Spatially varying coefficients improve discrete choice models for tuna purse seine fisheries in the Western-Central Pacific

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Integrating spatially varying coefficients into discrete choice models for tuna purse seine fisheries in the Western-Central Pacific

Abstract

The discrete choice model (DCM) is commonly used to analyze fishing behavior and model fishing location choices based on choice attributes such as expected revenue, cost, and previous effort. However, traditional or mixed DCMs treat parameters among each fishing location as independent and fail to account for spatial autocorrelation among fishing grounds. To address this limitation, we extend traditional DCM by incorporating spatial autocorrelation and spatially varying coefficients (SVCs) to account for latent processes linked to environmental conditions, referred to as spatial DCM. We first develop a diffusion-taxis movement simulation model to simulate fishing vessel behavior, where spatial preferences are influenced by tuna density and oceanographic indices such as the El Niño-Southern Oscillation (ENSO). ENSO is incorporated in the simulation as a time-varying climate index that interacts with a spatial preference weight, modeling how fishermen adapt fishing strategies in response to changing oceanographic conditions. The simulation testing shows the spatial DCM effectively estimates the spatial preference generated by the movement simulation model through incorporation of SVCs. Finally, we suggest that spatial DCM can be useful tools to analyze and forecast fishing behavior for tuna purse seine fisheries in the Western and Central Pacific Ocean (WCPO). The application results showed the spatial DCM can identify baseline fishing preferences, seasonal spatial variations, and spatially varying responses to environmental conditions beyond the utility predicted from covariates such as expected catch (previous year catch value) and cost (previous year effort and distance to port). Specifically, by incorporating spatially varying coefficients, the spatial DCM reveals that El Niño events enhance fishing activity in the western WCPO (Papua New Guinea and Federated States of Micronesia), while La Niña events increase fishing activity in the eastern WCPO (Kiribati), presumably representing how fishers adapt to changes in tuna distribution and catch efficiency driven by shifts in oceanographic conditions associated with climate events. We therefore conclude that the spatial DCM is a useful approach to account for spatial autocorrelation and latent oceanographic influences.

Keywords: Tuna purse seine, discrete choice model, spatially varying coefficients, El Niño-Southern Oscillation, Western and Central Pacific Ocean

1. Introduction

Previous studies on fisher behavior in fisheries management have emphasized how important it is to include fisher decision-making when designing and evaluating fisheries management strategies (e.g., Hilborn & Walters, 1987; Wilen et al., 2002; Salas and Gaertner, 2004; Fulton et al., 2011). For example, Wilen et al. (2002) incorporate the spatial behavior of California red sea urchin fishermen into a bioeconomic model, demonstrating that ignoring fishermen's spatial decisions can lead to misguided policy outcomes. Fulton et al. (2011) indicated that fisheries management has traditionally focused on the status of exploited resources while overlooking the critical role of fisher behavior and the resulting uncertainty, highlighting the need to incorporate human behavior into management design and to develop supporting empirical research and predictive models. More recently, Andrews et al. (2020) systematically reviewed literature on fisher behavior in coastal and marine fisheries, emphasizing the need to account for multifaceted, multilevel, and multiscale behavior into conceptual and empirical models to better understand behavioral change and inform fisheries governance. However, accurately modeling fisher behavior is difficult. A fisher's decision where and when to fish is influenced by various factors including fish density, fuel and market prices, regulations, differential pricing of fishing licenses across EEZ, individual habits and experience, previous catch rates, and competition with other vessels. These factors can result in variations in observed individual fisher behavior and how a group of fishers (a fleet) allocates their effort over time and space (Tidd et al., 2012).

To better understand the mechanisms of change in fisher behavior and their spatial allocation of effort, economists have developed various approaches to studying fisher decision-making and predicting fisher location choice (van Putten et al., 2012). Most of these methods are grounded in microeconomic theory (e.g., random utility model) and are typically modeled using discrete choice models (DCMs) (Girardin et al., 2017). Since the 2000s, the application of DCMs in predicting fisher behavior has grown, presumably due to enhanced computational power and increasing availability of fine-scale data, such as vessel-by-vessel trip records (Tidd et al., 2012). DCMs offer the advantage of analyzing individual behavior at finer temporal and spatial resolutions compared to other techniques (van Putten et al., 2012). Despite these advancements and the growing use of DCMs in fisheries management and policy scenarios (e.g. Dépalle et al., 2020; Hutton et al., 2004; Smith & Wilen, 2003), few studies have explicitly incorporated spatial dependency into DCMs (e.g. Hutniczak & Münch, 2018; Sampson, 2018; Schnier & Felthoven, 2011). Existing studies typically focus on spatial dependency by incorporating spatial autocorrelation in DCMs, highlighting the influence of spatial and temporal effects on decision-making processes. However, the interaction between spatial preferences and environmental and socioeconomic time-series indices still remain limited. For instance, Campbell and Hand (1999) incorporate the Southern Oscillation Index (SOI) as covariates to estimate how environmental fluctuations influence fishing location choices, by using area-covariate slopes to capture the interactions between oceanic time-series index and spatial strata, and have shown how regional environmental conditions affect spatial fishing choice. However, this method assumes that spatial preferences are patchy and independent, potentially overlooking the spatial autocorrelation inherent in regional environmental conditions. As a result, this method could lead to potential bias, especially when considering finer spatial and temporal resolutions. Additionally, the performance of this approach has not been tested using simulated data, resulting in uncertainty in practical use.

For these reasons, we propose the use of spatially varying coefficients (SVCs) within the DCM framework (hereafter called spatial DCM) to enhance predictions of fisher behavior. Oceanographic conditions are often summarized using one or more time-series indices (e.g., the Pacific Decadal Oscillation or El Niño-Southern Oscillation, ENSO). SVCs incorporate these time-series indices as proxies for unmeasured (latent) processes that affect catch efficiency, such as redistribution of tuna species driven by temperature-related habitat shifts, changes in vertical availability for vessels, or distribution shifts for bycatch species that are actively avoided. The latent processes directly or indirectly affect spatial fishing utility and, eventually, the choice of fishing locations. By incorporating time-series data in the spatial DCM and accounting for unmeasured processes, SVCs improve the model's ability to forecast and project future fishing activities.

In this study, we assess the proposed spatial DCM framework using both simulation experiments and real-world case study. First, we develop a diffusion-taxis movement simulation model, informed by foraging theory, to simulate fishing vessel behavior. This movement model assumes that fishers, similar to predators, optimize their strategies to maximize profits, moving toward areas with high densities of target species and adjusting their fishing choices in response to environmental conditions. The simulated data are then used to evaluate whether the estimation models (DCMs) can replicate the underlying spatial effects when fitted to data generated from a structurally different simulation model (diffusion-taxis movement model). Finally, we apply our estimation models to real-world data from tuna purse seine fisheries in the Western and Central Pacific Ocean (WCPO) as a case study to validate its applicability.

