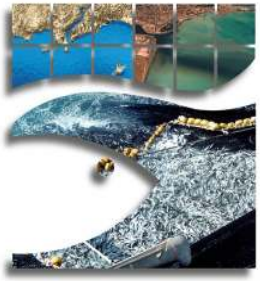

Toward a standardized abundance index for jack mackerel (*Trachurus murphyi*): spatio–temporal modeling of acoustic survey biomass data in northern Chile

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Jack mackerel stock assessment benchmark, May 2026

- Acoustic surveys provide key information for the stock assessment, but derived abundance indices can be affected by changes in spatial coverage and sampling design.

- In northern Chile, survey coverage has varied substantially over time, potentially introducing bias in annual indices and complicating the interpretation of temporal trends

- Traditional acoustic indices rely on direct observations and do not explicitly account for ecological and environmental drivers, limiting their ability to capture changes in habitat and spatial dynamics.

- Here, we develop a spatio-temporal modelling framework to estimate a standardized abundance index, including the integration of environmental covariates

- The objectives are to: (i) derive a robust index accounting for spatial and environmental variability, (ii) evaluate its sensitivity to changes in spatial coverage, and (iii) compare it with the historical acoustic index currently used in assessment.

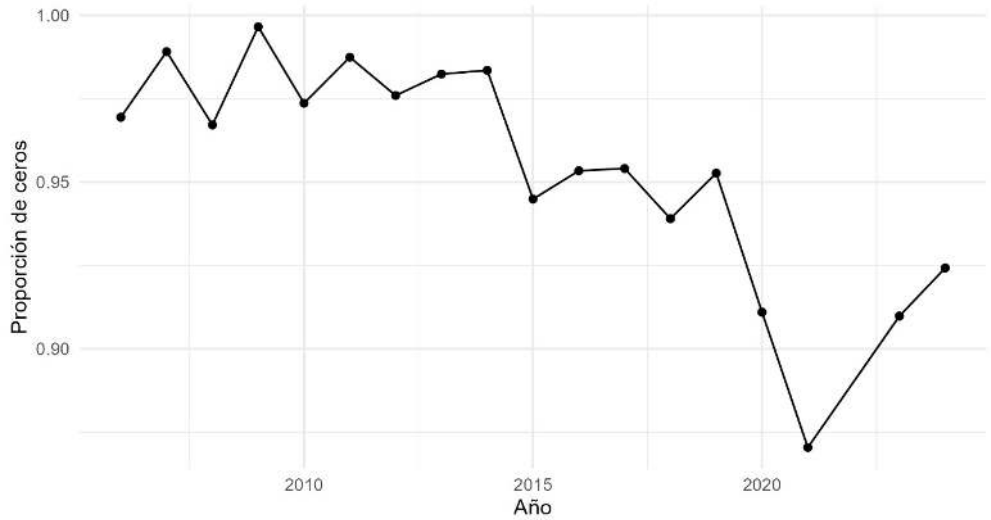
Métrica	Valor
Número de observaciones	133,906
Periodo	2006–2024
Número de años	18
Proporción de ceros	0.952
Densidad mínima	0
Mediana	0
Media	11.25
Densidad máxima	30,287

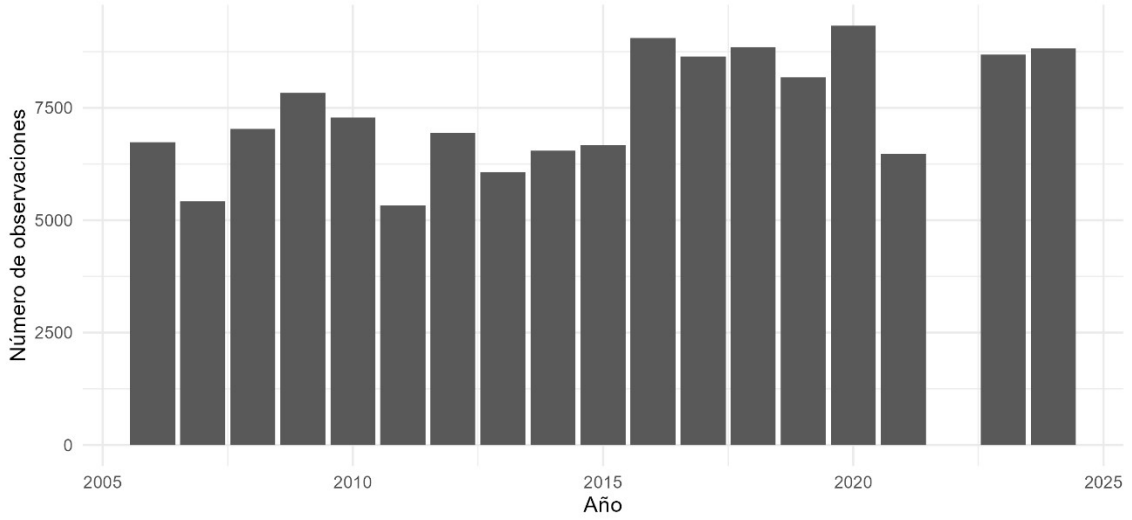
• The dataset shows a high proportion of zero-density observations, accounting for approximately 95.2% of all records.

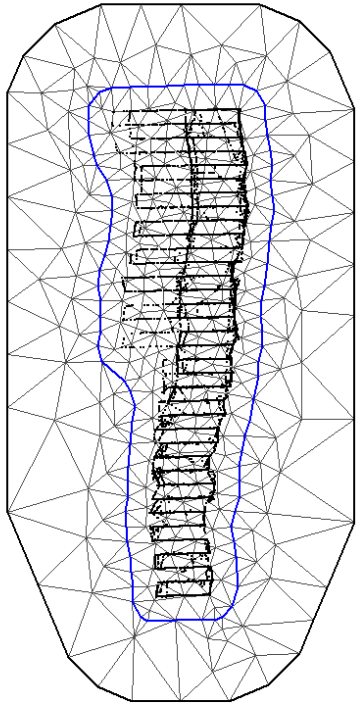
• The number of observations per survey remained relatively stable over time, ranging from approximately 5,000 to 9,000 records per year.

