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Spatiotemporal structure of sea turtle strandings reveals persistent coastal hotspots in southeastern Brazil

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Abstract

Long-term stranding programs can reveal where and when threatened marine vertebrates are detected, but observed patterns integrate ecological processes, carcass transport, monitoring, and human pressures. We analyzed 58,897 sea turtle strandings recorded by the Santos Basin Beach Monitoring Project along 2,012 km of Brazilian coastline from August 2015 to December 2024. The primary analysis used 38,878 records from regular monitoring. We combined negative binomial generalized additive models with coastline point-process and additive spatiotemporal models, and tested predictors representing coastal geography, ocean transport, sea-surface temperature, waves, fishing activity, vessel traffic, and coastal population. Observed strandings exhibited a strong nonlinear trend and cyclic seasonality. The temporal model explained 90.1% of deviance and achieved a mean absolute error of 44.7 strandings across 52 held-out months; strandings were seasonally highest in October and lowest in March. Spatial intensity was strongly heterogeneous: the coastline model explained 80.8% of segment-count deviance and was stable across spatial sensitivities, while the spatiotemporal model preserved the selected temporal and spatial structures. No environmental or anthropogenic predictor group improved blocked prediction enough to retain in pooled or species-specific models. Species-specific spatiotemporal structure was supported for *Caretta caretta* and *Lepidochelys olivacea*, whereas sparse records limited inference for rarer species. Our results identify persistent hotspots and predictable periods that can guide monitoring, response capacity, and targeted investigation. However, strandings provide limited information on abundance or mortality—identifying mortality processes requires integrating patrol effort, carcass drift, necropsy, and direct exposure data.

INTRODUCTION

Extinction is the process resulting in the loss of a species, on a global or regional scale, and may be caused by the interaction of extrinsic factors, such as climate change and habitat loss and degradation, or intrinsic factors – characteristics inherent to the species – such as low population density, very long generation times, and restricted geographic distribution (Purvis et al. 2000; Brook et al. 2008). These factors may act independently or synergistically, increasing the risk of population decline and extinction. In the marine environment, human activity can intensify these pressures and lead to species loss (Barnosky et al. 2011; Marques 2020), and understanding the impacts of these practices – and how these pressures are distributed in space and time – is therefore essential for informing conservation strategies.

Sea turtles are subject to multiple anthropogenic pressures, including bycatch in fishing activities, vessel collisions, pollution, climate change, urbanization and unregulated coastal development, hunting and egg poaching, and oil and natural gas exploration and production activities (Santos et al. 2023b, c, d, a; Thome et al. 2023). These pressures may affect different life-cycle stages, as sea turtles use coastal environments for reproduction, nesting, foraging, or resting (Marcovaldi and Santos 2011). Of the five sea turtle species occurring in Brazil, four are currently included in the National List of Threatened Species. *Dermochelys coriacea* is listed as Critically Endangered (CR), *Eretmochelys imbricata* as

Endangered (EN), and *Caretta caretta* and *Lepidochelys olivacea* as Vulnerable (VU), mainly as a result of population declines (Santos et al. 2023b, c, d, a). Globally, *E. imbricata* is classified as CR, while *C. caretta*, *D. coriacea*, and *L. olivacea* are classified as VU according to the IUCN Red List (IUCN 2008a, b, 2013, 2015); *Chelonia mydas*, in turn, is considered Near Threatened (NT) in Brazil and was recently reassessed as Least Concern (LC) at the global scale (Thome et al. 2023; IUCN 2024). The combination of multiple threats and varying vulnerability levels reinforces the need to understand the processes driving these species' mortality.

Mortality rates at different life stages for the population dynamics of sea turtles have been discussed in demographic modeling studies. Low survival in the early life stages makes these stages particularly sensitive to changes in survival rates (Iverson 1991). Population models suggest that increases in egg and hatchling production have a relatively limited effect on population growth when losses in subsequent stages are high (Crouse et al. 1987; Heppell et al. 1996). More recent studies, however, have shown that changes in survival during the oceanic stage can also significantly affect population persistence, highlighting the relevance of different life-cycle components to population dynamics (Mazaris et al. 2006). Thus, identifying potential factors associated with mortality can help us understand the processes that affect population persistence, especially in long-lived and late-maturing species.

A complementary source of information for investigating population aspects of marine vertebrates is records of stranded animals. A stranding is the occurrence of a marine animal found on the shore, unable to return to the sea because it is weak, lost, injured, or dead (Geraci and Lounsbury 1993). Records of stranded marine animals can be used to investigate spatial and temporal patterns of mortality, population structure, and threats to different groups of marine vertebrates (Lennon et al. 2025; Peltier et al. 2012, 2014). These data can provide information that is difficult to obtain through direct monitoring of live animals, particularly for large and migratory species that are rarely sighted or whose capture and data collection are constrained by logistical limitations. For sea turtles, long-term studies have also used stranding records to identify spatial and temporal patterns of occurrence and mortality and to investigate their association with various threats, including interactions with fisheries (Monteiro et al. 2016), vessel collisions (Foley et al. 2019), ingestion of plastic and other debris (Santos et al. 2015), pathologies (Da Silva-Júnior et al. 2019; Garcês and Pires 2022), and debilitating health conditions (Flint et al. 2015). Thus, temporal and spatial time series from stranding monitoring can provide important information on mortality patterns and their distribution, contributing to the development of conservation strategies.