2. Material and methods

We aim to evaluate whether the spatial DCM, a discrete choice model with SVCs, improves the prediction and forecasting of fishing behavior. In the following section, we first describe the traditional DCM framework, including fixed and mixed effects models, and then explain how spatial structure is introduced through spatial random effects. Next, we conduct simulation experiments using a diffusion-taxis movement model, where directional movement (taxis) is driven by tuna density and environmental conditions, while random movement (diffusion) accounts for unexplained variability. We then use simulated samples to test whether the estimation models can (i) identify spatial preference patterns and (ii) improve forecasts compared to models without spatial effects. Finally, we apply the models to real-world data from tuna purse seine fisheries in the Western and Central Pacific Ocean (WCPO) to evaluate their applicability. In this fishery, tuna fishing operations can generally be categorized into two types based on their fishing strategy: fish aggregating devices (FAD) fishing and free-school fishing. However, we treat both types as identical in terms of fishing location choice, due to due to computational constraints and data limitations

2.1 Overview of Models

2.1.1 Traditional discrete choice model (DCM)

In analyzing fishing behavior, the DCM helps understand how fishers select their fishing grounds based on factors such as expected catch, cost, and environmental conditions. The utility function U_{ijt} in the DCM for vessel i choosing fishing location j in time t (see Table 1 for full list of symbols used in describing models in this study) is traditionally defined as:

$$U_{ijt} = \sum_{n=1}^{N} X_{ijnt} \eta_n + \epsilon_{ijt} \tag{1}$$

where η_n is the coefficient of covariates, X_{ijnt}, and ϵ_{ijt} is a residual error term (McFadden, 1974). Here, n represents fixed effects, capturing common factors across vessels. In order to accommodate individual or spatial preference heterogeneity, the mixed logit model framework is often adopted (Girardin et al., 2017). By considering area intercepts, area-vessel intercepts, or vessel-covariate slopes as random effects, the model can address unobserved variability (e.g. Tidd et al., 2012; Wang et al., 2024).

Although modeling vessel-level heterogeneity (e.g., area-vessel intercepts or vessel-covariate slopes) can capture individual differences among vessels, it significantly increases complexity and computational cost, especially given the scale of our application. Moreover, our dataset lacks vessel-level information such as fishing type (e.g., FAD vs. free-school), further limiting the feasibility of modeling vessel differences. To keep the model manageable and focus on spatial preference heterogeneity (hereafter spatial heterogeneity), defined here as area-specific effects without assuming spatial autocorrelation, we do not model individual vessel preference heterogeneity but instead introduce two area-level random effects: area-intercept α and area-covariate slope β_k. This approach assumes that all vessels are identical and the spatial heterogeneity in fishing preference is captured through area-level random effects, which vary independently across locations. While this specification keeps the assumption of independence across locations, we later relax this assumption by introducing spatial correlation between neighboring grid cells (Section 2.1.2), allowing the model to account for spatial dependence in fishing behavior.

We now define these two area-level random effects, α and β_k, which capture regional variation in fishing preferences and are assumed to be spatially independent. Specifically, α is a vector of area intercepts, containing $\alpha_{s[j]}$ for each geographic location $s[j]$ at fishing location j, and β_k is a vector of area-covariate slopes for covariate k containing $\beta_{ks[j]}$, representing the response to covariate x_{kt} at location $s[j]$. Therefore, the utility function in the mixed logit framework, considering only spatial heterogeneity, becomes:

$$U_{ijt} = \underbrace{\sum_{n=1}^{N} X_{ijnt}\eta_n}_{Fixed\ effect} + \underbrace{\underbrace{\alpha_{s[j]}}_{Area\ intercepts} + \underbrace{\sum_{k=1}^{K} x_{ijkt}\beta_{ks[j]}}_{Area-covariate\ effect}}_{Random\ effect} + \epsilon_{ijt} \tag{2}$$

These random effect coefficients α and β_k then can be simply modelled as following a normal distribution:

$$\alpha \sim Normal(0, \sigma_{\alpha}^2) \tag{3}$$

$$\beta_k \sim Normal(0, \sigma_{\beta,k}^2) \tag{4}$$

where σ_{α}^2 and $\sigma_{\beta,k}^2$ is the variance of α and β_k (where $\sigma_{\beta,k}^2$ varies among random effects k). However, in the mixed logit model, each location is treated independently, which cannot effectively reflect the spatial correlation of fishing grounds. This limitation may lead to ineffective modeling of the spatial relationships and interactions within fishing grounds. We address this issue in the next section by introducing spatially structured variation to explicitly account for spatial autocorrelation within the DCM.

2.1.2 Spatial extension of the Discrete Choice Model (Spatial DCM)

To address the limitations of the traditional DCM in estimating spatial dependencies, we introduce spatial autocorrelation into the model by specifying two types of spatial random effects: spatial variation $\boldsymbol{\omega}$ and spatially varying coefficients (SVCs) $\boldsymbol{\gamma}$. Specifically, $\boldsymbol{\omega}$ is a vector of area-specific intercepts, containing intercept $\omega_{s[j]}$ for each geographic location $s[j]$ for fishing location j. Similarly, $\boldsymbol{\gamma}_k$ is a set of area-specific slopes for covariate k, containing $\gamma_{ks[j]}$, which represent the response to covariate x_{kt} at location $s[j]$. Here, we use the symbols $\boldsymbol{\omega}$ and $\boldsymbol{\gamma}$ to represent spatial random effects in our spatial DCM, distinguishing them from α and β used in the mixed model (see Eqs.[2–4]). The updated utility function, incorporating $\boldsymbol{\omega}$ and $\boldsymbol{\gamma}_k$, is defined as:

$$U_{ijt} = \underbrace{\sum_{n=1}^{N} X_{ijnt}\eta_n}_{Fixed\ effect} + \underbrace{\underbrace{\omega_{s[j]}}_{Spatial\ variation} + \underbrace{\sum_{k=1}^{K} x_{kt}\gamma_{ks[j]}}_{Spatially\ varying\ coefficient}}_{Random\ fields} + \epsilon_{ijt} \tag{5}$$

We treat $\boldsymbol{\omega}$ and $\boldsymbol{\gamma}_k$ as spatial random effects following a multivariate normal distribution:

$$\boldsymbol{\omega} \sim MVN(\mathbf{0},\ \mathbf{Q}_{\omega}^{-1}) \tag{6}$$

$$\boldsymbol{\gamma}_k \sim MVN(\mathbf{0}, \mathbf{Q}_{\gamma}^{-1}) \tag{7}$$

where $\mathbf{Q}_{\omega}$ and $\mathbf{Q}_{\gamma}$ is the precision (inverse-covariance) matrix for the spatial variation $\boldsymbol{\omega}$ and spatially varying coefficients (SVCs) $\boldsymbol{\gamma}_k$. We model spatial dependencies through the conditional autoregressive (CAR) approach, with the spatial precision matrix $\mathbf{Q}$ defined as :

$$\mathbf{Q} = \frac{1}{\sigma^2}(\mathbf{I} - \rho\mathbf{A}) \tag{8}$$

where σ^2 represents the variance, $\mathbf{I}$ is an identity matrix, ρ is the spatial autocorrelation parameter, and $\mathbf{A}$ is the adjacency matrix defining neighboring relationships based on rook-adjacency (i.e. sharing an edge rather than a vertex).

