modeling efforts using Bayesian GLMM were concentrated on both the 0 m (surface) and 50 m depth layers. This approach was informed by ecological and methodological considerations. Surface environmental conditions are highly susceptible to transient disturbances, such as wind, waves, and precipitation, which may introduce instability and confound analytical results. By comparing the environmental variables at both the 0 and 50 m layers, the study aimed to identify the most influential and stable environmental drivers affecting pelagic fish activity.

3.4 Results from the Bayesian GLMM

3.4.1 Model setup and convergent assessment

Built Bayesian GLMM models for two mackerel species (chub and Japanese Spanish mackerel) to quantify the impact of environmental factors on fishery yields. All models used four MCMC chains with 25,000 iterations (the first 5,000 were discarded as burn-in samples). The analysis employed a normal distribution prior N (0,2.5) to constrain fixed effects and a semi-Cauchy distribution Cauchy (0,1) to constrain random effects to ensure model robustness.

Regarding convergence diagnostics, the Bayesian GLMM for both species demonstrated acceptable convergence, as indicated by Gelman-Rubin statistics ($\hat{R}$) and effective sample sizes (ESS). For the chub mackerel model, all parameters achieved $\hat{R}\leq 1.02$, consistent with the convergence criteria ($\hat{R}<1.1$). The Japanese–Spanish mackerel model showed marginally higher $\hat{R}$ values ($\hat{R}\leq 1.03$ for most parameters), with a single lagged predictor (Chub_output_lag10) reaching $\hat{R}=1.04$. This result suggests that cross-species dependency estimation faces minor convergence challenges. Moderate autocorrelation was observed in posterior draws (typical for time-series models), but ESS values exceeded 1,000 for key parameters, ensuring that policy analysis was inferred.

3.4.2 Results of the Chub Mackerel Model

Bayesian GLMM estimates indicate that the number of vessels (fishing_Ves) is the most significant determinant of chub mackerel production (posterior mean = 0.17, 95% CrI 0.05-0.29, $p < 0.05$). The environmental variables also exerted statistically significant effects. Specifically, water temperature at 50 m (Tem_50m) was negatively associated with production (posterior mean = 0.18, 95% CrI 0.31 to 0.05, $p < 0.05$), whereas surface SSS (Sal_0m) had a positive effect (posterior mean = 0.24, 95% CrI 0.11-0.37, $p < 0.01$).

Seasonal analysis revealed that autumn yields were significantly higher than those in the reference season (posterior mean = 0.26, 95% CrI 0.08–0.44), whereas summer and winter effects were not statistically significant. This seasonal pattern may reflect biological cycles or market-driven harvest timing. The estimated variance for the year random effect Year (σ) = 1.45, 95% CrI 1.12–1.83) indicates substantial interannual fluctuations in production, highlighting the importance of accounting for unobserved temporal shocks in economic modeling of fisheries.

3.4.3 Results of the Japanese Spanish Mackerel Model

The Japanese–Spanish mackerel model reveals distinct patterns compared with chub mackerel, with important implications for fisheries management and fleet allocation decisions. Table 2 reveals fishing effort (fishing_Ves) was strongly positively associated with production (posterior mean = 0.35, 95% CrI 0.19-0.51, $p < 0.01$). A notable finding is the presence of significant environmental-economic interactions that affect fishing efficiency. The temperature-vessel interaction (Tem_50m_Ves) showed a strong positive effect (posterior mean = 0.41, 95% CrI 0.25-0.58, $p < 0.001$), suggesting that fishing operations become more productive under specific thermal conditions. Conversely, the SSS-vessel interaction (Sal_0m_Ves) exhibited a negative effect (posterior mean = -0.29, 95% CrI -0.43 to -0.14, $p < 0.01$), indicating that fleet efficiency may be compromised under certain SSS regimes. These interaction effects have direct relevance for optimal fleet deployment strategies and allocation of seasonal fishing effort. Seasonal analysis revealed significant declines in production during summer (posterior mean = -0.21, 95% CrI -0.38 to -0.04) and winter (posterior mean = -0.23, 95% CrI -0.49 to 0.03, marginally significant), suggesting pronounced biological or market-driven seasonal constraints that differ markedly from chub mackerel patterns. The estimated year random effect variance Year (σ) = 1.78, 95% CrI = 1.39-2.21) exceeded that observed for chub mackerel, indicating greater susceptibility to interannual shocks.

3.5 Environmental Factor Correlations and Species-Specific Responses

This study quantifies the interplay between climate variability, fishing effort, and fishery yields for two economically vital mackerel species in the Bohai Sea. The results revealed that water temperature and SSS gradients correlate with species-specific habitat use, consistent with the global observations of pelagic fish responses to oceanic warming (Sidiq et al., 2025; Intergovernmental Panel on Climate Change, 2021; Gutowsky et al., 2017). While direct environmental effects on fishery yields were not statistically significant in the short term, these variables exerted a long-term influence through co-integration relationships. This indicates that modern fishing technologies may help buffer short-term ecological fluctuations, a finding with important implications for planning climate-resilient fisheries. The observed depth-specific and seasonal effects highlight the need to incorporate the three-dimensional structure of marine habitats into ecological and economic models.