Population growth and rising energy demand have driven fossil fuel exploitation in Brazil, particularly after the 2007 discovery of oil reserves in the pre-salt layer (Riccomini et al. 2012). Exploitation of these reserves has intensified oil and gas exploration and production in Brazilian waters, expanding the presence of oil industry infrastructure and operations in the marine environment. This process can significantly harm ecosystems and biodiversity through physical and chemical changes to the environment, as well as the risk of spills and leaks of potentially toxic substances (Holdway 2002; Stacy

et al. 2017). Contact with spilled or leaked materials can cause physical harm, such as skin and eye injuries, and ingestion of toxic substances can compromise the health, reproduction, and survival of these species (Wallace et al. 2020).

Stranding patterns may result from interactions among biological, environmental, and anthropogenic processes, as well as factors that determine how animals are transported and deposited on shore (Peltier et al. 2012). Temporal variation in strandings may reflect seasonal changes in species distribution, migration, and activity, as well as variations in environmental conditions and mortality. Oceanographic conditions, such as currents and sea surface temperature, can influence both animal distribution and the transport of dead or debilitated individuals to shore (Hart et al. 2006). Similarly, geographical characteristics of the coastline can affect the likelihood of animals being washed ashore and detected, resulting in certain areas having a higher number of records regardless of the intensity of mortality (Nicolau et al. 2016; Tagliolatto et al. 2020; Rêgo et al. 2021). Human activities may also contribute to these patterns. Bycatch in fisheries and collisions with vessels can cause direct mortality (Monteiro et al. 2016), while the intensity of human occupation and use of the coastal zone can influence both the animals' exposure to different pressures and the likelihood of stranding detection and recording (Norman et al. 2004). Stranding occurrence along the coast therefore results from multiple processes that may act simultaneously and at different spatial and temporal scales.

The Santos Basin is particularly suitable for investigating these relationships because it combines a high occurrence of sea turtles with intense anthropogenic activity and extensive environmental heterogeneity. The region encompasses important feeding, breeding, and developmental areas for these animals and is a hub for fishing activities and intense maritime traffic, including two of Brazil's largest ports – the Port of Santos, in São Paulo, and the Port of Paranaguá, in Santa Catarina – as well as high coastal population density, with the largest human population on the Brazilian coast (Gherardi and Cabral 2007). The exploitation of pre-salt oil reserves has also increased the presence of oil industry facilities and operations in the region (Riccomini et al. 2012). These activities overlap with coastal habitats used by sea turtles and, together with environmental and oceanographic factors, may contribute to the spatial and temporal structure observed in stranding events. In addition, the Beach Monitoring Project (BMP) monitors an extensive coastline and provides a continuous time series of stranding records, allowing assessment of their distribution across spatial and temporal scales. This combination of systematic monitoring, environmental heterogeneity, and diverse anthropogenic pressures offers an opportunity to investigate which factors are associated with stranding patterns and to identify areas and periods of higher occurrence.

We investigated the spatiotemporal patterns of sea turtle strandings and assessed their association with environmental and anthropogenic factors in the Santos Basin. To this end, we built spatiotemporal models using 38,878 stranding records collected over approximately ten years of systematic monitoring to identify temporal trends, seasonality, and spatial structure, and to assess the relative contributions of climatic, geomorphological, oceanographic, and anthropogenic factors. Based on the mechanisms and patterns discussed above, we tested the hypotheses that (H1) strandings exhibit a temporal structure

characterized by trends and seasonality; (H2) geomorphological characteristics of the coast influence their spatial distribution; (H3) oceanographic and climatic conditions are associated with spatiotemporal variation in strandings; (H4) the intensity of fishing activity are associated with a higher occurrence of strandings; (H5) the intensity of maritime traffic is associated with the distribution of strandings; (H6) the intensity of human occupation and activity in coastal areas is associated with the occurrence of strandings; and (H7) responses to environmental and anthropogenic factors differ among sea turtle species.

MATERIALS AND METHODS

Study Area

We used data from the coastal region of the Santos Basin, a sedimentary basin in the South Atlantic on the Brazilian continental shelf (Fig. 1). This basin spans four states in Brazil's Southeast and South regions, between the municipalities of Saquarema (Rio de Janeiro) and Laguna (Santa Catarina), covering 54 municipalities and approximately 2 012 km of monitored beaches, divided into 13 mesoregions and 15 monitoring sections (PETROBRAS 2025). This region encompasses a wide variety of coastal and oceanic environments, such as sandy beaches, rocky shores, estuaries, bays, and extensive areas of the continental shelf, and it also hosts Brazil's main province for offshore oil exploration and production (Gherardi and Cabral 2007).

We used data from the Santos Basin Beach Monitoring Project (BMP), part of the Environmental Monitoring Program established as an environmental requirement for federal licensing of oil exploration and production activities and conducted by the Brazilian Institute of Environment and Renewable Natural Resources (IBAMA). The BMP systematically monitors beaches throughout the entire study area to record live or dead marine tetrapods (birds, turtles, and mammals), as well as the occurrence of solid and oily waste and abnormal mortalities of fish and invertebrates (PETROBRAS 2025). This monitoring can be carried out using three different strategies, namely: (i) active land-based monitoring, conducted daily or, in exceptional cases, weekly; (ii) active vessel-based monitoring, conducted weekly on beaches inaccessible by land, rocky shores, and islands; and (iii) reporting through a network of collaborators, when third parties notify the implementing unit of a stranded animal. All information is recorded individually and consolidated in the Aquatic Biota Monitoring Information System (SIMBA), which constitutes the official database for storing and managing data produced by the BMP.