Finally, the probability of choosing fishing location j, denoted as $Prob_{it}(j)$, is modeled as using the multinomial logit function:

$$Prob_{it}(j) = \frac{e^{U_{ijt}}}{\sum_j e^{U_{ijt}}} \tag{9}$$

The log-likelihood function for parameter estimation within the models is given by:

$$LL(\boldsymbol{\theta}|y, X, x) = \sum_{i=1}^{n} \sum_{j} I(y_{it} = j) \cdot \log(Prob_{it}(j)) \tag{10}$$

where $\boldsymbol{\theta} = \{\eta_n, \alpha_s, \beta_{ks}, \boldsymbol{\omega}_s, \boldsymbol{\gamma}_{k,s}, \boldsymbol{\delta}_{k,s}, \sigma_{\alpha}^2, \sigma_{\beta,k}^2, \rho\}$ represents the parameters to be estimated, depending on the model specification, y_{it} is the observed location selected by vessel i at time t, and $I(y_{it} = j)$ is an indicator function that equals 1 when vessel i selects location j

at time t, and 0 otherwise. X contains covariates for vessel i, location j, and time t, (e.g., lagged VPUE for three tuna species, lagged effort, and distance to port), while x is a vector of temporal covariates at time t, including the Niño 3.4 index and seasonal indicators.

2.2 Simulation and model testing

2.2.1 Diffusion-taxis movement simulation model

We first test how incorporating SVCs within a DCM (the spatial DCM) affects model performance, using data generated from a diffusion-taxis simulation. Specifically, we assess the model performance in analyzing fishing vessel movements and the resulting spatial distribution of location choices. The simulation model involves simulating numerical density $n_{s,t}$ at each location s (of $\mathrm{S} = 1{,}905$ total sites), time t on a daily basis for 10 years (i.e., $t \in \{1,2,\dots,T\}$), resulting in $\mathrm{T} = 3{,}652$ time intervals (from Jan. 1 2011 to Dec. 31 2020, including leap days). The simulation is restricted to the WCPO, and the spatial domain is discretized into 1° × 1° grid cells, spanning from 130°E to 210°E longitude and 20°N to 20°S latitude (Figure 1, left panel).

We simulate individual movement using a habitat preference function, where fishing vessels tend to move towards cells with higher preference (termed "taxis") while also undergoing some unexplained movement (termed "diffusion"). Fishing decisions are then simulated based on local tuna density. Preference driving taxis is then based on the density of skipjack tuna, yellowfin tuna, and bigeye tuna (Figure 1, right panel), surface temperature and ENSO-driven spatial effects. This movement simulation model assumes that fishing vessels tend to move toward areas with high tuna density and certain temperature range (from 28 to 32 degree Celsius). We include ENSO-driven spatial adjustment term to explicitly simulate how oceanographic (ENSO) forecasts influence regional fishing preferences across the exclusive economic zones (EEZs) of Parties to the Nauru Agreement (PNA) members. The spatial adjustment captures how fishers' spatial preferences respond to potential changes in catch efficiency driven by ENSO variability. This term reflects broad-scale behavioral shifts influenced by ENSO while allowing us to evaluate how the SVCs within the spatial DCM capture finer-scale spatial preferences in the estimation model. This approach extends upon research conducted by Thorson (2021) and Thorson et al. (2021a, b), which used a habitat-preference function to approximate individual movement and our study represents the first application to fishing vessel movements.

Specifically, we define a preference function $h_{s,t}$ for purse seines as an additive function based on the densities of skipjack tuna $x_{1,s,t}$, yellowfin tuna $x_{2,s,t}$, bigeye tuna $x_{3,s,t}$, surface temperature $x_{4,s,t}$ and ENSO-driven spatial adjustment $E_t W_s$. The densities of tuna species are modeled using catch per unit effort (CPUE), calculated as the total catch divided by the total number of sets for each species, using monthly aggregated data provided by WCPFC (2024) at a 1°×1° resolution. We simulate surface temperature based on the MODIS-Aqua Level 3 SST dataset (NASA/JPL, 2020), and ENSO condition based on the Niño 3.4 SST Index from the HadISST1.1 (Rayner et al., 2003). In the preference function, we specify hypothetical weights (constants) to each factor to reflect their relative importance. For tuna species, we assign weights that reflect their roles in purse seine fisheries, with skipjack tuna given the highest weight (0.2) as the primary target species, followed by yellowfin (0.05) and bigeye (0.02), which are often caught as secondary targets or bycatch. The surface temperature and ENSO-driven adjustment terms are each given a weight of 0.5. The surface temperature term reflects short-term fishing strategies and is explicitly included in the simulation to assess whether the fitted model can indirectly capture SST-driven behavior through SVCs, which serve as a proxy for latent environmental processes. The ENSO-driven adjustment term captures broader-scale spatial shifts associated with ENSO-related variability. These values were selected to give environmental drivers a noticeable yet balanced influence on fishing preferences, while allowing tuna density to remain the dominant factor. The preference function is defined as:

$$h_{s,t} = \underbrace{0.2 \times \log(x_{1,s,t})}_{Skipjack\ tuna} + \underbrace{0.05 \times \log(x_{2,s,t})}_{Yellowfin\ tuna} + \underbrace{0.02 \times \log(x_{3,s,t})}_{Bigeye\ tuna} + \underbrace{0.5 \times f(x_{4,s,t})}_{Temperature} + \underbrace{0.5 \times E_t W_s}_{ENSO-driven} \tag{11}$$

where $f(x)$ is a Gaussian density function bounded between 0 and 1, representing a temperature preference that increases as temperature above 28°C, peaks at 30°C, and then decreases until 32°C (Wu et al., 2023). Eq. 11 specifies that fishing preference is positive within a certain temperature range while also increasing with higher tuna densities. To simulate fishing vessel movements and incorporate the impact of ENSO on fishing preferences, we introduce an ENSO-driven adjustment term $E_t W_s$ (see Figure 2). The spatial adjustment term explicitly links the ENSO index (E_t, ranges from approximately -2.5 to 2.5) to spatial fishing-preferences weight W_s, i.e., E_t is a time-varying climate index (e.g., Niño 3.4 index) that is uniform across all locations at each time step, and is multiplied by W_s, a spatially varying coefficient (response) that reflects how each location responds differently to the same ENSO conditions. When the index is positive, $E_t W_s$ increases preference in the eastern region (e.g., Kiribati, abbreviated as KIR) while reducing preference in the western region (e.g., Papua New Guinea, abbreviated as PNG). Conversely, a negative ENSO index has the opposite effect, enhancing preferences in the western region and diminishing them in the eastern region. W_s was constructed using a Gaussian random field with an east–west gradient and regional adjustments, designed to simulate broad-scale spatial shifts in fishing preference under different ENSO phases (see Figure 2 caption for details). By explicitly representing the spatial variation, the movement simulation directly reflects the influence of ENSO on fishing vessel behavior.