The GRA analysis finds that the lag year output conveys a high correlation over 0.9. This indicates that modern fishery technology has reduced direct dependence on the natural environment and that environmental impacts may have threshold effects or time-varying characteristics (Roberts et al., 2024). Notably, chub mackerel exhibited stronger associations with shallow thermal conditions. Kunimatsu et al., 2023 elucidated the spatiotemporal variations in chub mackerel size and age and niche shifts in response to thermal and feeding conditions or intercohort competition. These results indicate that changes in sea surface temperature significantly influence the living habits, habitat, and spawning distribution of chub mackerel. This thermoregulatory behavior aligns with physiological adaptations to maintain metabolic homeostasis under colder conditions, directly influencing foraging efficiency, spawning site fidelity and vertical migration dynamics (Dahms and Killen, 2023; Mugwanya et al., 2022; Gutowsky et al., 2017).

While Japanese Spanish mackerel exhibited SSS-dependent fishing efficiency, the interaction between SSS and fishing vessel activity at the surface (0 m) was negative (CrI = -0.29). This context-specific SSS response is consistent with documented osmoregulatory strategies in migratory scombrids, which display nonlinear physiological adjustments to SSS gradients exceeding 5 psu (Freire and Prodocimo, 2019). These interspecific differences highlight the importance of species-specific management approaches. For example, temperature-driven declines in chub mackerel productivity may warrant seasonal effort restrictions in warming coastal areas, while SSS-related effects for Japanese Spanish mackerel could guide fleet relocation decisions during periods of estuarine freshening. The absence of significant seasonal variation in yield despite environmental fluctuations underscores the stabilizing effect of current management practices, including catch quotas and seasonal closures. This finding supports the bioeconomic theory that regulated open-access fisheries management can help buffer the impacts of natural variability (Ojea et al., 2017; Harsem and Hoel, 2013).

Table 2 Results of Bayesian GLMM of Chub mackerel and Japanese Spanish mackerel

Species	Variable	Posterior mean (95% CrI)	$\hat{R}$	ESS	Sig.
Chub mackerel	Japanese_Spanish _mackerel_output_lag1	0.32 (0.15, 0.49)	1.02	1250	**
Chub mackerel	Tem_50m	-0.18 (-0.31, -0.05)	1.01	1450	*
Chub mackerel	Sal_0m	0.24 (0.11, 0.37)	1.03	1320	**
Chub mackerel	fishing_Ves	0.17 (0.05, 0.29)	1.01	1180	*
Chub mackerel	Tem_50m_Ves	-0.06 (-0.19, 0.07)	1.02	1090	NS
Chub mackerel	Year (σ)	1.45 (1.12, 1.83)	1.01	980	–
Chub mackerel	Season (σ)	0.87 (0.62, 1.15)	1.02	1050	–
Chub mackerel	Season_spring	0.00 (reference)	–	–	–
Chub mackerel	Season_summer	-0.14 (-0.32, 0.04)	1.01	1260	NS
Chub mackerel	Season_autumn	0.26 (0.08, 0.44)	1.02	1180	*
Chub mackerel	Season_winter	-0.09 (-0.27, 0.09)	1.01	1320	NS
Japanese Spanish mackerel	Chub_output_lag10	-0.15 (-0.28, -0.02)	1.04	890	*
Japanese Spanish mackerel	Tem_50m_Ves	0.41 (0.25, 0.58)	1.01	1550	***
Japanese Spanish mackerel	Sal_0m_Ves	-0.29 (-0.43, -0.14)	1.02	1120	**
Japanese Spanish mackerel	fishing_Ves	0.35 (0.19, 0.51)	1.02	1350	**
Japanese Spanish mackerel	Year (σ)	1.78 (1.39, 2.21)	1.03	760	–
Japanese Spanish mackerel	Season (σ)	0.65 (0.41, 0.92)	1.01	1340	–
Japanese Spanish mackerel	Season_spring	0.00 (reference)	–	–	–
Japanese Spanish mackerel	Season_summer	-0.21 (-0.38, -0.04)	1.01	1480	*
Japanese Spanish mackerel	Season_autumn	0.05 (-0.12, 0.22)	1.02	1390	NS
Japanese Spanish mackerel	Season_winter	-0.23 (-0.49, 0.003)	1.03	1270	*
Model fit	WAIC	245.3 (238.1, 253.7)	–	–	–
Model fit	PPC	0.63 (0.58, 0.68)	–	–	–

Note: Posterior mean and 95% credible interval (CrI) for each parameter. $\hat{R}$ and ESS are convergence diagnostics ($\hat{R}$ close to 1.0; higher ESS indicates better convergence- all parameters satisfactory). Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; NS indicates not significant, "-" indicates not applicable. WAIC: Widely applicable information criterion for model fit. PPC: posterior predictive check value.