Database and Data Preparation

The database used in this study was constructed by integrating monitoring records from SIMBA, bringing together information produced by the BMP between August 2015 and December 2024. We used three main sets of information: (i) stranding event records, containing information on location, date, species, and circumstances of the event; (ii) biometric data obtained during the stranding record; and (iii)

information from necropsies performed. We constructed the analytical database by integrating these datasets, using monitoring effect identifiers to link duplicate records, consolidate complementary information across spreadsheets, and resolve inconsistencies. The taxonomic information underwent validation. When species identification differed, we adopted the classification most reliable under the database's previously established hierarchical sequence, prioritizing records from expert assessments. Records for which the species could not be determined with confidence were excluded. After integrating and standardizing the records, we applied quality-control procedures to verify consistent dates, geographic coordinates, taxonomic identification, and biological variables. Records with essential information missing or inconsistent for a given analysis were excluded only from that specific step. This strategy allowed us to maximize the use of the time series without compromising the methodological consistency of the models employed. The final database comprised 57,928 identified sea turtle stranding records distributed throughout the monitoring area, forming the basis for the descriptive, temporal, spatial, and spatiotemporal analyses presented in this study. Table 1 summarizes the main sample sizes and analytical datasets.

Table 1
Study scope and analytical sample sizes.

Quantity	Value	Interpretation
Canonical observed strandings	58,897	All preserved events
Primary regular-monitoring strandings	38,878	Primary inferential scope
Primary temporal-model strandings	38,770	September 2015 to December 2024
Complete months in temporal model	112	August 2015 excluded as an incomplete opening month
Identified strandings in species analysis	37,905	Five identified species
Reconstructed analytical coastline km	2,470.17	Spatial integration measure, not patrol effort
Coastline quadrature segments	1,342	Maximum segment length 5 km
Events inside spatiotemporal coastal strip	38,033	Events outside the strip remain documented

Response Variable and Sampling Unit

The primary response variable was the number of sea turtles found stranded during regular beach monitoring. For temporal analyses, we aggregated records into monthly counts across the entire study area. For spatial and spatiotemporal analyses, we represented stranding events by their geographic coordinates along the monitored coastline. We used only records from regular monitoring, as this method provides a standardized sampling effort over time and space. We excluded records from third-

party reports from the inferential analyses because they were subject to factors that could introduce heterogeneity unrelated to the ecological processes investigated (n = 3 056). For temporal analyses, we used only complete months of monitoring, covering September 2015 to December 2024 (112 months). In all analyses, we interpreted the results as stranding patterns observed by the monitoring program.

Descriptive Analysis

To investigate temporal patterns and estimate the trend, seasonal, and residual components, we decomposed the time series using the *stl* function from the stats package, applying the STL (Seasonal-Trend decomposition using LOESS) method. This step allowed us to assess recurring seasonal cycles, long-term trends, and possible changes in temporal variability throughout the historical series.

Temporal Model

We investigated temporal patterns of strandings using generalized additive models (GAMs), an approach increasingly used for ecological time series that exhibits nonlinear relationships between the response variable and time (Simpson 2018; Pedersen et al. 2019). We fitted the models in R using the mgcv package (Wood 2017). We first assessed whether the Poisson distribution was suitable for modeling monthly counts. We evaluated monthly count distributions for overdispersion (i.e., variance exceeding that expected under a Poisson distribution) and serial autocorrelation. These characteristics are common in ecological count data and, if ignored, can underestimate uncertainty (Ver Hoef and Boveng 2007; Richards 2008), as they directly influence model structure in regression analyses. We identified overdispersion and therefore adopted the negative binomial distribution, which explicitly accommodated extra-Poisson variation through its mean-variance relationship (Lindén and Mäntyniemi 2011). We represented the temporal structure using two complementary components: long-term trend and monthly seasonality. To estimate the long-term trend, we applied a smoothing function to the chronological sequence of months, allowing us to identify variations in stranding intensity across the time series. To estimate seasonality, we used a cyclical smoothing function applied to the months of the year, ensuring continuity between December and January. We estimated the smoothing parameters using restricted maximum likelihood with the mgcv package.

We assessed the relative importance of the long-term trend and seasonality by comparing hierarchical models that included only one temporal component with models that included both (Zuur and Ieno 2016). We compared the model fit by penalizing model complexity using the likelihood and the Akaike (AIC) and Bayesian (BIC) information criteria. Because these criteria impose different penalties, we interpreted them together, without treating either as universally preferable (Brewer et al. 2016). We assessed predictive performance through temporal validation using months not included in model fitting. The first 60 months constituted the initial training period, and we generated predictions for each of the final 52 months using data available before that month. We compared mean absolute error (MAE), root mean square error (RMSE), and mean Poisson deviance, prioritizing models that simultaneously

showed good fit to the observed data, consistent predictive performance, and a residual structure compatible with model assumptions. We adopted this design, which respects temporal order, to reduce information leakage resulting from temporally dependent observations (Tashman 2000; Roberts et al. 2017). After fitting the models, we investigated residual autocorrelation using the autocorrelation function (ACF) and the global Ljung–Box (Ljung and Box 1978; Simpson 2018). We considered additional temporal structures only when they substantially improved predictive performance and residual quality, avoiding unnecessary increases in model complexity.

Spatial Model

We analyzed the spatial patterns of strandings by considering the geographic location of each event along the monitored coastline. Because strandings are single occurrences distributed continuously in space, we modeled their spatial intensity using a point-process approach, preserving individual record locations rather than aggregating them a priori into arbitrary spatial units. We reconstructed a continuous representation of the coastline independently from the Natural Earth database (1:10 million scale) using the rnaturalearth package (Massicotte and South 2026), defining the spatial domain used in the analyses. To identify records with potential georeferencing errors and select data for the spatial analyses, we used maximum distance to water bodies as a criterion. Geographic coordinates were converted into a spatial object using the sf package. We then overlaid water-body polygons with the point distribution and calculated the distance from each point to the water bodies.

