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A spatiotemporal population model for stock assessment: Application to North Pacific albacore tuna

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Abstract

Stock assessment models play a crucial role in fisheries management. However, they are increasingly affected by process errors in population dynamics, which can lead to overly optimistic stock estimates. One major issue is the inadequate separation of changes in catchability from process error. Traditional CPUE standardization has difficulty distinguishing true population density signals from observational errors, which reduces the accuracy of stock assessments. Moreover, existing stock assessment models do not adequately account for spatial and migratory dynamics, which is particularly problematic for highly migratory species. To overcome these limitations, we developed the Spatio-Temporal Population Model (STPM), which separates population dynamics from observational processes using a state-space modeling approach. We applied STPM to North Pacific albacore tuna and estimated spatial stock depletion and quarterly population density from 1994 to 2023. The model successfully distinguished process and observation errors, providing a more detailed representation of spatial stock structure than traditional approaches. Despite these advancements, challenges remain, particularly in computational efficiency and model refinement. Future efforts will focus on optimizing computational performance, integrating a logistic production function, and improving the observation model to enhance stock assessment reliability.

Introduction

For the sustainable use of fish stocks, stock assessments are conducted worldwide for over 331 stocks (Ricard et al., 2012). However, various issues persist in stock assessments. The most serious issue is the increasing trend of process errors in many stock assessment models over the years (Merino et al., 2022). Estimates derived from these models tend to be more optimistic than reality, raising concerns that appropriate stock management might not be implemented (Edgar et al., 2024). One possible cause of this issue is that the increase in catchability has not been adequately reflected in the stock assessment models. This oversight may lead to a rise in process errors.

To account for changes in catchability, CPUE standardization has been applied (Maunder 2001). However, traditional CPUE standardization simultaneously handles variations in population dynamics and observational errors in fishery data, complicating accurate correction. For example, spatial effects strongly depend on the spatial density of the target species, and fishing patterns are influenced by changes in the species distribution. Therefore, constructing stock assessment models that separate population processes from observational errors, such as state-space models, is essential (Punt et al., 2020).

Accurately understanding the population dynamics of highly migratory species like tuna requires proper incorporation of the movement process. However, current stock assessment models do not adequately consider this aspect. Highly migratory species like tuna move significantly between time steps, prompting the proposal and development of stock assessment models that account for migration (Fournier et al., 1998). However, existing models assume meta-population frameworks that divide the sea area into large regions. The estimation of migration rates and stock quantities can vary significantly depending on the area definitions. To address this issue, introducing spatial statistical knowledge into population dynamics models is effective (Thorson et al., 2017).

Furthermore, current stock assessments face a challenge: changing the settings of the stock assessment model requires modifications to the input data, reducing the model's reproducibility and complicating comparisons and validations between different models. For example, different models may use distinct methods for CPUE standardization, making comparisons with the same data difficult. Additionally, when the model structure differs, necessary preprocessing changes, complicating the uniform processing of data. As a result, applying criteria such as AIC and cross-validation becomes challenging, and objective evaluation between models is difficult. To resolve this issue, it is necessary to model the process up until data collection, which can be achieved by constructing a state-space model.

To address these problems, we extended the time-series stock assessment model to a spatiotemporal model and developed the Spatio-Temporal Population Model (STPM), which separates population dynamics processes from observation processes. This paper provides an overview of STPM and presents preliminary analysis results from applying it to North Pacific albacore. Additionally, we discuss future challenges and perspectives.

Material and methods

Data set

We used the total catch of North Pacific albacore and Japanese longline catch-and-effort data. We compiled data from 1994 to 2023 for each. For the total catch, we aggregated the values for Japanese longline and pole-and-line fisheries quarterly based on the logbook data, while we calculated the total catch for other countries as a quarter of the total (Figure 1). Additionally, to reduce computational costs, we used Japanese longline catch-and-effort data aggregated by year, quarter, and 1° × 1° grid.

Process model

We created the mesh using the R software package fmesher (Figure 2). The population dynamics model varies over time at each node of the mesh, and we assumed that there is correlation between the nodes. In this study, we adopted a spatially extended discrete Gompertz population dynamics model as the process model. Specifically, we used model where the logarithmic population density $b_{n,t}$ at node *n* and time step *t* is described by equation:

$$b_{n,t+1} = \alpha_n + \beta b_{n,t} - f_t + \epsilon_{n,t},$$

where, α_n and β are parameters of the Gompertz population model. α_n depends on space, thus α_n

follows a Gaussian Markov random field (GMRF) with mean α_0, $\alpha_n \sim \mathrm{GMRF}(\alpha_0, \Sigma)$. f_t represents the fishing mortality coefficient at time step t, and $\epsilon_{n,t}$ is the spatially dependent process error, which follows $\epsilon_t \sim \mathrm{GMRF}(0, \Sigma)$. The time step t is set as a quarter, with the assumption that a constant recruitment occurs each quarter.