Finally, we define an instantaneous daily vessel movement rate:

$$\mathbf{M}^* = \mathbf{D}^* + \mathbf{Z}^* \tag{12}$$

where $\mathbf{D}^*$ is a diffusion matrix:

$$d^*_{s_2,s_1} = \begin{cases} D\dfrac{1}{\Delta_s^2} & \text{if } s_1 \text{ and } s_2 \text{ are adjacent} \\ -\sum\limits_{s' \neq s_1} d^*_{s',s_1} & \text{if } s_1 = s_2 \\ 0 & \text{otherwise,} \end{cases} \tag{13}$$

where $d^*_{s_2,s_1}$ represents the diffusion rate from location s_1 to neighboring cell s_2, and Δ_s is the resolution of each grid cell, and diffusion coefficient D infers the patterns of vessels dispersal across space and time. We here define a fixed-value diffusion D derived from mean-squared displacement (MSD) of the vessel positions. The MSD is defined as averaging the squared distances between successive positions over a time interval, and is expressed as:

$$MSD = \mathbb{E}(| s_{t+\Delta t} - s_\text{t} |^2) = 2nD\Delta t \tag{14}$$

where n is the number of spatial dimensions and Δt is the time interval. Rearranging this formula, the diffusion coefficient D is given by:

$$D = \frac{MSD}{2n\Delta t} \tag{15}$$

and $\mathbf{Z}^*$ is a taxis matrix representing advective toward preferred habitats:

$$z^*_{s_2-s_1} = \begin{cases} h_{s_2} - h_{s_1} & \text{if } s_1 \text{ and } s_2 \text{ are adjacent} \\ -\sum\limits_{s' \neq s_1} \left(h_{s_2} - h_{s_1}\right) & \text{if } s_1 = s_2 \\ 0 & \text{otherwise.} \end{cases} \tag{16}$$

where $z^*_{s_2-s_1}$represents the directional gradient in preference function h between cells s_1 and s_2. The daily movement matrix $\mathbf{M} = e^{\mathbf{M}^*}$ is then calculated by integrating the movement-rate matrix $\mathbf{M}^*$ over each daily interval using the matrix exponential function.

For each of 20 simulation replicates, we initialized vessel abundance by allocating 100 vessels across major ports, including Majuro, Pohnpei, Rabaul, Pago Pago, Kiritimati, Tarawa, and Funafuti, to generate the initial distribution $n_{s,1}$ for the first simulation month. Then we project vessel movement forward for each day over 10 years and simulate the daily tracks for 10 representative vessels based on the generated numerical density $n_{s,t}$. At each time step t, fishing activity is simulated following movement, based on the combined density of skipjack, yellowfin, and bigeye tuna at each vessel's updated location. For simulating fishing decision, the combined tuna density across all grid cells within the unit time is divided into 10 quantiles, with each quantile assigned a hypothetical, linearly increasing probability: 5%, 10%, 15%, ..., 50%. These probabilities represent the likelihood of a vessel making a fishing decision in each grid cell, i.e., the higher tuna density, the greater the probability of fishing in that grid cell. At the end of each month, vessels are simulated to return to the nearest preferred port (each vessel has different preferred ports), reflecting the docking behavior of the fishing vessels and serving as the starting point for the subsequent month's activities. The preferred ports for each vessel were determined based on an analysis of Global Fishing Watch (GFW) for tuna purse seine vessels. Detailed percentages for all preferred port combinations for tuna purse seine vessels is provided in Table A1 (Appendix).

2.2.2 Testing and comparison

For simulation model testing, we fit simulated samples using three models: conventional DCM, mixed DCM and spatial DCM, to evaluate whether adding SVCs improves performance within the DCM framework. The models are based on the utility function structure described in Eq. (5), with 1° × 1° grid cells serving as the choice alternatives. We then define three alternative estimation models as follow:

1. *Conventional DCM*: Spatial components are not considered. We specify $\boldsymbol{\omega}_{\mathbf{s}} = 0$ and $\boldsymbol{\gamma}_{\mathbf{s}} = 0$, leaving only the fixed effects specified earlier (see Eq.[1]).

2. *Mixed DCM*: Random effects are modeled by setting $\boldsymbol{\omega}_{\mathbf{s}} = \alpha_s$ and $\boldsymbol{\gamma}_s = \beta_s$, where $\alpha \sim Normal(0, \sigma_\alpha^2)$ and $\beta \sim Normal(0, \sigma_\beta^2)$ as described in the mixed model framework (see Eqs. [2–4]). This model accounts for heterogeneity across areas, but it treats spatial locations as independent, i.e. it does not account for spatial autocorrelation between fishing locations.

3. *Spatial DCM*: We treat $\boldsymbol{\omega}_s$ and $\boldsymbol{\gamma}_s$ as spatial random effect following a multivariate normal distribution, $\boldsymbol{\omega} \sim MVN(0,\ \mathbf{Q}_\omega^{-1})$ $\boldsymbol{\gamma} \sim MVN\left(0,\ \mathbf{Q}_\gamma^{-1}\right)$, and modeled using CAR model previously described for $\boldsymbol{\omega}_s$ and $\boldsymbol{\gamma}_{k,s}$. This approach allows us to account for spatial autocorrelation between locations (see Eq. [5–8]).

For all three models, we include as covariates the lagged catches and fish price for skipjack tuna, yellowfin tuna, bigeye tuna from the same month of the previous year as the expected catch and revenue, lagged fishing effort and the distance to the port as the expected cost, which are included in covariate matrix X_{ijnt}. We also include Niño 3.4 index in x_{kt} as a proxy for regional latent process to reflect potential ENSO impacts.

For each simulation replication, we record the estimated SVCs $\boldsymbol{\gamma}_k$ from both mixed and spatial DCMs, and calculate the allocation of fishing effort within two main PNA party countries significantly affected by ENSO: KIR and PNG, by aggregating predicted effort across grid cells with centroids located within each country's EEZ. In addition, we conducted forecasts for the years 2018 through 2020 to test the predictive capabilities of three alternative models. Specifically, for each forecast year t_{year} (where $t_{year} = 2018, 2019, 2020$), the models were fitted using data from 2011 to $t_{year} - 1$, and forecasts were made for year t_{year}. Given the simulation design, an ideal estimator should capture the spatial varying response to ENSO-driven from the movement model while accurately predicting fishing behavior influenced by tuna species density and ENSO effects.

2.3 Case study: PNA Western and Central Pacific tuna purse seine fishery

We explore the use of the spatial DCM by fitting WCPO tuna purse seine fisheries data from Global Fishing Watch. Previous studies have shown a strong link between spatial shifts in the distribution of skipjack tuna and ENSO events. Specifically, the skipjack tuna population shifts in response to the zonal movements of the warm pool induced by ENSO events (Lehodey et al., 1997), and WCPO tuna purse seine often integrates ENSO forecasts (e.g., IRI Columbia ENSO Forecasts, https://iri.columbia.edu/our-expertise/climate/enso/) into strategic planning to optimize fishing locations and operational days.

Through this case study, we explore the application of the widely used Niño 3.4 SST anomaly to define El Niño and La Niña events as a monthly oceanographic index for describing spatiotemporal variation in the decision-making of purse seine vessels. The Niño 3.4 SST anomaly index is calculated based on a 5-month running mean in the Niño 3.4 region (5°N–5°S, 170°W–120°W), with El Niño or La Niña events being defined when the Niño 3.4 SSTs exceed +/- 0.4°C for a duration of six months or more (Rayner et al., 2003). In this analysis, we do not distinguish between fishing set types (e.g., floating-object sets and unassociated/free-school sets), assuming that the decision-making process is primarily driven by overall tuna density and environmental conditions. We use vessel tracking data for tuna purse seine vessels obtained from Global Fishing Watch (Kroodsma et al., 2018), coupled with the publicly accessible WCPFC data on catches (WCPFC, 2024) assuming that information is shared among vessels. For analysis, we discretized spatial data into 1° × 1° grid cells to match the WCPFC public data resolution. Both datasets are publicly available online at WCPFC Scientific Data Dissemination (https://www.wcpfc.int/scientificdatadissemination) and Global Fishing Watch (https://globalfishingwatch.org).