• In addition to acoustic density, the dataset includes key environmental covariates relevant to jack mackerel distribution, such as sea surface temperature (SST), chlorophyll-a, sea level anomaly (SLA), and wind-driven turbulence.

• Given strong zero inflation and a heavy-tailed positive distribution, we applied a spatio-temporal delta model separating occurrence (P[density > 0]) and intensity (density | density > 0), a standard approach for acoustic survey data.







Parámetro	Valor
Escala espacial inicial (*range guess*)	200 km
Tamaño máximo de triángulo interior (*max.edge*)	100 km
Parámetro *cutoff*	25 km
Número de observaciones	~133 000
Número de vértices del mesh	(del csv)
Puntos por vértice	(del csv)
Distancia nodo más cercano (p50)	~30 km
Distancia nodo más cercano (p95)	~45 km

• Spatio-temporal models were fitted with sdmTMB, using an SPDE-based Gaussian random field to represent continuous spatial variation.

• Given zero inflation and aggregation, a delta model was applied with binomial occurrence and Gamma positive density components.

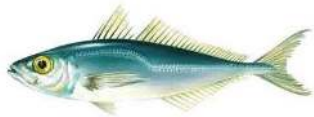
• Temporal structures (off, iid, AR1, RW) were evaluated, with selection based on AIC and spatial cross-validation performance

• Isotropic and anisotropic formulations were compared; the anisotropic model provided better fit, revealing direction-dependent spatial correlation consistent with coastal elongation.

• Spatial dependence was represented via a triangular mesh using the SPDE approach implemented in INLA and used internally by sdmTMB.

• Annual indices were derived by spatial integration of predictions over a grid. Sensitivity to domain definition was evaluated using survey footprints.

• The model index was compared with the acoustic index (2006–2024) using standardized series and correlation metrics.



(i) Occurrence (presence/absence)

$$Z_i \sim Bernoulli(p_i)$$
$$\text{logit}(p_i) = \eta_i^{(p)}$$

(ii) Positive density (conditional on presence)

$$Y_i \mid (Z_i = 1) \sim Gamma(\mu_i, \phi)$$
$$\log(\mu_i) = \eta_i^{(\mu)}$$

(iii) Combined delta expectation

$$E(Y_i) = p_i \cdot \mu_i$$

This represents the expected biomass (or density) at each location

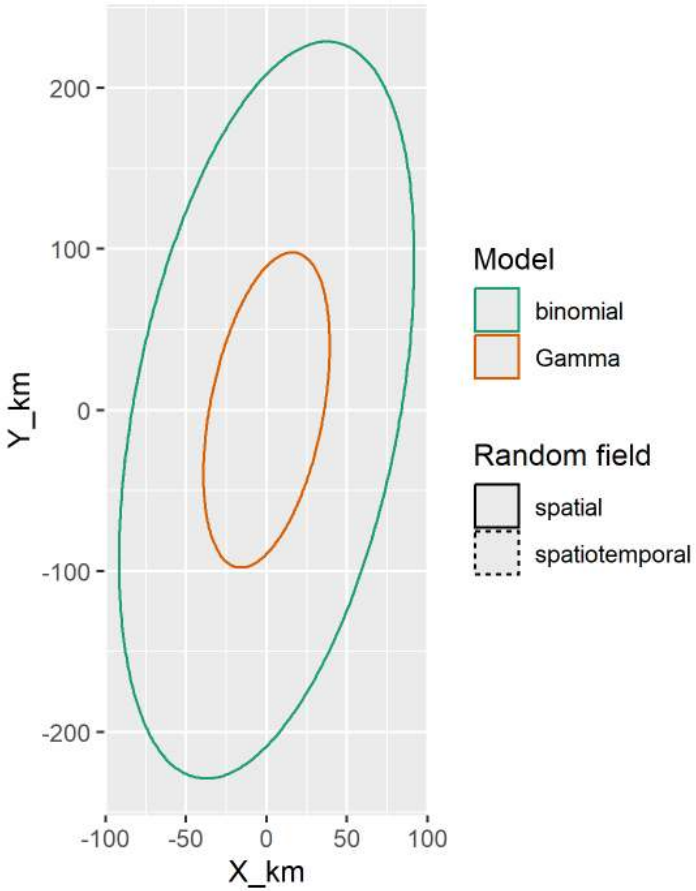
The annual index is obtained by spatial integration:

$$I_t = \frac{1}{|\mathcal{D}|} \sum_{s \in \mathcal{G}} \hat{p}(s, t)\, \hat{\mu}(s, t)$$

Key implications: Depends on the **integration domain**

Sensitive to: spatial coverage, extrapolation and mesh resolution

Anisotropy



- The spatial extent of the binomial (occurrence) component is substantially larger than that of the Gamma (positive density) component, indicating broader habitat occupancy than areas of high biomass.