Observation model

In the observation model, we considered the process by which Japanese longline logbook data and total catch data are obtained at different spatiotemporal scales. We assumed that the catch data in logbook obtained from observations follow a Tweedie distribution, expressed as $C_i \sim Tw(\mu_i, p, \phi)$, $1 < p < 2 \wedge \phi > 0$, where p is the power parameter, and ϕ is the dispersion parameter. The expected catch μ_i is defined as $\ln(\mu_i) = b_i + q_i + \ln(\mathrm{effort}_i)$, where b_i, q_i, and effort_i represent the logarithmic population density at observation point i, the catchability coefficient, and the effort level, respectively. The population density b_i is estimated using design matrix $\mathbf{A}$, $b_i = \mathbf{A} b_n$. We also assumed that the catchability coefficient q_i follows a normal distribution with mean q_0 and variance σ_q^2 and the effort was set to 1,000 hooks.

Parameter estimation and total biomass calculation

Considering that the area of the Voronoi regions centered around each node varies, the total biomass (B_t) is calculated by summing the product of population density and the area of each Voronoi region:

$$B_t = \sum_{t=1}^{T} \exp\left(b_{n,t} + \ln(w_n)\right) \mathrm{flag}_n,$$

where w_n represents the area of the Voronoi region at node n, and flag_n is a binary vector used to distinguish areas where stock estimates are made. The smallest unit of area is set to 1° × 1°, which matches the resolution of the observation data. Although the actual size of 1° × 1° regions varies, for simplicity, we used an average value. The observed total catch Y_t is calculated using f_t and B_t with the following equation: $\ln(Y_t) = \ln(B_t) + \ln\left(1 - exp(-f_t)\right) + \varepsilon_t$, were, ε_t represents the observation error, and we fixed its variance σ_ε^2 at 0.1. Although estimating the observation error is possible, preliminary simulation tests showed a strong correlation with f_t making convergence difficult. Therefore, this study assumes high accuracy in the catch statistics. For parameter estimation, we applied maximum likelihood estimation using TMB. The likelihood was calculated based on Japanese longline catch-and-effort data and total catch.

Result and discussion

Unfortunately, the program has not yet converged, requiring further adjustments. As in conventional stock assessments, we organized the time-series data on population dynamics, catch, and fishing mortality (Figure 3). While spikes (periodicity) in catch and fishing mortality were aligned, they did not necessarily match the periodicity of stock size. The periodicity in catch is likely influenced by fishing grounds, which are affected by the migration of small fish. To eliminate these spikes, it may be necessary to develop an age-structured model.

Catchability was estimated based on the number of catch and effort data points, that is, the total number of observations, while process errors were estimated for each node, year, and quarter (Figure 4). Fishing catchability remained nearly constant over time. In contrast, process errors exhibited a slight but noticeable trend similar to fluctuations in population dynamics. These results suggest that process errors and observation errors were effectively separated.

Quarterly spatial density estimates from 1994 to 2023 were also obtained (Figure 5). Although Japanese longline operations in the northeastern Pacific have significantly declined, a certain level of density was still estimated. In spatial statistical models, estimating density in areas with no data is inherently difficult. However, state-space models allow population dynamics to fluctuate even in the absence of observations, making such estimations possible.

Using this new model, it became possible to visualize spatial depletion rates (Figure 6). The reference stock condition was set as the equilibrium state of the Gompertz model, $Beq_i = \alpha_i/(1-\beta)$. High depletion rates appeared near the equatorial western region and north of Hawaii. Since the equatorial region originally has low catch levels, its reliability as an information source is questionable. Additionally, large fluctuations in areas where stock abundance is inherently low may not be meaningful, requiring careful consideration in their presentation.