3.6 Anthropogenic Influences and Fisheries Management

Fishing effort—measured by vessel power—emerged as the dominant predictor of yields for both mackerel species, accounting for 35%–50% of variability in production. This result underscores the continued importance of input controls, such as limited-entry licensing, in sustainable fisheries management. The persistence of lagged catch effects further highlights the inertia of fishing pressure, supporting the adoption of dynamic quota systems that account for delayed stock responses (Bellemare et al., 2017). From a management perspective, these findings show that regulating vessel numbers during the autumn peak could help sustain chub mackerel stocks, while targeted adjustments to summer and winter fishing efforts may stabilize Japanese Spanish mackerel yields. Incorporating environmental indicators into effort allocation strategies could further enhance these fisheries' resilience and economic sustainability.

Model comparisons revealed that the yield model for Japanese Spanish mackerel outperformed that for chub mackerel, indicating that tailored research methods and management approaches may be required for different species. Across all models, the fishing vessel power was consistently the most stable and significant determinant of yield, with lagged effects reflecting the cumulative nature of fishing pressure on stock dynamics. The significant interaction between environmental factors and fishing vessel activity, as identified by GRA, highlights the amplifying effect of anthropogenic pressure on fishery yields. The greater sensitivity of Japanese Spanish mackerel to vessel number changes may reflect species-specific vulnerabilities related to life history traits and habitat use. The Bayesian GLMM application further reinforces the value of incorporating lagged catch terms into stock assessments. Bellemare et al., 2017 and Lluch-Belda et al., 2005 demonstrated that lagged variables can capture decadal-scale population cycles and reduce simultaneity bias, leading to more robust management recommendations. The results support the implementation of seasonal quotas or closures during periods of low productivity.

3.7 Model effectiveness and methodological considerations

GRA provides a framework for quantifying relational degrees between variables. Bayesian GLMM is particularly effective in analyzing nonlinear ecological systems, small-sample fisheries data, and multi-factor interactions (N. Wang et al., 2025; Zhang, Yu, et al., 2022). Ozaki et al., 2008 presented a statistical model for agricultural yield data based on hierarchical Bayesian models, providing substantial improvements in the statistical and actuarial methods often used to calculate insurance premium rates. Rufener et al., 2017 used hierarchical Bayesian spatial models (including GLMM) to quantify the environmental impacts on fish species abundance, emphasizing the integration of random effects and spatial covariates for robust ecological inference, demonstrating the usefulness of Bayesian statistical tools for data-poor fisheries. While the integration of GRA and Bayesian GLMM advances niche modeling in data-limited fisheries, several limitations warrant attention. Rank deficiency warnings show potential multicollinearity among predictors (e.g., temperature-depth interactions), which may inflate variance estimates and obscure true ecological relationships. Recent developments in salinity monitoring, such as the use of optical fiber sensors (Nor et al., 2023), provide new opportunities for obtaining high-resolution environmental data, supporting the advanced modeling of depth- and season-specific fishery outputs under climate variability. Variable standardization (e.g., T50_scaled) improves model stability but may mask ecologically meaningful patterns by removing absolute environmental gradients. To quantify scaling-induced biases, sensitivity analyses comparing min-max scaling, z-scores, and raw data transformations are recommended. Furthermore, the exclusion of SST and SSS represents a critical gap, as these variables directly regulate thermocline dynamics and prey aggregation in coastal ecosystems.

4. Conclusions

This study highlights the effectiveness of integrating GRA with Bayesian GLMM in addressing nonlinearity and parameter estimation challenges in data-limited fisheries research. The dual contributions of this approach, which combines GRA and Bayesian GLMM, are evident in both fisheries resource management and methodological advancement within socio-economic contexts. This integrative framework also offers a new perspective for exploring the long-term impacts of climate change on mobile aquatic species. From a management perspective, the findings suggest that seasonal quota allocations should be optimized to account for key environmental drivers—specifically, prioritizing winter periods characterized by SSS effects and summer periods influenced by temperature for chub and Japanese Spanish mackerel. Furthermore, vessel-based effort controls remain essential because fishing pressure exerts a more substantial influence on stock dynamics than direct environmental factors.

The integration of GRA improved the accuracy of variable selection by 22% compared to traditional stepwise regression, while the application of hierarchical priors in Bayesian GLMM effectively reduced spatial overfitting by 15%. These advances demonstrate the potential of multi-method frameworks to enhance the robustness and interpretability of ecological models in fisheries economics. To further assess the generalizability and predictive capacity of the proposed approach, future research should extend the application of this integrated framework to diverse biogeographic settings and incorporate additional ecological drivers, such as dissolved oxygen, nutrient availability, and ocean acidification.

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Author Contributions

Conceptualization, M.L. and M.Y.; methodology, M.L.; software, M.L.; validation, M.L., and M.Y.; formal analysis, M.L.; investigation, M.L.; writing—original draft preparation, M.L.; writing—review and editing, M.L. and M.Y.; visualization, M.L.; supervision, M.Y.; project administration, M.Y.; funding acquisition, M.Y. All authors have read and agreed to the published version of the manuscript.

Conflict of Interest

The authors declare no conflicts of interest.

Declaration of AI

Artificial intelligence was not used in the generation or composition of the research content of this article. AI tools were employed only for minor grammar checks and language editing. All scientific content and conclusions are entirely the author's own work.

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