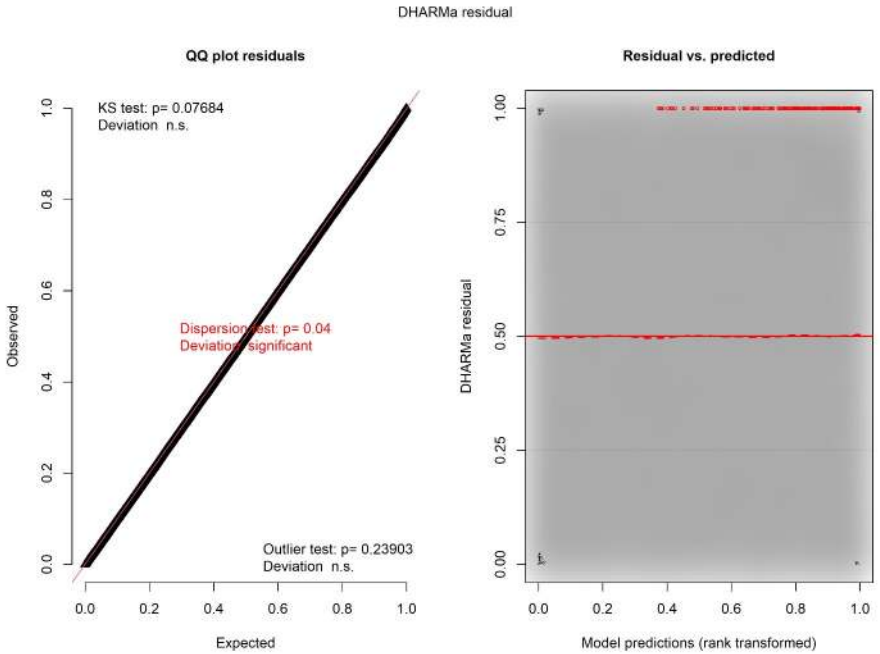
- The Gamma component is nested within the binomial field, suggesting that high-density aggregations occur only within a subset of the suitable habitat.

- Both components exhibit a similar anisotropic spatial structure, with elongation along a preferential axis, consistent with directional spatial processes (e.g., coastline orientation).

- The difference in spatial scales between components highlights a decoupling between presence and biomass intensity, with environmental conditions primarily influencing occurrence over a wider area.

- The results support the interpretation that habitat suitability (occurrence) extends beyond core aggregation zones, which has implications for how abundance indices integrate spatial information.

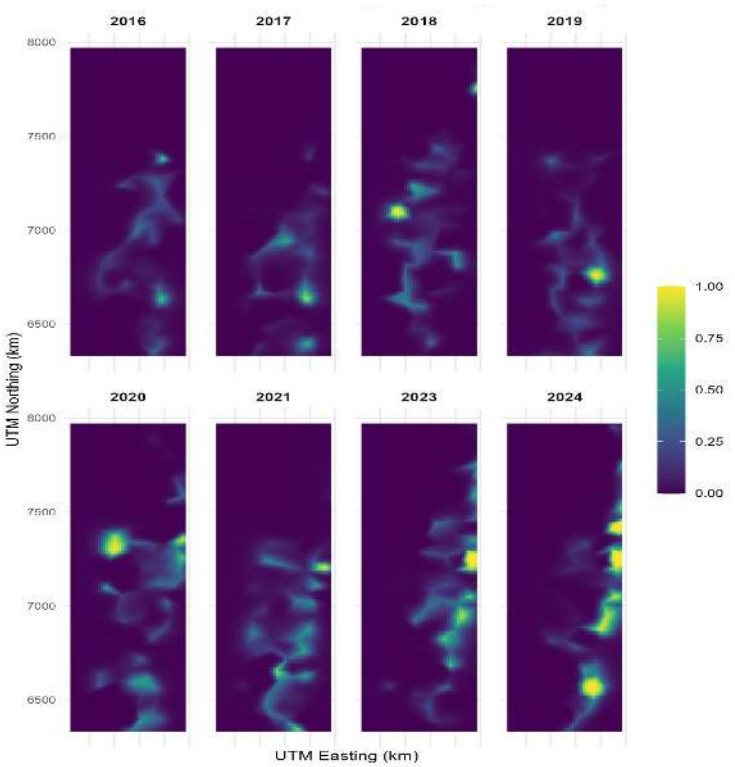
Model diagnosis



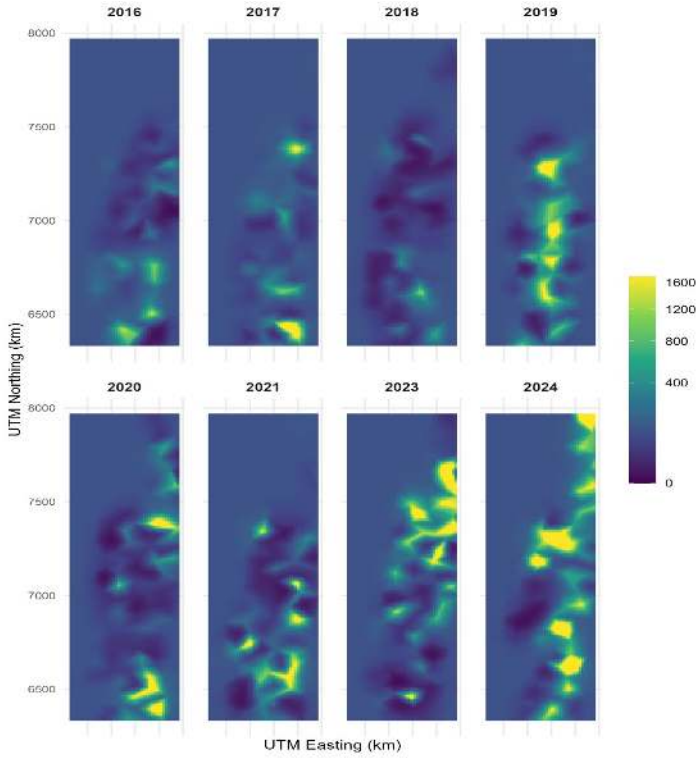
Model diagnostics indicate an overall good fit, although some residual dispersion suggests remaining unexplained variability.