Challenges and Future Plans

- The computational burden is high, requiring a review of the code. In particular, the calculation of f_t is computationally intensive, necessitating a reconsideration of the model itself.
- To apply this model in stock assessments, it is necessary to estimate Maximum Sustainable Yield (MSY). Therefore, instead of the Gompertz population model, a logistic production function should be considered.
- The observation model needs to be expanded. In this study, aggregated observation data at the year, quarter, and 1×1 degree resolution were used to reduce computation time.
- The model should allow the incorporation of covariates, similar to CPUE standardization. This improvement may facilitate convergence.
- f_t also varies spatially, it may need to be incorporated into the model. While technically feasible, spatially aggregated catch data may be required.
- The model does not currently account for migration rates. Although this is technically possible (Thorson et al., 2017), it has a lower priority due to potential convergence issues and computational costs.

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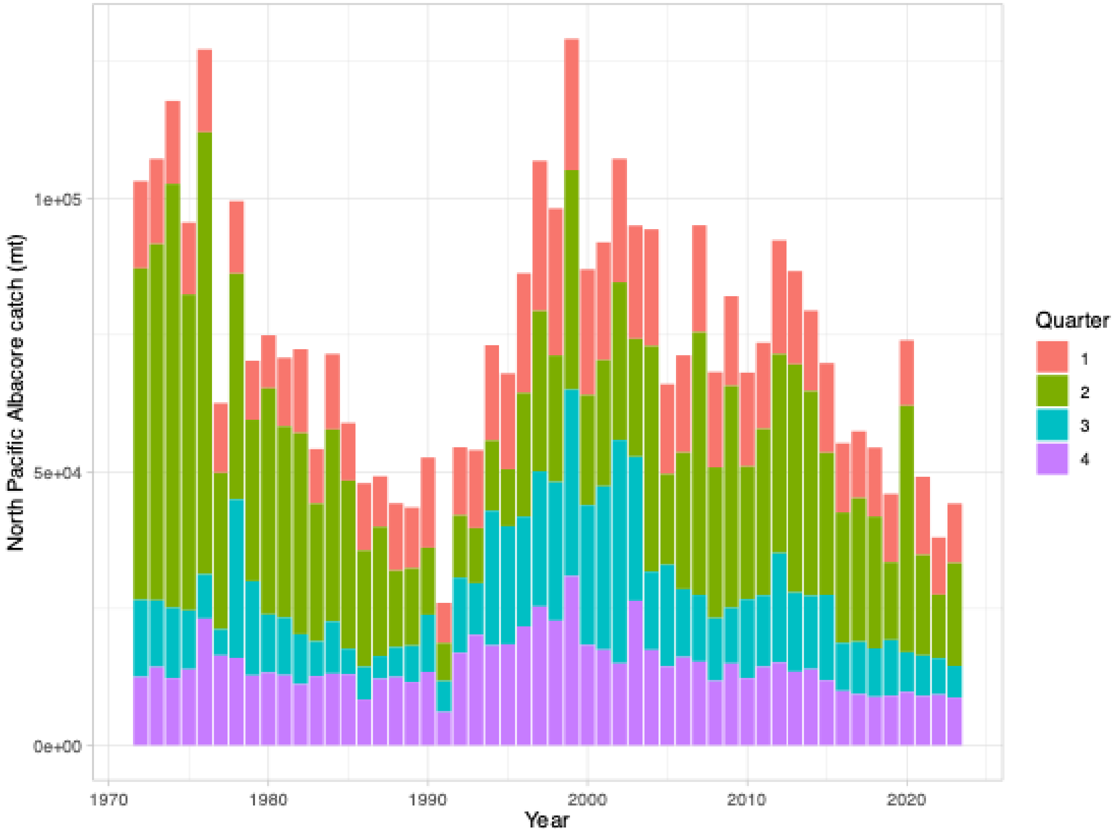

Figure 1. Total historical albacore catches in the North Pacific (1971-2023).