We modeled stranding intensity using a Log-Gaussian Cox Process (LGCP) (Møller and Waagepetersen 2007), using the Stochastic Partial Differential Equation (SPDE) approach to represent the continuous spatial random field (Lindgren et al. 2011). We conducted inference in a Bayesian framework, using the deterministic Integrated Nested Laplace Approximation (INLA) (Rue et al. 2009) to estimate posterior distributions of model parameters. This approach allowed us to estimate spatial dependence among events without imposing artificial boundaries between neighboring areas. We assessed model adequacy using residual diagnostics, dispersion measures, and analysis of residual spatial autocorrelation. In addition, we conducted prior sensitivity analyses to assess the robustness of estimates to the spatial resolution used to discretize the coastline and to the criteria adopted to exclude potentially inconsistent records. The spatial patterns estimated at this stage represent the relative intensity of observed strandings throughout the monitored area. We used these results as the spatial component of the spatiotemporal model, allowing persistent spatial variation to be integrated with temporal effects and environmental and anthropogenic covariates.

Spatiotemporal Model

We investigated spatiotemporal patterns of strandings using models that simultaneously integrated the temporal and spatial components previously characterized. This approach allowed us to estimate variation in stranding intensity along the coastline while accounting for spatial persistence and temporal change. To identify factors potentially associated with the spatiotemporal distribution of stranding

records, we incorporated environmental and anthropogenic covariates as fixed effects in the spatiotemporal model, hereafter defined as predictors. Thus, the estimated effects for each predictor represent associations additional to the spatial and temporal patterns already explained by the model. We fitted the models hierarchically, starting with a reference model containing only the spatial and temporal components. We then individually evaluated different groups of predictors and models containing combinations of them. We assessed each set of predictors using the Watanabe-Akaike Information Criterion (WAIC), with lower WAIC values indicating better relative support from the data. We compared models to assess whether including covariates improved fit relative to the reference model.

Predictors

To investigate factors potentially associated with the distribution of strandings, we selected covariates representing different ecological or anthropogenic processes that may influence the occurrence, transport, retention, or detection of stranded sea turtles along the coast. We organized the variables into thematic groups according to the ecological hypotheses evaluated, including coastal geomorphological characteristics, oceanographic conditions, fishing activity, maritime traffic, and human occupation pressure. We harmonized all covariates with the spatiotemporal unit used in the models. The Supplementary Material (Table S1) presents detailed procedures for variable construction, temporal-lag assessment, redundancy analysis among predictors, and initial model screening.

Coastal Geomorphology and Carcass Retention

We hypothesized that coastline configuration plays a fundamental role in stranding dynamics by influencing carcass transport and retention, as well as beach exposure to wave and current action. To represent this hypothesis, we selected variables describing both coastline geometry and the characteristics of adjacent coastal environments. We obtained geomorphological information from the official cartographic databases used in the study. These included continental shelf width, coastline orientation, coastline curvature, and the sheltered water index (i.e., a measure used to classify water bodies protected from strong winds and large waves, such as bays, lakes, rivers, or channels). We estimated continental shelf width as the shortest distance from each coastline segment to the 200-m isobath from the GEBCO 2026 database (GEBCO Bathymetric Compilation Group 2026). Coastline orientation was represented by angular components appropriate for directional variables, whereas curvature was calculated from local changes in coastline direction. We obtained the shelter index from bathymetric openness relative to the adjacent ocean. These variables represent relatively constant structural characteristics of the coastal landscape and were considered static spatial predictors in the models.

Oceanographic Conditions

To test the hypothesis that oceanographic conditions influence the spatiotemporal distribution of strandings, we evaluated predictors associated with ocean transport and thermal conditions. We

considered that advection (i.e., the movement of a mass of fluid and the transport of properties such as heat, moisture, or pollutants) toward the coast and exposure to waves increase carcass delivery to beaches, whereas alongshore transport redistributes them among coastal segments. Additionally, we evaluated sea surface temperature (SST) as an indicator of environmental conditions potentially associated with temporal variation in strandings. To represent these processes, we used Copernicus Marine Service reanalysis data covering August 2015 to November 2024. The selected variables included sea surface temperature (SST), surface currents, surface winds, significant wave height, mean wave direction, and mean wave period (European Union-Copernicus Marine Service 2015, 2018, 2019a, b). We decomposed current and wind vectors into components perpendicular and parallel to each segment's coastline, allowing us to distinguish transport toward the coast from longitudinal redistribution of carcasses. To reduce the influence of background climatic seasonality, we also calculated monthly anomalies relative to the climatology corresponding to each month. We represented wave influence with a directional exposure index that integrates wave height, period, and propagation direction relative to local coastline orientation. We then aggregated all variables to the spatiotemporal resolution used in the modeling and evaluated them individually and in combination during model selection.

Fishing Activity, Vessel Traffic, and Coastal Human Footprint

We considered three groups of indicators of anthropogenic activities: fishing activity, maritime traffic intensity, and human occupation of the coastal zone. These groups represent distinct processes that may influence both turtle mortality and the probability of observing and recording strandings. We estimated fishing activity using information derived from the Automatic Identification System (AIS) made available by Global Fishing Watch (GFW), expressed as apparent fishing hours (Kroodsma et al. 2018; Global Fishing Watch 2025). As a complement, we used annual records from the National Program for Satellite Tracking of Fishing Vessels (PREPS), made available by IBAMA, representing the activity of vessels monitored by the national tracking system (Instituto Brasileiro do Meio Ambiente e dos Recursos Naturais Renováveis 2026). For both databases, we calculated activity intensity as a function of the proximity between records and each coastline segment, using distance-weighting functions. Different spatial scales and representations of the variables were evaluated during the model selection stage.