We explore the potential effect of regional conditions (a spatially varying effect of ENSO) on the decision-making process of purse seine vessels, and use the following utility function:

$$U_{ijt} = \underbrace{\sum_{n=1}^{N} X_{ijnt}\eta_n}_{Fixed\ effect} + \underbrace{\underbrace{\omega_{s[j]}}_{Spatial\ variation} + \underbrace{E_t\gamma_{s[j]}}_{Spatially\ varying\ coefficient} + \underbrace{\sum_{k=1}^{4} S_{k,t}\delta_{k,s[j]}}_{Seasonal\ \text{spatial variation}}}_{Random\ fields} \quad (17)$$

where X_{ijtn} includes the lagged VPUE (value per unit effort, calculated as the product of catch and fish price at that time) for skipjack tuna, yellowfin tuna, and bigeye tuna, as well as lagged fishing effort from the same month of the previous year, as well as the distance to the port as the expected cost. $\boldsymbol{\omega}$ is the persistent spatial variation, E_t is the Niño 3.4 SST anomaly index, and $\boldsymbol{\gamma}_s$ represents the SVCs) to oceanographic index E_t. S_{kt} is a binary indicator for season *k* (i.e., 0 or 1), and $\boldsymbol{\delta}_{k,s}$ represents the spatial variation specific to each season, included to account for within-year variation in fishing preference not explained by ENSO or other covariates.

For the case study, we assess the performance of the spatial DCM model by comparing it with two alternative models (conventional DCM and mixed DCM), with 1° × 1° grid cells serving as the choice alternatives. We first specify the $\boldsymbol{\omega}_s$, $\boldsymbol{\gamma}_s$, $\boldsymbol{\delta}_{k,s} = 0$ for conventional DCM that assumes no spatial variation, no SVCs, and no seasonal spatial variation. We then assume $\omega_s \sim \text{Normal}(0, \sigma_{\omega}^2)$, $\gamma_s \sim \text{Normal}(0, \sigma_{\gamma}^2)$, and $\delta_{k,s} \sim \text{Normal}(0, \sigma_{\delta,k}^2)$ for the mixed DCM, incorporating random effects to account for spatial heterogeneity and varying environmental conditions. We fit the three models (conventional DCM, mixed DCM and spatial DCM) using the leave-future-out approach and evaluated performance through three approaches:

1. **Parsimony**: we calculate the marginal Akaike Information Criterion (AIC) (Akaike, 1974) and directly compare the models as an estimate of predictive error, considering both bias and imprecision.
2. **McFadden's Pseudo-R^2**: we assess the goodness-of-fit of the models using McFadden's pseudo-R^2, which provides a measure of how well the model explains the observed choices relative to a null model with no predictors.
3. **Predictive Capability**: finally, we use external validation through a retrospective (leave-future-out) analysis to assess the model's predictive capability. Specifically, we fit the model using data up to year t_{year} (e.g., 2014–2017), and predict the effort allocation for year $t_{year} + 1$ (e.g., 2018) repeating this process until 2020. Predicted probabilities are aggregated to the country level by summing grid cells with centroids located inside each country's EEZ, and the resulting effort allocations are compared to observed values using the Pearson correlation coefficient.

3. Results

3.1 Diffusion-taxis simulation and model testing

We visualize variables and results for the first replicate of the simulation experiment to provide intuition about the model behavior. In this replicate, maps of simulated purse seine preference for December (Figure 3, left column) show distinct spatial patterns over the years. Specifically, in the first simulated year (2010, Figure 3, top row), the preference was markedly higher in the western WCPO than the eastern WCPO, corresponding to a La Niña event. In the fourth simulated year (2013, Figure 3, second row), a neutral year, there was no noticeable difference in preference between the western and eastern regions, but the pattern reversed in 2015, showing a significantly higher preference in the eastern WCPO compared to the western WCPO in December (Figure 3, third row). This difference in preference is driven by the predefined tuna distribution and the ENSO effect (Figure 3, middle column), which is positive in the western WCPO and negative in the eastern WCPO during La Niña (2010), near zero effects during neutral year (2013), and reversed during El Niño (2015). As a result, the model-simulated vessel tracks (Figure 3, right column) reflect these changes in simulated preference, generating concentrated activities in the western WCPO during La Niña, evenly broad distribution in central WCPO during the neutral year, and a shift to the eastern WCPO during El Niño.

Fitting the simulated data to spatial DCM and mixed DCM estimates the SVCs $\boldsymbol{\gamma}$ from the spatial DCM and area-covariate slope β from the mixed DCM for ENSO effects on fishing preference, as shown in the Figure 4, and comparable to the simulated W_s pattern in Figure 2 (upper panel). The estimated SVCs $\boldsymbol{\gamma}$ from the spatial DCM show a clear spatial pattern, being nearly three units higher in the eastern WCPO compared to the western WCPO, transitioning around 170°E longitude (Nauru and Gilbert Island in Kiribati) across the simulation replications. The spatial DCM estimates closely matches the simulated changes in purse seine preference and fishing activities, showing the ability to capture the spatial preference driven by ENSO events. In comparison, the area-covariate slope β estimated by the mixed DCM shows similar overall pattern but appears more fragmented and scattered, particularly in areas with sparse data coverage.

For simulated fishing activities, both spatial DCM (green line) and mixed DCM (purple line) capture the model-generated fishing activity across the simulation replications, while the conventional DCM (orange line) shows less sensitivity to the variations in simulated fishing effort (Figure 5). For example, during simulated La Niña years (e.g., 2011, 2012, 2017, 2018), spatial DCM and mixed DCM estimate low levels of simulated fishing activities (spatial DCM: 10~20%, mixed DCM: ~20%) in Kiribati and high level of activities (spatial DCM: 20~50%, mixed DCM: 20~50%) in Papua New Guinea. Conversely, during simulated El Niño years (e.g., early 2010, 2015, 2016), both models predict higher level of activities (spatial DCM: 20~50%, mixed DCM: 20~50%) in Kiribati and lower level (spatial DCM: 5~15%, mixed DCM: 10~20%) in Papua New Guinea. Overall, spatial DCM shows better performance, particularly during periods of significant variability of fishing activity driven by ENSO, as the mixed DCM tends to slightly underestimate the magnitude of changes. In contrast, the conventional DCM predicts relatively constant fishing activities for Kiribati and Papua New Guinea remain (approximately 20% and 25%, respectively) throughout the simulated time period, showing a weaker correlation with the simulated fishing activities. For the simulated forecast years 2018, 2019 and 2020 (light-colored line), both spatial DCM and mixed DCM predicts the initially high and then declining fishing activities in Kiribati, and initially low and then increasing activities in Papua New Guinea. However, the mixed DCM tends to produce more conservative predictions, underestimating the magnitude of the simulated changes. In contrast, the conventional DCM continues to predict unchanged levels of fishing activity, failing to capture the variations in the simulated data.