- The QQ plot shows a good overall agreement between observed and expected residual distributions, indicating no major deviation from model assumptions.
- The Kolmogorov–Smirnov test is non-significant ($p \approx 0.08$), supporting an adequate global fit of the model.
- The outlier test is non-significant ($p \approx 0.24$), suggesting no evidence of extreme values poorly captured by the model.
- However, the dispersion test is significant ($p \approx 0.04$), indicating potential overdispersion or underdispersion not fully accounted for.
- The residuals vs. predicted plot shows no strong structure, suggesting that the model captures the main patterns in the data without obvious systematic bias.
- The horizontal banding pattern is consistent with the discrete nature of the delta model (binomial + Gamma) rather than a clear model misspecification.

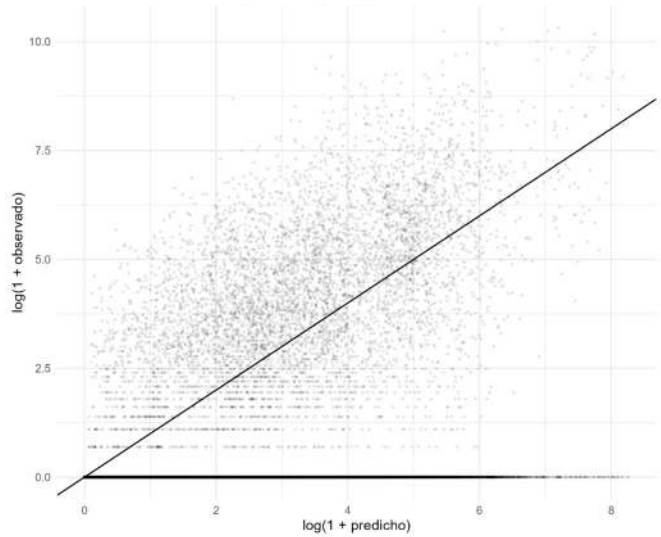
Presence probability



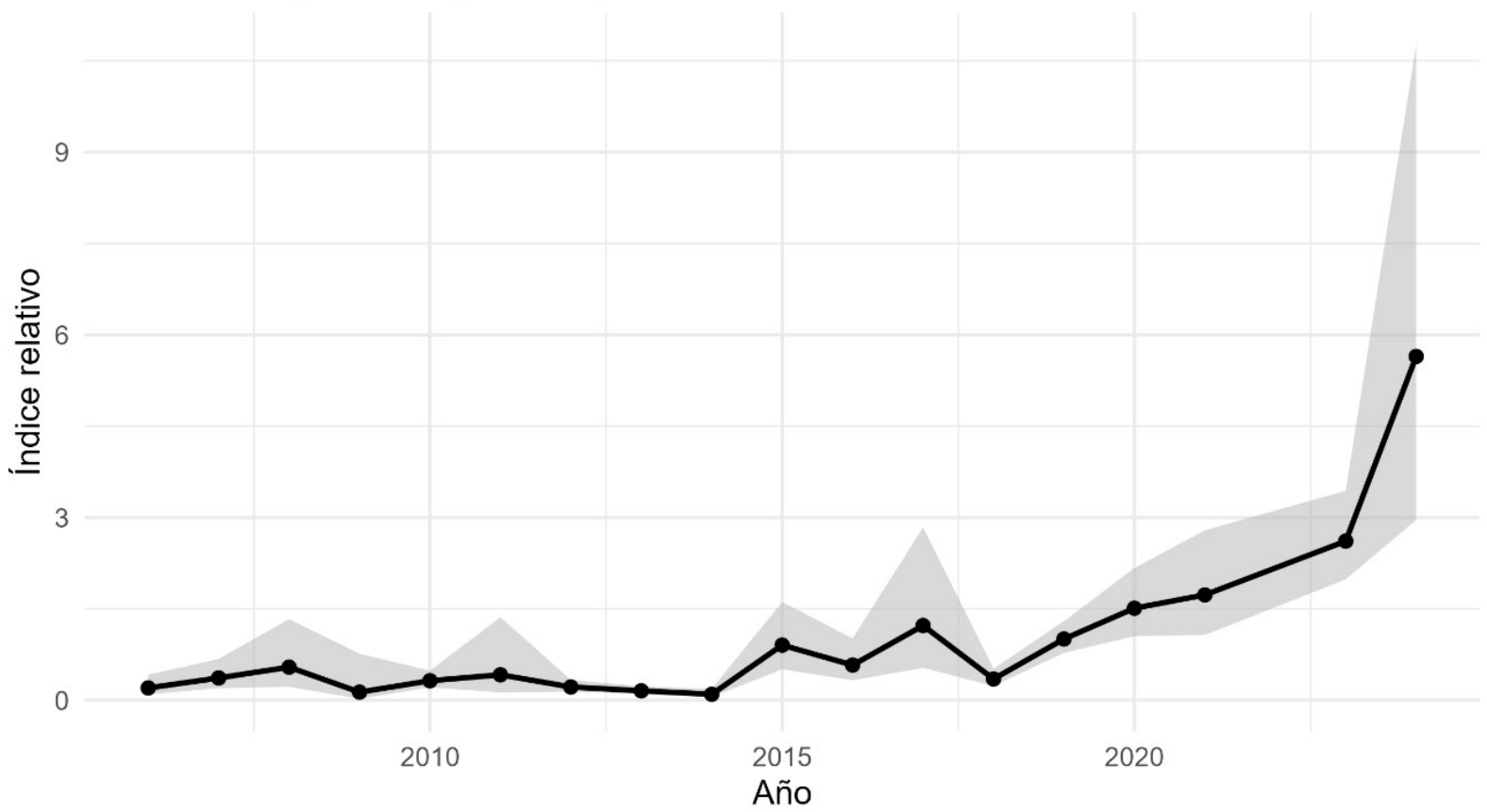
Delta combined



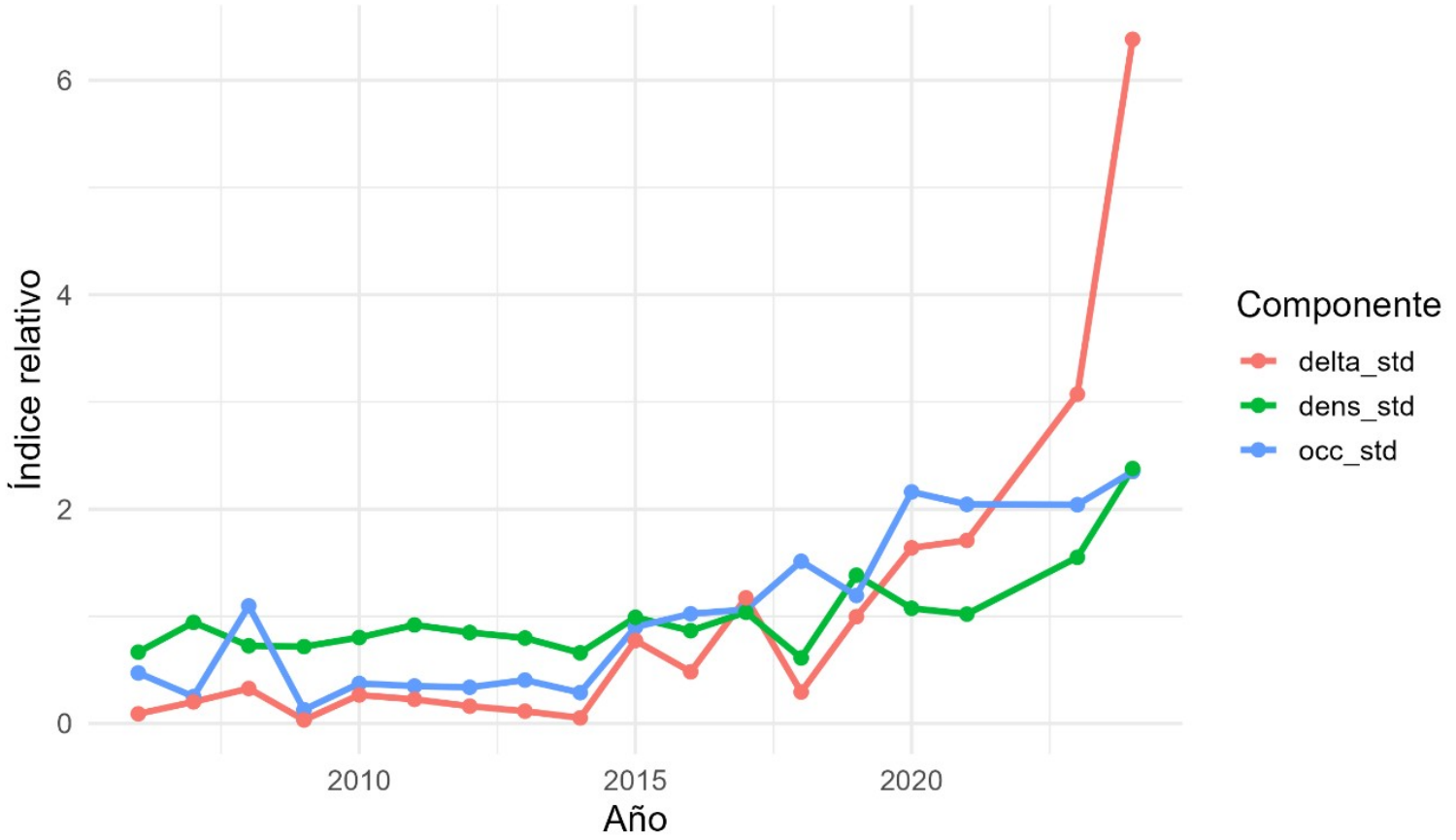
observations vs predictions