We represented maritime traffic intensity using two complementary approaches. The first used vessel-presence data derived from AIS and obtained through Global Fishing Watch as an indicator of observable maritime activity. The second used public statistics from the National Waterway Transport Agency (ANTAQ), including port calls and berthing hours, as indirect indicators of the operational intensity of the main ports in the region (Agência Nacional de Transportes Aquaviários 2026). As with fishing activity, we estimated the spatial influence of these variables using distance weighting between ports or grid cells and the analyzed coastal segments. Although the study area concentrates intense oil and gas exploration and production activity, direct tracking data from the Santos Basin Vessel Traffic Monitoring Project (PMTE-BS) concerning traffic supporting the petroleum industry were not available.

We represented human occupation of the coastal zone using municipal indicators of resident population and population density obtained from the 2022 Demographic Census of the Brazilian Institute of Geography and Statistics (IBGE) (Instituto Brasileiro de Geografia e Estatística 2022). We interpreted these variables as indicators of urbanization intensity and the opportunity for stranding detection. We recognize that AIS-derived indicators do not represent all maritime activity, as some small vessels do not transmit this type of information. Similarly, PREPS data represent only vessels tracked by the national system. Therefore, we interpreted these covariates as indicators of observable activity intensity rather than as absolute estimates of fishing effort or maritime traffic in the study region.

Model Selection and Validation

We evaluated model predictive performance through cross-validation using strategies compatible with each covariate group's structure. We evaluated spatial predictors using approximately contiguous spatial blocks distributed among eight subsets (folds). We evaluated predictors with temporal variation using moving-origin temporal windows, whereas we evaluated models based on PREPS data using leave-one-year-out validation because of this dataset's shorter temporal extent. We compared models using Poisson deviance, mean absolute error (MAE), and root mean square error (RMSE), calculated exclusively on the test sets. We selected the most parsimonious model among those whose predictive performance differed by no more than one standard error from that of the best-performing model (Hastie et al. 2009). Supplementary Material, Table S1 presents the complete covariate screening process and model-comparison results.

Species-Specific Analyses

Species-specific analyses investigated whether factors associated with strandings differed among the main species recorded during monitoring. We conducted comparisons using *Chelonia mydas*, the most frequently recorded species, as the reference category. For each of the other species, we fitted negative binomial generalized additive models (GAMs) using the mgcv package, incorporating the same spatial and temporal components used in the main modeling. We followed the same conceptual organization as for the spatiotemporal models in covariate selection, separately evaluating the effects of coastal geomorphology, oceanographic conditions, fishing activity, maritime traffic, and human occupation, as well as models containing all covariates available for the common period across the datasets. We evaluated predictive performance using temporal cross-validation, successively excluding each year from 2016 to 2023 as the test set. We compared models using mean binomial deviance and the Brier score (Brier 1950), again adopting the one-standard-error rule to select the most parsimonious model among those with equivalent predictive performance. We evaluated PREPS-based models separately, considering only the period from 2019 to 2023, when this dataset was available. For species with low record frequencies, we retained more complex structures only when they consistently improved predictive performance.

Software, Reproducibility, and Reporting

We conducted the analyses using R 4.6.1 (R Core Team 2026). The mass package enabled the negative binomial GLMs (Venables and Ripley 2002), httr2 managed authenticated requests to the API (Wickham 2025), jsonlite was used to read metadata from web services (Ooms 2014), and all package versions are listed in Supplementary Material, Table S3. The complete workflow records source-file checksums, cleaning decisions, exclusions, model objects, diagnostics, and session information. A Dryad package (link) prepared for deposition includes the complete workflow, the data required for execution, anonymized analytical tables, derived results, file checksums, and an explicit deposition-decision manifest. We will deposit exact event coordinates and the project's raw data spreadsheets only after redistribution and sensitivity review. The complete hierarchy of primary, sensitivity, and supplementary analyses, together with their inferential roles, is summarized in Supplementary Material, Table S4.

Use of Large Language Models (LLMs)

We used OpenAI Codex, a large-language-model-based coding assistant, during development of the analytical workflow and preparation of the manuscript. The tool assisted with organizing data and scripts, drafting and revising R code, documenting analytical decisions, checking consistency among code, outputs, tables, and text, and drafting or editing portions of the manuscript. The authors defined the research questions, selected and approved all data-processing and modeling decisions, reviewed the generated code, verified the analyses against their outputs, assessed the scientific interpretations, and revised and approved the final text. Large-language-model outputs were not treated as scientific evidence, and the tool did not generate or alter the underlying observations. The authors retain full responsibility for the accuracy, integrity, interpretation, and reproducibility of the work.

RESULTS

Stranding sample and species composition

The reconstructed database contained 58,897 unique observed strandings, of which 38,878 were recorded during regular monitoring and defined the primary inferential scope. Excluding the incomplete opening month of August 2015 left 38,770 strandings across 112 complete months for temporal analyses. The coastline spatial model used all 38,878 regular-monitoring records, whereas 38,033 occurred within the coastal-strip domain used by the spatiotemporal model. Restricting the complete-month series to the five identified species yielded 37,905 strandings for species-composition analyses.