3.2 Application to the PNA case study

In the case study for tuna purse seine fisheries in the WCPO, we first compared three models: conventional DCM, mixed DCM, and spatial DCM, using statistical performance metrics. We found consistent support for the spatial DCM as best-performing model (Table 2). In particular, AIC indicates that the spatial DCM is more parsimonious (i.e., expected to improve predictive performance) and also has a substantial increase in Pseudo-R^2 (i.e., a higher proportion of variance explained) relative to models without spatial autocorrelation. We next examined the estimated spatial components of the fitted spatial DCM to better understand spatial patterns in fishing effort allocation. Results from the case-study application, based on purse seine fisheries data within the WCPO, indicate that the estimated spatial term $\boldsymbol{\omega}$ (Figure 6, top left), which structurally represents the baseline spatial preference, is extremely small in magnitude, (ranging from approximately 2×10^{-7} to -1×10^{-7}), suggesting almost no effect on fishing activity. The near-zero estimates of $\boldsymbol{\omega}$ imply that baseline spatial preferences may play a limited role in this case, with most spatial variation instead captured by the SVCs and seasonal spatial terms. As shown in the parameter estimates for the spatial DCM (Table 3), the standard deviation σ_ω and the spatial correlation ρ_ω are effectively zero or uninformative, further supporting that ω plays a minimal role in explaining spatial variation in fishing activity. The near-zero estimates of $\boldsymbol{\omega}$ imply that most spatial variation is instead captured by the SVCs and seasonal spatial terms.

In contrast, the estimated SVCs γ (Figure 6, top right) and the seasonal spatial terms δ (Figure 6, second and third columns) show clear and significant spatial structure. For the estimated SVCs $\boldsymbol{\gamma}$ (Figure 6, top right), as expected, the spatial DCM estimates nearly 4 units higher for the eastern region than the western WCPO, with a transition of around 160°–180°longitude. This spatial pattern shows that positive values of $\boldsymbol{\gamma}$ in the eastern WCPO and negative values in the western WCPO, suggesting El Niño events enhance fishing activity in the west (Solomon Island, Papua New Guinea and Federated States of Micronesia), while La Niña events increase fishing activity in the east (Kiribati). As for the central region (Nauru and the Gilbert Islands in Kiribati), the estimated SVCs shows mixed effects on ENSO, with positive values in the Gilbert Islands (Kiribati) and negative values in Nauru, showing a transitional shift between the two regions. The significance of the SVCs is also supported by Table 3, with a significant spatial standard deviation (σ_{γ}= 0.007, 95% CI: [0.005, 0.011]), a high spatial correlation (ρ_{γ}= 0.930, 95% CI: [0.905, 0.949]).

For the estimated seasonal spatial terms $\boldsymbol{\delta}$ (Figure 6, second and third columns), the spatial DCM estimates a clockwise shift in spatial variation over seasons (four quarters). Specifically, the first seasonal spatial term $\boldsymbol{\delta}_1$ (middle left, January–March) is low in certain northern and lowest in eastern areas but high in most WCPO regions. The second seasonal spatial term $\boldsymbol{\delta}_2$ (middle right, April–June) is low in the east and south regions and high only in the west region around the Federated States of Micronesia. The third season spatial term $\boldsymbol{\delta}_3$ (bottom left, July–September) is significantly low in the southern regions, especially in the southwestern area around the Solomon Islands. The fourth seasonal spatial term $\boldsymbol{\delta}_4$ (bottom right, October–December) is notably low in specific northwestern and northeastern regions but high in eastern south WCPO around Tuvalu and Kiribati, showing a redistribution of fishing activities. Parameter estimates in Table 3 highlight the significance of seasonal spatial variation through δ, with high spatial correlation (ρ_{δ}= 0.902, 95% CI: [0.884, 0.917]) and a significant standard deviation (σ_{δ}= 0.021, 95% CI: [0.016, 0.026]).

Finally, to further evaluate model performance, we examined the ability of the spatial DCM to estimate and forecast fishing effort allocation. Fitting the model to WCPO purse seine data for 2014–2017 and forecasting shifts for 2018–2020 (Figure 7) shows that incorporating SVCs improves both estimates and forecasts of allocation shifts. The results also show clear regional differences in ENSO-driven fishing utility patterns. For example, observed effort allocation in FSM and PNG shows a strong ENSO effect, with high fishing efforts in La Niña conditions (blue shaded area) and low in El Niño conditions (red shaded area), while KIR and HS exhibit a reversed ENSO response, with low fishing efforts in La Niña and high efforts in El Niño.

The correlation results further indicate the performance advantage of the spatial DCM over both mixed DCM and the conventional DCM. For 2014–2017 estimates, the spatial DCM shows higher correlations with observed effort allocations across all regions: FSM (0.63), PNG (0.84), SLB (0.60), TUV (0.32), KIR (0.75), and HS (0.62). In contrast, the conventional DCM underestimates the spatial variations, producing much lower correlation: FSM (0.11), PNG (0.46), SLB (0.14), TUV (-0.04), KIR (0.57), and HS (0.06). The mixed DCM produces intermediate correlations, indicating that incorporating random effects can capture part of the spatial variation, with values of FSM (0.44), PNG (0.78), SLB (0.56), TUV (0.14), KIR (0.73), and HS (0.50). For 2018–2020 forecasts, both spatial DCM and mixed DCM perform better than the conventional DCM. The spatial DCM show better forecasting capabilities, with high correlations in most region such as FSM (0.62), PNG (0.63), SLB (0.41), TUV (0.37), and HS (0.51). In contrast, the conventional DCM shows poorer predictive capability, particularly in regions like SLB (0.02) and TUV (0.24), failing to capture temporal and seasonal variations. The mixed DCM performs comparably to the spatial DCM in some regions, such as FSM (0.61), PNG (0.62) and KIR (0.54), but overall, spatial DCM slightly outperforms mixed DCM. Notably, the inclusion of the seasonal spatial term in both spatial DCM and mixed DCM significantly improved the estimates and forecast seasonal shifts, especially in SLB, which shows little ENSO impact but high seasonal variation. Given this positive statistical support, we emphasize the benefits of including spatial autocorrelation and SVCs, both in terms of predictive accuracy and descriptive power.

4. Discussion

In this paper, we extend the DCM by incorporating SVCs (forming the spatial DCM) so that spatial preferences respond vary by location in response to time-varying indices (e.g., ENSO). We also explored the use of both simulated and real data to test and analyze fishing effort allocation behavior under different spatial-temporal and oceanic environmental conditions. This study is the first (to our knowledge) to use movement models based on forage theory to simulate fishing vessel behavior for testing the statistical performance of a spatial DCM. In the movement simulation model, spatial preferences are modulated by time-series data (ENSO indices) through a spatial fishing-preference weight, resulting in zonal positive and negative impacts in the eastern and western regions of the WCPO. Despite structure differences between the simulated movement model and the DCM-based estimation model, the estimated spatial preference is strongly correlated with the simulated preference function. The simulation study and case-study performed as expected, showing the benefits of extending DCM with spatial autocorrelation and SVCs for predicting and projecting fishing behavior, particularly in regions with significant spatial correlation. In the simulation, we excluded other possible factors that could affect fishing efforts allocation, such as bilateral agreements or the location of tuna processors, to conduct a more controlled simulation test, and show that incorporating spatial correlation into DCM can be used to improve forecasts or projections of future fishing activities. We applied this method to the WCPO tuna purse seine fishery and found that purse seine fishing activities are significantly affected by both ENSO variations and seasonal effects. By fitting the estimation model, we can estimate and separate the spatial preference effects, visualizing how the spatial distribution of fishing activity changes in response to environmental factors such as ENSO variations and seasonal dynamics.