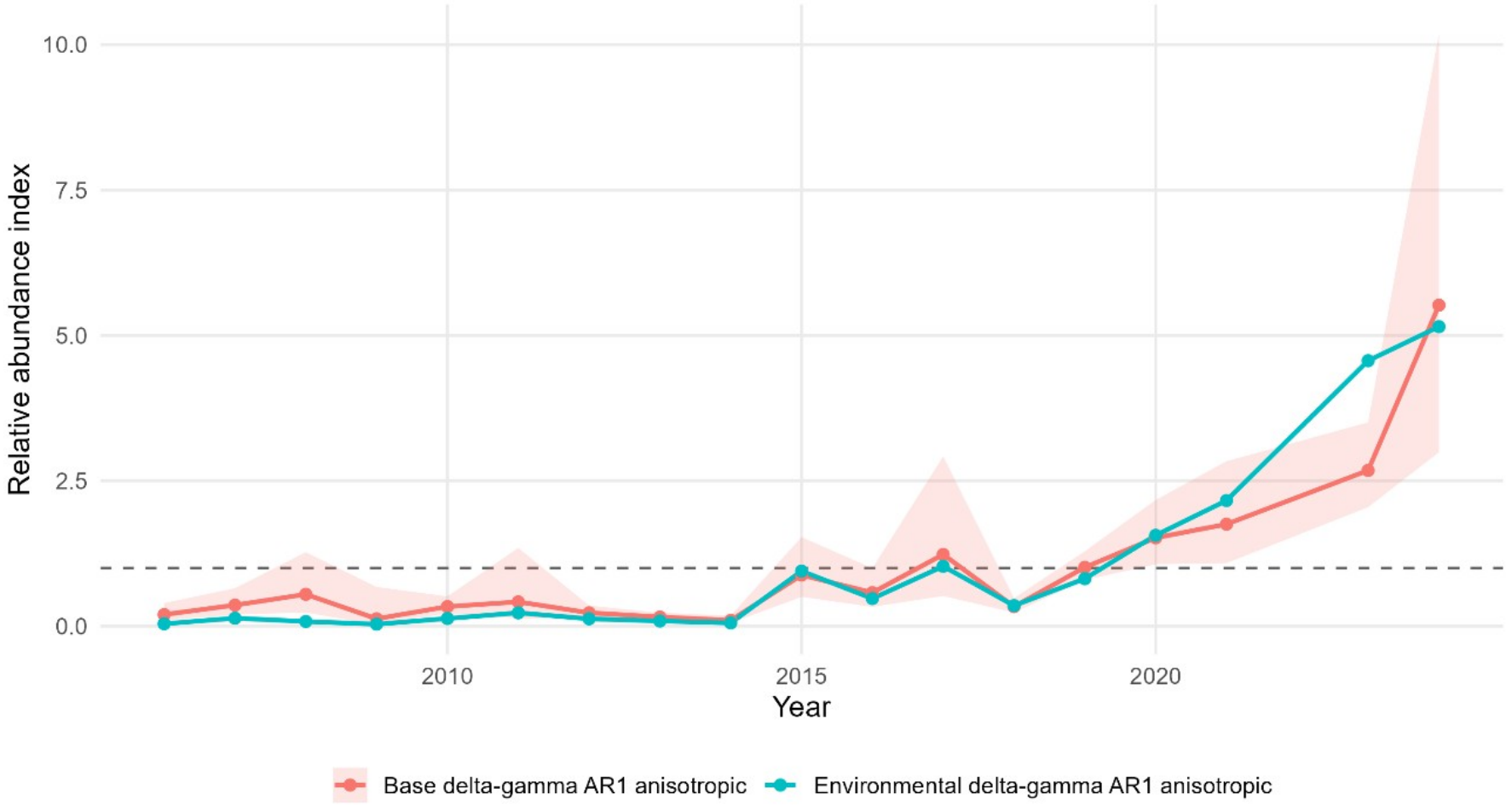
- The model performs well in capturing central tendencies, but struggles with:
  - ➢ extreme values
  - ➢ high-density aggregations
- The pattern is consistent with:
  - ➢patchy spatial structure
  - ➢schooling behavior (typical in pelagic species)



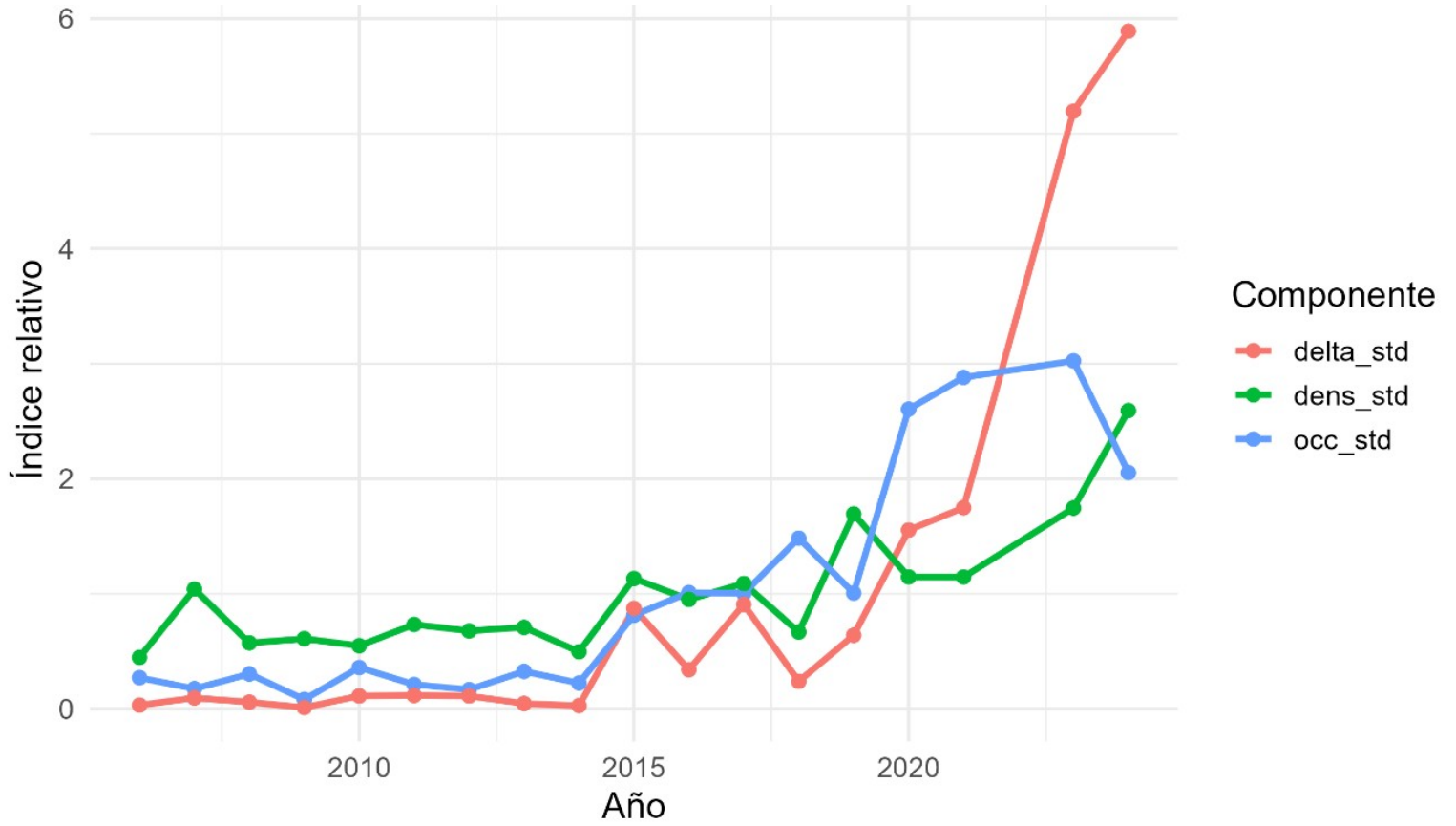
Annual standardized abundance index derived from a spatio-temporal delta–gamma model, obtained by integrating predicted density over the study area; shaded area denotes uncertainty.