All five marine turtle species recorded along the Brazilian coast were found in the study area. *Chelonia mydas* was the dominant species, accounting for the largest proportion of identified records, followed by *Caretta caretta*, *Lepidochelys olivacea*, *Eretmochelys imbricata*, and *Dermochelys coriacea* (Table 1). These frequencies describe the composition of recorded strandings exclusively and should not be interpreted as estimates of the relative abundance of populations.

The mean size of stranded individuals, considering curved carapace length (CCL), was 44.65 cm, with the smallest individual measuring 4.90 cm and the largest 171 cm. *C. mydas* had a mean size of 39.37

cm, with the largest individual measuring 138.50 cm; *C. caretta* had a mean size of 76.45 cm, with the largest individual measuring 144 cm; *D. coriacea*, the largest marine turtle species, had a mean size of 136.50 cm, with the largest individual measuring 171 cm; *E. imbricata* had a mean size of 49.81 cm, with the largest individual measuring 92 cm; and *L. olivacea*, the smallest species found in Brazil, had a mean size of 66.63 cm, with the largest individual measuring 87 cm. The geographic distribution of strandings varied across the monitored states. São Paulo had the most records, followed by Santa Catarina, Rio de Janeiro, and Paraná.

Long-Term and Seasonal Temporal Structure

Strandings exhibited a temporal structure characterized by two complementary components: a long-term trend and a recurring seasonal pattern throughout the year. Including both components significantly improved model fit compared with models containing only one (Table 2), indicating that temporal variation in strandings cannot be explained by gradual changes over the years or by annual seasonality alone. The temporal trend showed a non-monotonic pattern (Fig. 2). After an initial increase, relative stranding intensity peaked in September 2017 (relative effect = 1.65; 95% CI: 1.47–1.84), then gradually declined through August 2021 (0.63; 95% CI: 0.56–0.71). From this period onward, we observed a partial recovery in stranding intensity, without a return to the highest levels observed at the beginning of the series.

Table 2
Primary temporal-model results and diagnostics.

Result	Estimate	Detail
Selected model AIC	1,236.3	Negative-binomial GAM
Selected model BIC	1,300.8	Negative-binomial GAM
Deviance explained	90.1%	Fraction
Rolling-origin MAE	44.7 strandings/month	52 sequential held-out months
Rolling-origin RMSE	55.2 strandings/month	52 sequential held-out months
Peak long-term effect	1.65	01/09/2017
Minimum long-term effect	0.63	01/08/2021
Peak seasonal effect	1.56	October
Minimum seasonal effect	0.52	March
Residual ACF at lag 1	0.054	Pearson residuals
Largest residual ACF	0.234	Lag 3
Ljung-Box p value through lag 24	0.030	Modest higher-lag dependence remains

Seasonality was the most consistent temporal component of the model. The lowest values occurred between February and May, with a minimum in March (0.52; 95% CI: 0.47–0.56), whereas the highest values were concentrated between September and November, reaching a maximum in October (1.56; 95% CI: 1.44–1.68). This pattern was consistent with the observed distribution of records, which showed more strandings during the colder, drier months and fewer during summer and the end of the rainy season. The negative binomial model with smoothing functions for trend and seasonality explained 90.1% of the observed deviance (Table 2) and performed better than models with only linear components or unstructured monthly factors. In the temporal validation, performed using months not included in model fitting, the model yielded a mean absolute error (MAE) of 44.7 strandings and a root mean square error (RMSE) of 55.2, indicating strong generalization. The residual structure showed that the model adequately captured the main temporal patterns. First-order residual autocorrelation was low ($p = 0.054$), and adding an AR1 autoregressive component did not improve model fit. Although slight residual autocorrelation was observed at larger *lags*, the effect was small: the highest residual ACF was 0.234 in the third month, indicating that the combination of long-term trend and seasonality adequately captured the temporal dependence present in the series (Supplementary Material, Figure S1). State-specific trend and seasonal models reduced rolling-origin MAE from 22.68 to 18.35 strandings per state-month and mean Poisson deviance from 11.81 to 8.59. Because improvement was not uniform among states, we retained the common temporal structure as the primary model and treated regional departures as sensitivity evidence (Supplementary Material, Figure S4).

Spatial and Spatiotemporal Structure

Stranding records exhibited strong spatial structure along the monitored coastline. After removing 112 records classified as potential georeferencing errors (0.19% of the dataset), we reconstructed the spatial domain used in the modeling, allowing the event distribution to be represented continuously along the coastline. The Poisson point process approach proved inadequate because of the strong overdispersion observed. In contrast, the Log-Gaussian Cox Process (LGCP) model adequately reproduced the spatial heterogeneity of strandings, explaining 80.8% of the observed deviance and showing residual dispersion close to 1.05. The estimated spatial patterns remained consistent across sensitivity analyses, indicating high robustness to the methodological choices adopted (Supplementary Material, Figure S2).

We found strong heterogeneity in data distribution across the spatial field (Fig. 3). The estimated mean spatial range was 33.3 km, indicating that coastal segments separated by distances smaller than this value tend to exhibit similar stranding intensities. We emphasize that these estimates represent the relative intensity of observed strandings, not absolute measures of risk or mortality. Incorporating the temporal dimension into the spatial model preserved the main patterns previously identified. The spatiotemporal model showed high agreement with the independent estimates of the temporal, seasonal, and spatial components, indicating that integrating these structures into a single model did not substantially alter their representation (Supplementary Material, Figure S3). Residual analysis confirmed the spatiotemporal model's adequacy. Although the observed data showed significant spatial autocorrelation, model fitting virtually eliminated this structure, leaving residuals without significant

spatial autocorrelation. Similar results emerged in analyses conducted separately for each species, indicating that the SPDE spatial component adequately captured the spatial dependence in the stranding records.