Using the spatial DCM allows the model to better capture spatial autocorrelation and regional variations in fishing behavior, which are often missed by mixed effects models. By incorporating SVCs, the model can provide more precise predictions by treating time-series data as a proxy for unmeasured (latent) conditions like regional water temperature, particularly in areas with strong spatial autocorrelation. However, the introduction of spatial autocorrelation into DCMs, while improving overall predictive performance, inevitably increases computational time and costs due to the additional effort required to estimate spatial autocorrelation parameters and precision matrices. Additionally, dealing with a large number of potential fishing grounds increases the computational burden due to an expanded choice set, further increasing the computational load. In our study, we used the CAR approach for spatial autocorrelation estimation, which improved model performance in analyzing geographically contiguous areas. However, the spatial DCM did not show substantial improvement in dispersed nations like Kiribati. This reflects the challenge of capturing spatial variation in widely dispersed regions, which may cause excessive smoothing between neighboring grids (called “oversmoothing”) (Song et al., 2024). In the case of Kiribati, the EEZ are separated by areas of high seas, increasing the risk of oversmoothing across neighboring grids. For example, in 1-degree resolution fishing location choices, the relatively small size of the EEZ in Kiribati, coupled with the small spatial scale of the grids, can result in excessive correlation with adjacent grids, introducing estimation biases. This issue of spatial scale arose because mismatches between the spatial scale of the data-generating process and the aggregation level in models can lead to significant biases (Dépalle et al., 2021). Possible approaches to mitigate this issue could involve increasing the local resolution in certain areas, e.g. around Kiribati, to better reflect finer spatial variations, or estimating spatial variation in the decorrelation rate (sometimes called “spatial nonstationarity”). However, as the regional spatial resolution and potential fishing locations increase, the computational cost increases simultaneously (Dépalle et al., 2021), potentially outweighing the benefits of improved spatial modeling. Therefore, although the spatial DCM provide better spatial predictions, it requires careful consideration of computational trade-offs, particularly in regions that are geographically dispersed. Another plausible reason for the limited contribution of spatial DCM in some contexts may be the temporal dynamics of ENSO. Specifically, transitional ENSO years, those that do not exhibit strong El Niño or La Niña signals and are often classified as neutral, tend to flatten the variability observed in both fish distribution and fleet behavior. During neutral periods, oceanographic drivers influencing spatial responses become less well-defined, resulting in subdued spatial preferences (see Figure 3, second row). Consequently, the spatial variation estimated by the model may be more moderate, limiting the explanatory contribution of spatial DCM. A similar situation was observed in the redleg banana prawn fishery in Australia. For example, Plagányi et al. (2020) suggested that moderate ENSO phases may weaken the linkage between environmental variability and biological responses, describing ENSO-neutral years as a "neutral zone" in which redleg banana prawn recruitment became more difficult to explain and model performance declined.

In our case study application, we included the VPUE and fishing effort from the same month in the previous year as lagged indicators of expected catch and effort, as well as the distance to port to represent expected cost. We compared three model structures, without random effects, with area-level random effects, and with spatial random effects, to evaluate model performance and better understand spatial fishing behavior. Among the three models, the spatial DCM provides comparatively stronger forecasting performance and better captures spatial variations in response to environmental changes (Figure 7). However, we note that in the spatial DCM, the estimated variance (σ_ω) of the spatial variation $\boldsymbol{\omega}$ was close to zero, indicating limited residual spatial variation beyond what was accounted for by covariates and other spatial terms. The near-zero estimate of the spatial variance (σ_ω) reflects a form of regularization (sometimes called "penalization" or "shrinkage") where likelihood-based estimation shrinks the variance of weakly supported random effects toward zero, thereby reducing model complexity and enhancing predictive performance (Hooten and Hobbs, 2015). Future studies could also explore model selection to assess whether such components should be retained.

To understand how the spatial DCM captures the influence of environmental factors on the spatial distribution of fishing effort, we examined the estimated SVCs (γ; Figure 6, top right) and seasonal variations (δ; Figure 6, second and third columns). The estimated SVCs exhibit a clear east–west contrast (positive in the east, negative in the west), and the seasonal variations follow a clockwise spatial shift across seasons. These spatial patterns show alignment with the seasonal and interannual dynamics of the Western Pacific warm pool, which are driven by changes in monsoons, trade winds, ocean currents, and climate events (Lindstrom et al., 1987; Picaut et al., 1996; Wang et al., 2019; Wyrtki, 1989). These regional oceanographic conditions of Western Pacific warm pool influence skipjack tuna habitat suitability and, in turn, shape their spatial distribution. The Western Pacific warm pool provides favorable physiological and foraging conditions, supporting a highly productive tuna population (Lehodey et al., 1997; Mugo et al., 2010), and skipjack tuna to locate and forage on the periphery of highly productive frontal or upwelling zones, while remaining within tolerable temperatures (Ramos et al., 1996; Mugo et al., 2010). However, the location of the warm pool is not stationary, as it shifts in response to seasonal changes and ENSO events. The large-scale shifts in the location and extent of the warm pool, in turn, influence the distribution of skipjack tuna across the Western and Central Pacific. To better understand the drivers behind the seasonal and interannual shifts, including the interactions among tuna movement, fishing behavior, and large-scale oceanographic conditions, we focus on two major spatial signals captured by our model estimates:

1. ENSO effect: In El Niño years (Niño 3.4 index > 0.5, see Figure 2, lower panel), the estimated SVCs (Figure 6, top right panel), when combined with positive ENSO index, yield

an east-positive, west-negative spatial preference pattern. This east-positive and west-negative pattern captures the eastward shift of the warm pool, driven by weakened trade winds and associated changes in ocean circulation (Picaut et al., 1996), which in turn causes skipjack tuna to migrate eastward to the central and eastern Pacific (around Kiribati) (Lehodey et al.,1997). Consequently, fishing activity shifts from Papua New Guinea toward the central and eastern Pacific, extending into Kiribati and surrounding waters. In contrast, during La Niña events (Niño 3.4 index > -0.5), the product of the estimated SVCs and ENSO anomalies generates a west-positive, east-negative spatial preference. This west-positive and east-negative pattern reflects the westward retraction of the warm pool due to enhanced trade winds (Picaut et al., 1996), keeping skipjack tuna and fishing activity concentrated in the western Pacific.