The delta index is decomposed into occupancy (mean P[presence], blue) and conditional positive density (green), whose product yields the total index (red). Values are scaled relative to the temporal mean.



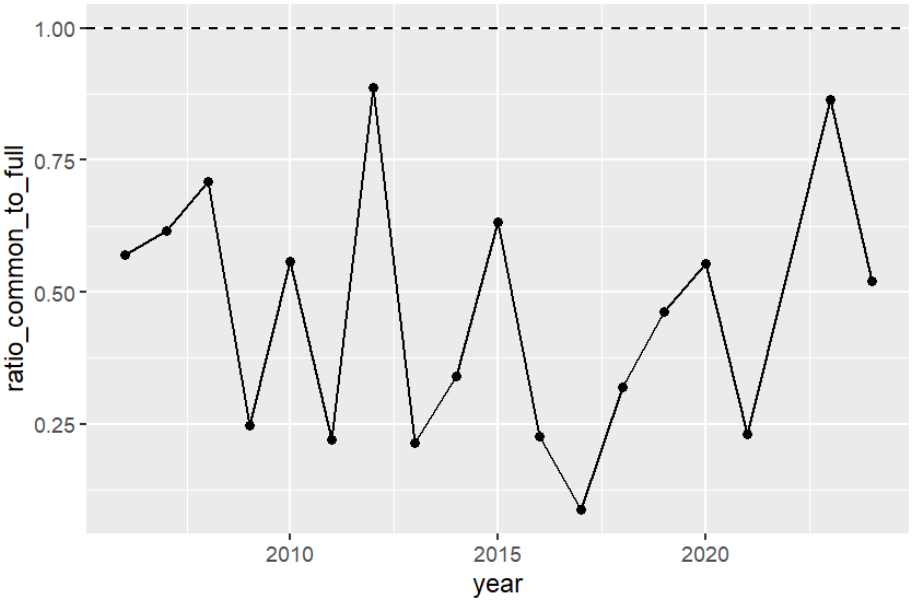
Annual standardized abundance index derived from a spatio-temporal environmental delta–gamma model.

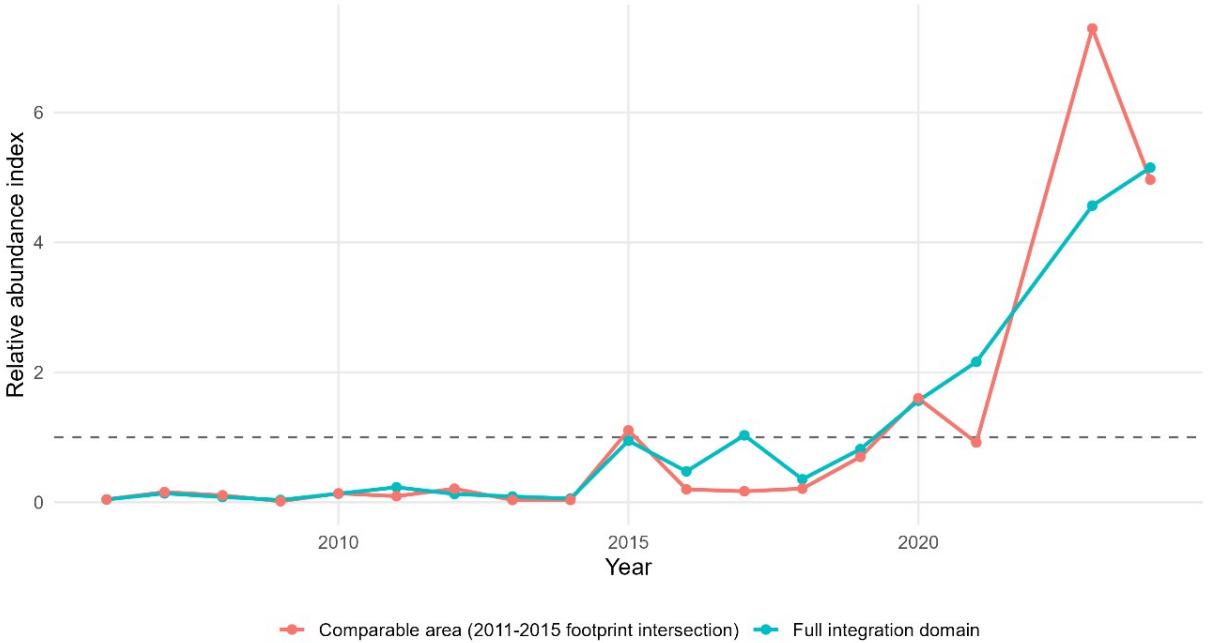


The standardized delta index is decomposed into occupancy, positive density, and total index, revealing a two-phase dynamic: spatial expansion followed by density intensification within occupied areas.

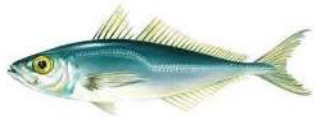
1. Full-domain index: spatial integration of predictions over the full mesh (baseline).