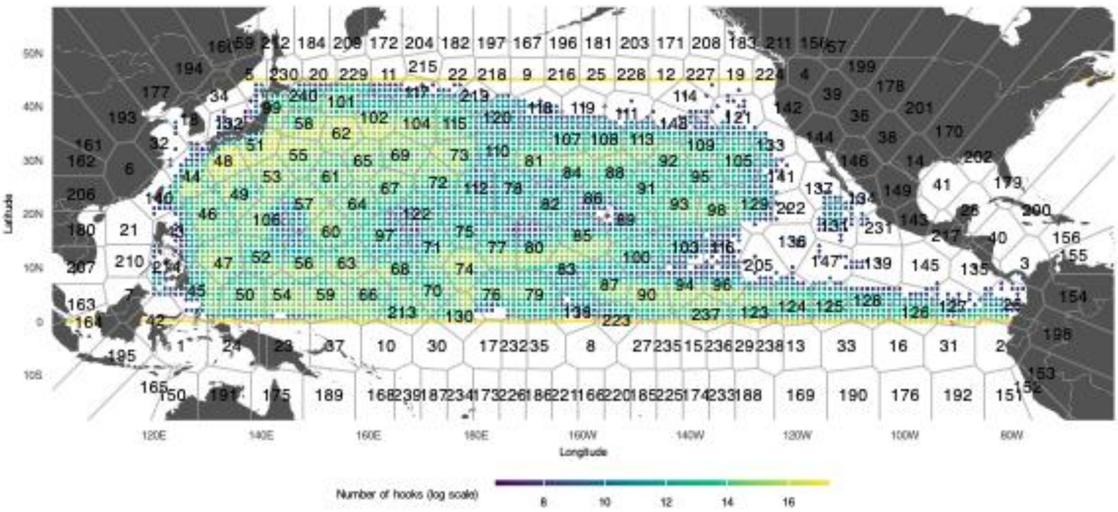

Figure 2. Spatial effort of Japanese longline fishery and nodes for spatiotemporal population model.