Hypothesis-Based Predictor Tests

After establishing the reference spatiotemporal model, we evaluated the contribution of covariate groups associated with the proposed ecological hypotheses. Although some predictors produced small reductions in deviance during cross-validation, none of the improvements exceeded the selection criterion based on the one-standard-error rule. Thus, we retained the reference spatiotemporal model in all comparisons, indicating that the spatiotemporal structure captured most of the observed variation in strandings. We organize predictor results according to the hypotheses established in the study (Table 3). Supplementary Material, Table S1, presents details on predictor construction and complete block-based validation.

Table 3
Hypothesis-led predictor tests and conclusions.

Hypothesis	Predictor or test	Blocked result	Conclusion
H1: Long-term and seasonal temporal structure	Nonlinear time and cyclic calendar month	Nonlinear trend and cyclic seasonality supported	Supported for observed strandings
H2: Coastal geometry and carcass retention	Shelf width, orientation, curvature, and shelter	No primary term	
H3: Ocean transport and thermal conditions	Onshore and alongshore current, wind, SST, and waves	No anomaly improved rolling-origin prediction	Not supported with the tested temporal summaries
H4: Fishing activity	Annual PREPS activity and monthly GFW apparent fishing effort	Neither PREPS nor GFW improved blocked prediction	Not supported by the available tracking and AIS indices
H5: Vessel traffic	Monthly GFW all-vessel presence and ANTAQ port activity	Neither GFW presence nor ANTAQ improved blocked prediction	Not supported for AIS-visible traffic
H6: Coastal human footprint or detection	Municipal population and population density	No spatially blocked predictive improvement	Not supported as an observation-opportunity proxy
H7: Species-specific responses	Species composition models with all tested covariates	Spatial-temporal structure supported for two species	No species-specific covariate group retained
H8: ENSO	No ENSO index available in the completed analysis	Not tested	Must be added or removed as a manuscript hypothesis
H9: SST and carcass decomposition	Requires decomposition state as the response	Not tested in the pooled stranding-count analysis	Separate response and analysis required
H10: Diet, health, and petroleum exposure	Required diet, health, and operational petroleum data absent	Not tested	Outside the evidence supplied by the current data

H2 – Coastal geomorphology and carcass retention.

Variables related to coastal geomorphology varied substantially across the study area. Although the shelter index was the most promising predictor during the initial screening, its inclusion, either alone or in combination with variables related to wave direction, did not improve predictive performance after controlling for the spatiotemporal structure. Thus, we did not include any coastal geography predictors in the final model.

H3 – Ocean transport, waves, and thermal conditions

The different representations of currents, winds, sea surface temperature, and wave exposure produced very similar predictive performance. Sea surface temperature anomaly showed the best nominal performance among the candidates in this group. However, the observed reduction in deviance was small and remained within the uncertainty estimated by cross-validation. We retained no interaction between ocean transport and environmental conditions.

H4 – Fishing Activity

Fishing activity indicators derived from both the National Satellite Vessel Tracking Program (PREPS) and Global Fishing Watch performed similarly to the reference model. We evaluated different spatial scales and variable representations, but none consistently improved model predictive performance. Thus, the available data provided no evidence that the intensity of observable fishing activity helped explain spatiotemporal variation in strandings.

H5 – Vessel Traffic

Maritime traffic indicators derived from the Automatic Identification System (AIS) and port statistics from the National Waterway Transportation Agency (ANTAQ) produced only marginal reductions in deviance, insufficient to justify their inclusion in the final model. Therefore, the final model retained no terms related to vessels or port activities. However, this conclusion does not exclude the possibility of influence from vessels not monitored by AIS or from specific operational activities associated with the oil and gas sector. Data from the Vessel Traffic Monitoring Project (PMTE), conducted by Petrobras, remain unavailable.

H6 – Coastal Human Footprint

Indicators of resident population and population density also did not improve model predictive performance. Although the municipal population variable produced a small reduction in *deviance* during cross-validation, this improvement was insufficient to offset the increase in model complexity and was therefore not incorporated into the final structure. The results indicated that none of the hypotheses represented by environmental or anthropogenic covariates provided sufficient predictive power after explicitly controlling for the spatial and temporal structure of strandings; therefore, these results remain exploratory (Supplementary Material, Figure S5). Thus, we retained species-specific spatiotemporal structure only for *C. caretta* and *L. olivacea*, without including any species-specific covariate groups.

H7 – Species-Specific Responses

Stranding composition varied among species over time (Fig. 4), indicating differences in the temporal distribution of records. However, these variations reflect only the composition of observed strandings and should not be interpreted as changes in the relative abundance of natural populations. Leave-one-year-out cross-validation showed that species-specific spatiotemporal models performed better than constant-composition models for *C. caretta* and *L. olivacea*. In contrast, for *D. coriacea* and *E. imbricata*, the constant-composition model performed comparably, indicating that the smaller number of records

for these species did not support complex species-specific patterns (Supplementary Material, Table S2). Adding additional covariate groups related to coastal geography, oceanographic conditions, fishing activity, vessel traffic, port activity, and human occupation did not consistently improve predictive performance for any species. Similarly, models fitted using PREPS data for the 2019–2023 period did not outperform the reference spatiotemporal model. Although some individual coefficients had 95% confidence intervals that did not include zero, these associations did not translate into improved predictive performance on independent data and therefore remain exploratory in nature (Supplementary Material, Figure S5). Thus, the final models retained only the spatiotemporal structure for *C. caretta* and *L. olivacea*, with no evidence supporting the inclusion of species-specific covariates for any of the species analyzed.