2. Seasonal variation: The estimated seasonal preference $\boldsymbol{\delta}_1 - \boldsymbol{\delta}_4$ reflect the influence of warm pool shifts on the spatial distribution of skipjack tuna and, subsequently, on fishing activity throughout the year. Specifically, in the first season (January to March), the estimated seasonal variation δ_1 reveals higher preference values in the western Pacific, corresponding to the seasonal positioning of the warm pool near Papua New Guinea and the Solomon Islands, where skipjack tuna and fishing activity concentrate during this period. In the second season (April to June), the estimated δ_2 shows higher preference values in the region north of Papua New Guinea and extending toward Micronesia. During this period, the southwest monsoon begins, and increasing solar radiation and surface heat flux (Wang et al., 2019) drive the warm pool to expand northwestward, leading to a shift in the distribution of skipjack tuna and fishing activity toward the northwestern region. In the third season (July to September), the estimated δ_3 indicates a spatial preference shift toward Kiribati and the adjacent high seas pocket, broadly between 180° and 160°W. Seasonal solar heating peaks in the Northern Hemisphere during this time, causing the warm pool to expand eastward and reach its largest extent (Wang et al., 2019; Wyrtki, 1989). As the warm water spreads, fishing activity follows, gradually moving

toward the central and eastern equatorial Pacific. Finally, in the fourth season (October to December), the estimated δ_4 shows a return of preference values to the central and southern parts of the western Pacific. During this period, solar heating decreases and trade winds resume, causing the warm pool to retreat westward toward areas near Papua New Guinea and the Solomon Islands. Correspondingly, fishing activity concentrates once again in these waters. By visualizing the spatial variations, we have gained insights into the underlying mechanisms driving spatial fishing choices, which provide a foundation for predicting future behavior.

By visualizing the seasonal and ENSO-driven spatial variations, we have gained insights into the behavioral pathway linking environmental variability to fleet dynamics. The estimated spatial preference patterns (SVCs and seasonal variation δ_1–δ_4) reveal latent processes through which fishers respond to environmental variability, influencing spatial utility and, eventually, the choice of fishing locations. These results suggest that fishing effort is indirectly driven by fishers responding to unmeasured ecological processes associated with warm pool movement.

The implications of this result extend to the management of fleet dynamics and spatial policy planning. This proposed framework offers a behavior-based tool for understanding fleet dynamics and supporting management decisions. In the PNA case study, for example, the Vessel Day Scheme (VDS) enables member states to allocate and trade fishing days in response to changing fishing pressure (Havice, 2013). Integrating spatial effort forecasts with ENSO predictions (e.g., using products like COLA CCSM4 or GFDL SPEAR) could further enhance the ability of managers to anticipate potential hotspots of purse-seine activity up to nine months in advance. This proactive approach may help member states optimize VDS allocations, reduce the risk of running out of fishing days, and manage associated costs. Additionally, early identification of high-risk zones would support early deployment of area-based measures to avoid bycatch or sensitive species before pressure builds, particularly those species and fisheries that respond to dynamic oceanographic conditions (Soykan et al., 2014).

Moreover, the spatial DCM developed in this study could inform the development of operating models for management strategy evaluation (MSE) by explicitly accounting for dynamic fishing behavior across space. Fulton et al. (2011) highlight that uncertainties related to fisher behavior and fleet responses to environmental variability and policy changes often lead to management failures. To reduce such uncertainties, explicitly modeling spatial fisher behavior within MSE frameworks has been recommended as a promising approach (Punt et al., 2016). For example, Rose et al. (2015) integrated a random utility model (RUM) with an agent-based framework to simulate realistic spatial distributions of fishing effort as inputs to operating models, thereby enhancing the realism of spatial fishing pressure. Similarly, Siple et al. (2021) emphasized the importance of accounting for fisher responses to spatially varying fishing pressure and range to support robust management strategies for small pelagic fishes. The spatial DCM proposed here provides a practical tool for linking climatic time-series indices (e.g., Pacific Decadal Oscillation, PDO; North Atlantic Oscillation, NAO), to latent, spatially varying behavioral responses. This approach enables simulations of how fishers may respond unevenly to changing climate conditions, supporting scenario-based policy evaluation.

We note that several institutional changes occurred in the WCPO during the modeling period, e.g., the full closure of the Phoenix Islands Protected Area (PIPA) in 2015, extensions of FAD closures, and increased VDS access fees (Mallin et al. 2019, WCPFC, 2021). These measures likely affected spatial choices by restricting access to previously available areas or altering the economic incentives associated with fishing in particular zones. Although institutional factors were not explicitly modeled in this case, some of these effects may have been partially reflected through defined choice sets and captured through lagged covariates and spatial effects. Nonetheless, unmodeled policy dynamics may contribute to unexplained spatial variation, and future model extensions could benefit from explicitly incorporating institutional indicators to improve interpretability and support policy evaluation.

Additionally, future shifts in institutional conditions may also limit the predictive performance of existing models. Fishing policy changes, such as closed fishing areas or effort control, can alter spatial incentives and prompt vessels to reallocate their effort accordingly (Reimer et al., 2017). Modeling fishing area restrictions using choice sets is one effective approach, e.g., fishing vessels will move to other open areas when access to specific areas is restricted (Hutton et al., 2004). Still, understanding the basic behavioral mechanisms of spatial choice is crucial because, even under institutional changes, fishing location decisions are influenced not only by fish distribution and economic returns but also by habits and past experiences (Holland & Sutinen, 2000). Another limitation of current models is the assumption that all vessels follow the same decision-making process, regardless of differences in fishing strategies. Since our analysis uses AIS-based vessel monitoring (e.g., Global Fishing Watch) as the foundation for our dataset of observed fishing activities, it is important to acknowledge that we are unable to distinguish between set types in the current analysis. In practice, purse seine vessels fishing on drifting FADs may exhibit different spatial behaviors compared to those targeting free-school tuna. For example, FAD sets may depend more on the location and timing of earlier deployments than on real-time fish distribution, whereas free-school sets tend to respond more directly to current tuna movement (Gomez et al., 2020). As a result, behavioral differences between fishing strategies may be absorbed into other estimated effects and may introduce uncertainty into the interpretation of estimated spatial preferences.

Finally, recent studies have expanded the applicability of mechanistic movement models in fisheries science (Thorson et al., 2021a,b), and this approach has already been applied to simulate how climate change may shift species geographic distributions (Ovando et al., 2024). We therefore recommend further development of this approach by integrating known behavioral mechanisms with models of incentive changes or species redistribution to simulate fishing activity under evolving policy or environmental regimes. Additionally, we suggest the joint development of DCMs and movement models. In our simulation testing, the spatial DCM used for estimation closely approximated the underlying preference structure from the movement model. This joint development allows for cross-testing and could support future studies exploring changes in fishing activity dynamics under shifting climate and institutional conditions. Future work should consider applying this integrated approach to scenario analyses, evaluating fleet responses under various policy alternatives, such as different degrees of area closures or effort restrictions, combined with projected environmental changes.

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Author contributions

All authors were involved in the design and conception of this study. Hsing-Han Wu and James T. Thorson were responsible for all code produced during this project and led the analysis of the data, with additional advice and assistance from Ray Hilborn, Yi Chang. Hsing-Han Wu led the writing of the manuscript and all authors contributed critically to the drafts and gave final approval for publication.

Data availability statement

All datasets analyzed in this manuscript are publicly available online at WCPFC Scientific Data Dissemination (https://www.wcpfc.int/scientificdatadissemination), Global Fishing Watch (https://globalfishingwatch.org) and NASA Ocean Color (https://oceancolor.gsfc.nasa.gov/).

Conflict of interest statement.

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

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