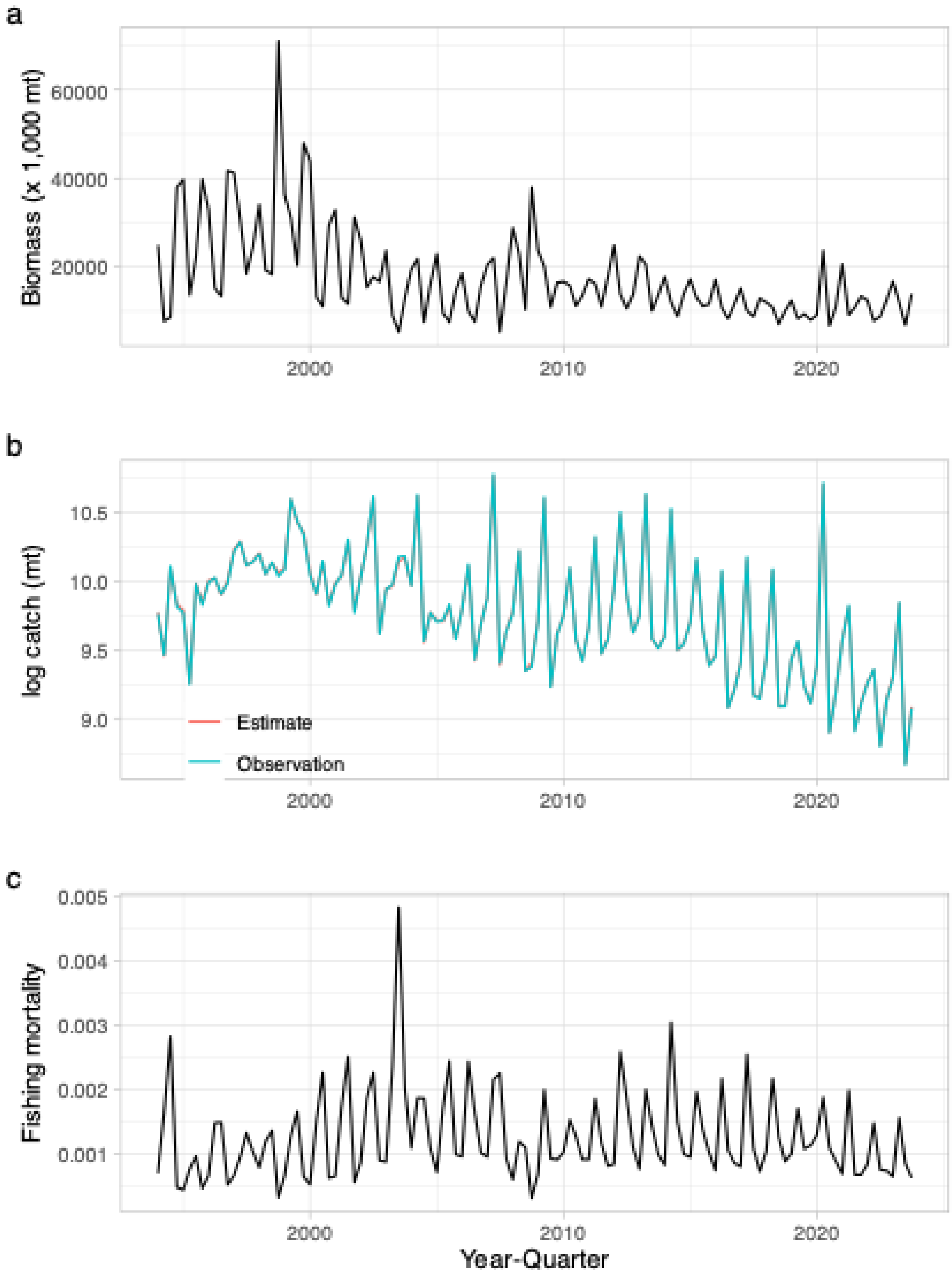

Figure 3. Time series results from spatiotemporal population model.

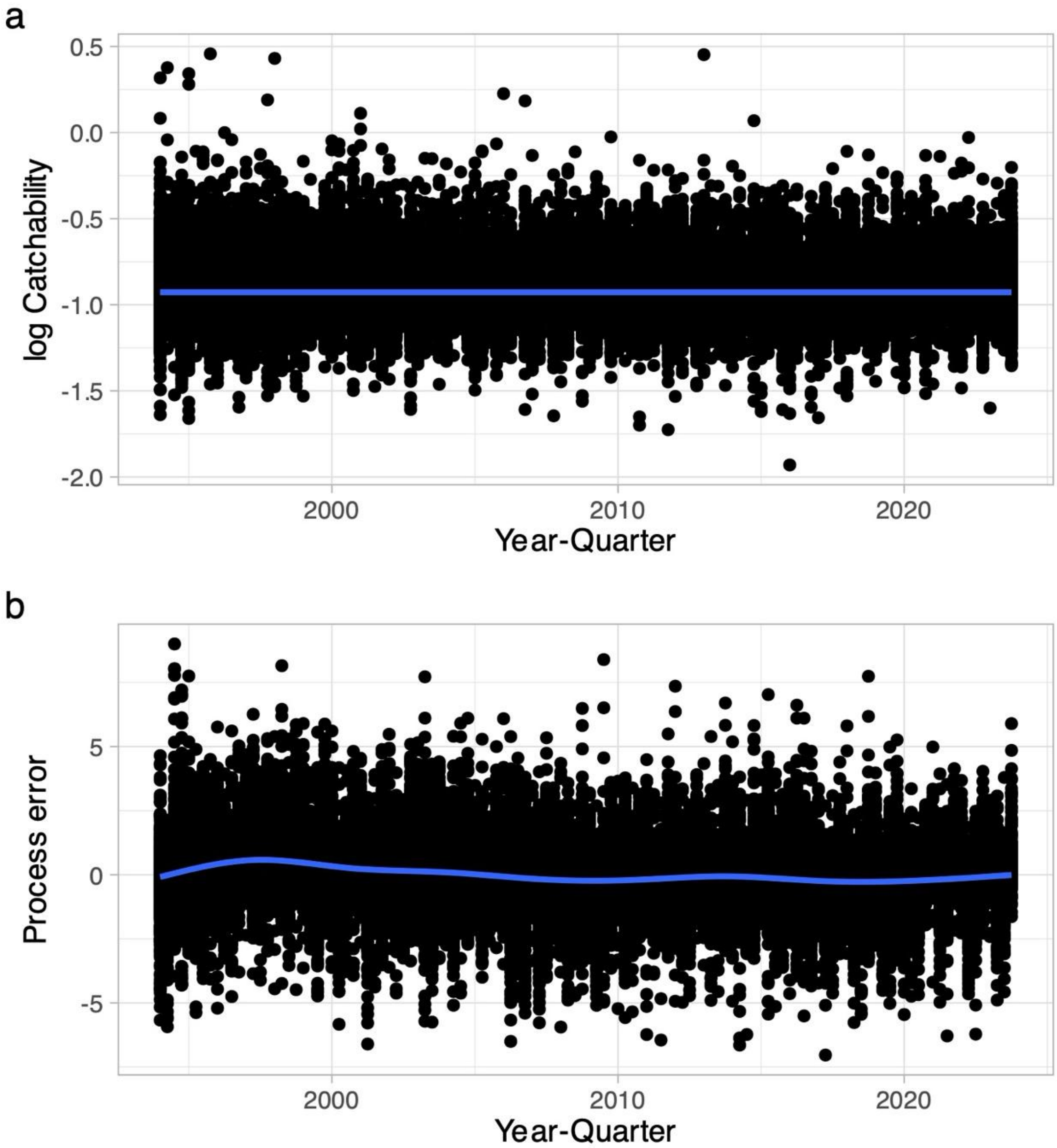

Figure 4. Comparison of historical changes in log catchability and process error.