2. Comparable-area index: integration restricted to a temporally consistent subdomain with homogeneous sampling coverage. Standardized series and correlation metrics.





Comparison between full-domain and comparable-area abundance indices (2011–2015), both derived from the spatio-temporal model with environmental covariates.



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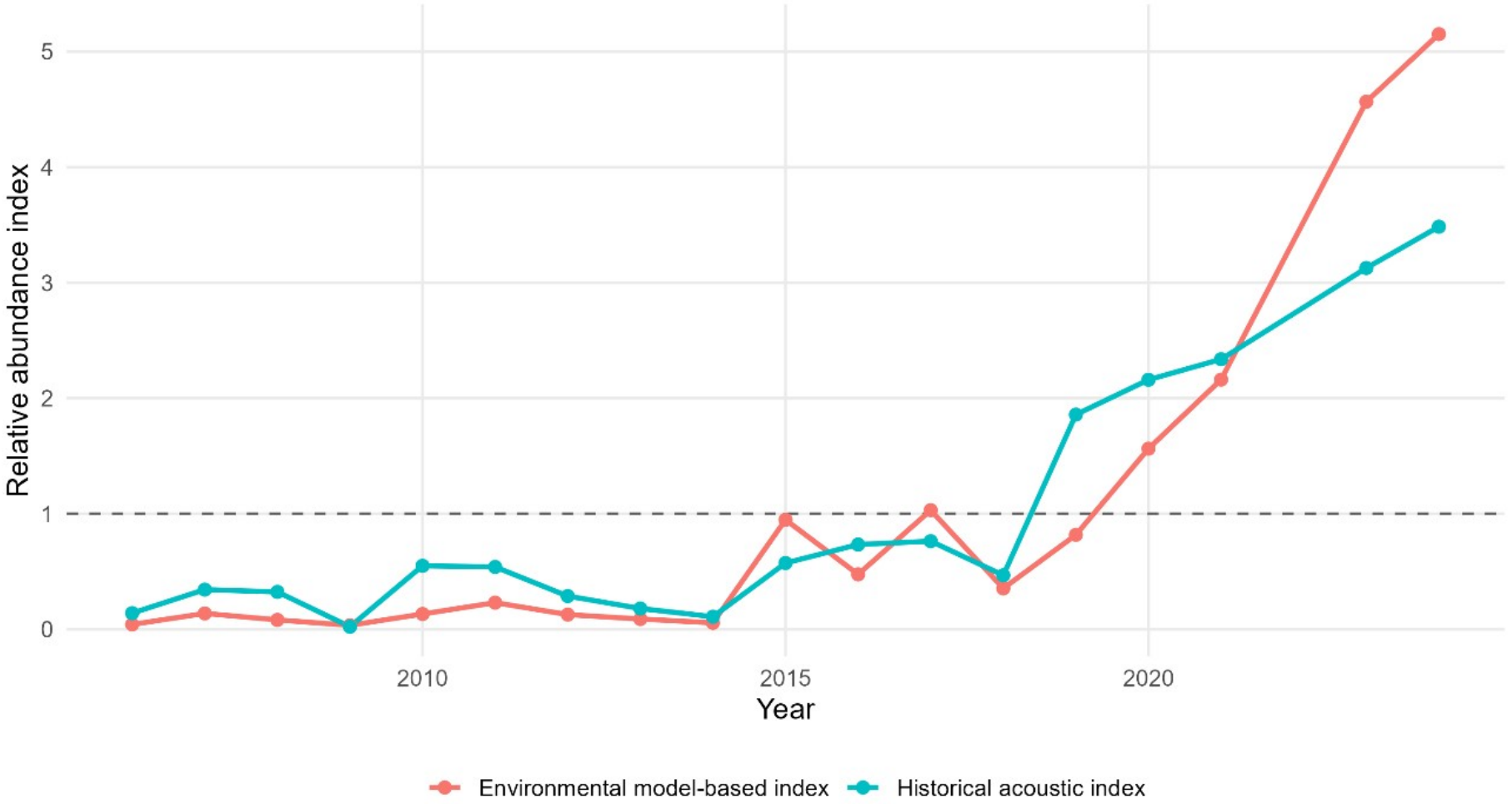


Comparison of the spatio-temporal environmental index and the historical acoustic index in northern Chile (2006–2024), with both series standardized to the mean of the overlapping period.

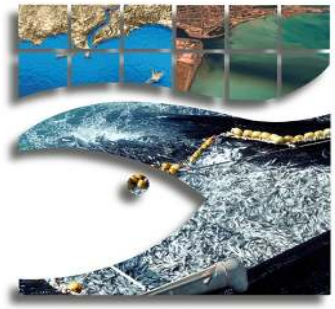
1. The spatio-temporal delta framework successfully reproduces the main structural features of the acoustic data, including zero inflation and spatial aggregation, providing a coherent basis for index derivation.

2. The integration of environmental covariates improves model fit and helps interpret variability in terms of habitat suitability, although their influence is stronger on occurrence than on positive density.

3. The standardized abundance index captures the main temporal patterns observed in the historical series, with strong correlations, but differences in magnitude—particularly in recent years—highlight potential effects of extrapolation and model structure.

4. Sensitivity analyses demonstrate that while temporal trends are relatively robust, the absolute magnitude of the index is highly dependent on the spatial integration domain, emphasizing the importance of consistent spatial coverage.

5. Overall, the framework represents a flexible and promising approach for deriving environmentally informed abundance indices, but particular attention should be given to key sources of uncertainty, especially those related to spatial extrapolation and the interpretation of recent increases



Thank you!

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South Pacific Regional Fisheries Management Organisation