Figure 5. Spatiotemporal density trend of North Pacific albacore stock estimated by spatiotemporal population model.

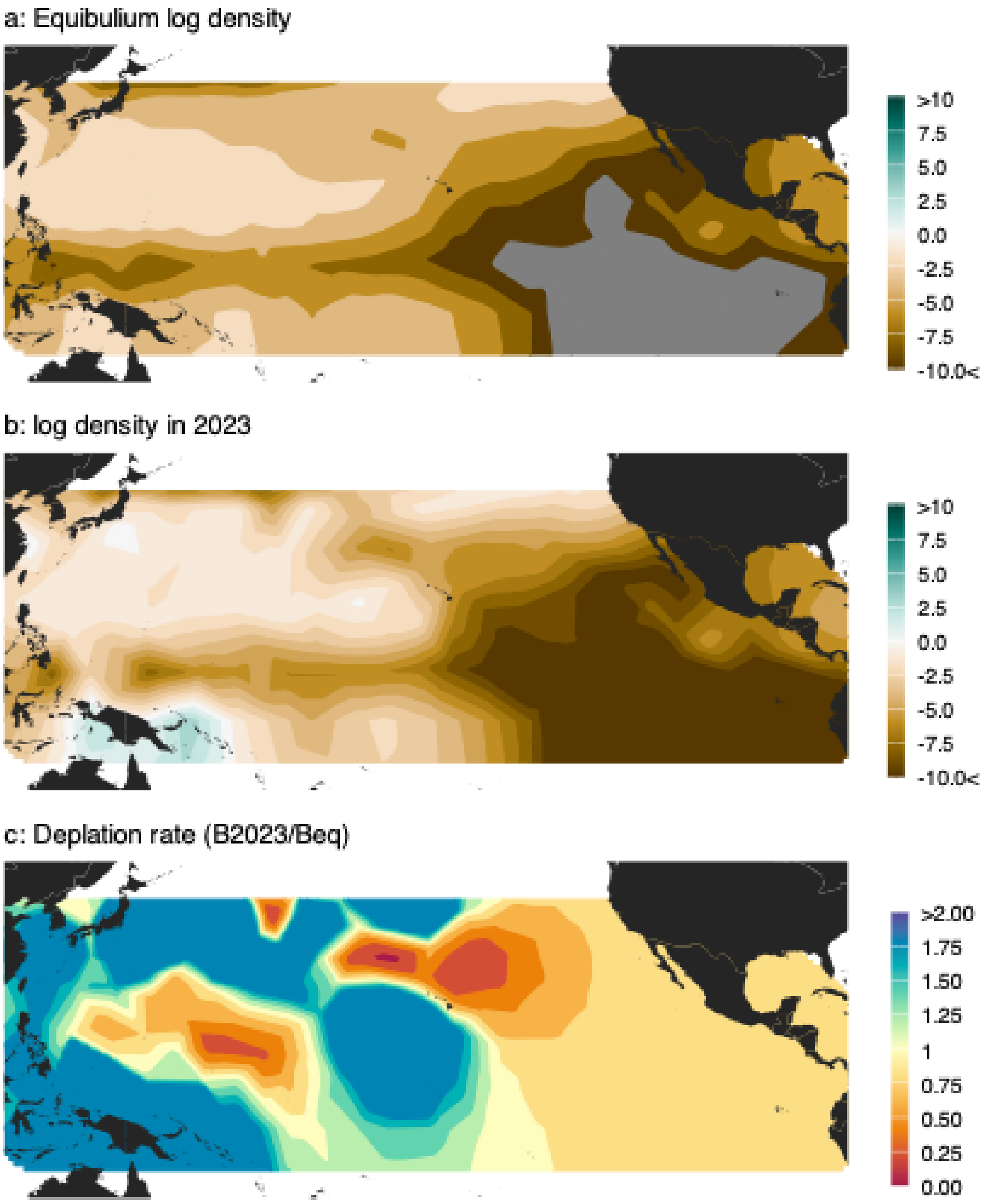

Figure 6. Spatial depletion of North Pacific albacore.