DISCUSSION

Our analysis of marine turtle strandings in the Santos Basin revealed highly structured temporal and spatial patterns, with marked seasonality, a nonlinear temporal trend, and persistent spatial aggregation along the coastline. The spatiotemporal models indicated that stranding intensity is not randomly distributed and that the patterns are relatively stable, whereas the environmental and anthropogenic variables evaluated contributed little additional explanatory power. Taken together, these results support the hypothesis that strandings exhibit a temporal structure characterized by trend and seasonality (H1) and demonstrate a consistent spatial structure. Conversely, the models did not support the hypotheses concerning associations with geomorphological characteristics (H2), oceanographic and climatic conditions (H3), fishing activity (H4), maritime traffic (H5), and intensity of human occupation (H6). The hypothesis of differentiated responses among species (H7) received partial support, as spatiotemporal models performed better for *Caretta caretta* and *Lepidochelys olivacea*, indicating that stranding dynamics are not necessarily homogeneous among species.

From a conservation perspective, these results show that strandings concentrate in specific periods and along specific sections of the coastline. Thus, identifying periods of higher occurrence, particularly between July and November, and areas with greater relative stranding intensity may help direct monitoring, response, and mortality-cause investigation efforts. The temporal and spatial concentration of records also suggests prioritizing monitoring during periods and in areas of higher stranding occurrence. For threatened species, this information may be particularly relevant for increasing the capacity to detect mortality events and guiding investigations into their causes.

Temporal structure was one of the most consistent patterns observed in this study. Strandings increased progressively throughout the austral winter and spring, with higher occurrence between July and November and a peak in October, and this pattern is consistent with seasonal patterns described in different regions. Along the coast of Portugal, higher stranding densities were observed during spring and summer for *C. caretta* and during autumn and summer for *D. coriacea* (Nicolau et al. 2016). Similar patterns, with higher occurrence during warmer months, were recorded in North Carolina, United States, and Baja California Sur, Mexico (Hart et al. 2006; Koch et al. 2013), whereas in the Canary Islands

archipelago, in northwestern Africa, higher frequencies were observed during the period corresponding to summer and autumn (Hurtado-Pampín et al. 2024). The authors related part of this variation to food availability, water temperature, and exposure to threats. These results, together with the pattern identified in the Santos Basin, reinforce that stranding seasonality is widespread, but differences in peak periods suggest that its mechanisms may vary by region.

In the Santos Basin region, oceanographic processes associated with productivity and the distribution of marine organisms may help explain part of the seasonality observed in our results. In the region, northeastern winds drive coastal upwelling of South Atlantic Central Water (SACW) at Cabo Frio (RJ) and Cabo de Santa Marta (SC). These upwelling currents – which bring cold, low-salinity, nutrient-rich waters – are primarily responsible for the increase in primary productivity in this region, particularly between October and April (Valentin 2001). The temporal variability of upwelling results in higher biological production during the austral spring and summer. The highest chlorophyll concentrations, reaching 5 mg/m³, occur in Guanabara Bay, Marambaia Restinga, Santos, Cananéia, and Paranaguá (Gherardi and Cabral 2007). Fuentes et al. (2020) identified, through satellite tracking, six intensively used feeding areas for juvenile *C. mydas* along the southern and southeastern Brazilian coast: five along the coast of São Paulo and one in the Paranaguá Estuarine Complex, Paraná. In addition, we identified movement corridors between them, with the longest extending 85 km from the Paranaguá Estuarine Complex to Peruíbe (SP), with areas of greatest use located 2 to 6 km from the coast. The spatial overlap between intensively used areas and the region studied provides a plausible ecological context for strandings, but the lack of a substantial effect of the predictors indicates that these processes alone did not explain the spatiotemporal variation in strandings in our models. Thus, the relationship between productivity, turtle distribution, and stranding occurrence remains a hypothesis to be investigated, particularly through variables that directly represent food availability and habitat use by different species and life stages.

The predominance of juvenile *C. mydas* is another important aspect for interpreting the observed patterns. Most recorded individuals had a mean curved carapace length (CCL) of 39.37 cm, a pattern consistent with studies conducted in southeastern and southern Brazil and in other regions of the world (Nicolau et al. 2016; Tagliolatto et al. 2020; Cantor et al. 2020; Hurtado-Pampín et al. 2024). The size of stranded individuals suggests that the study area represents an important developmental region for this species, which undergoes an ontogenetic shift in its feeding and habitat use, adopting an herbivorous diet and using neritic areas (up to 200 m depth) for feeding and resting (Bjorndal and Bolten 1988). According to Werner and Gilliam (1984), ontogenetic changes in habitat use may occur when different environments offer distinct advantages for growth and survival. The transition to coastal environments, however, also exposes these juvenile individuals to a new and unfamiliar habitat, where they must learn to locate new food sources and avoid an entirely new range of predators and anthropogenic threats, including vessel traffic, port activities, unregulated tourism, human occupation, pollution, and fishing (Thome et al. 2023). The high representation of juvenile *C. mydas* among strandings may therefore reflect both the region's importance as a feeding area and greater exposure to anthropogenic activities, making these individuals more susceptible to coastal-zone impacts. This characteristic gives conservation relevance to the observed strandings, since juvenile mortality represents the loss of

individuals that have not yet contributed to the reproductive population (Iverson 1991). Although the relationship between juvenile mortality and population dynamics depends on age structure and survival throughout the life cycle, the high density of juveniles among strandings reinforces the need for measures to reduce mortality sources at this life stage. Thus, coastal areas used as resting and feeding grounds by juveniles should be considered priorities for impact prevention and mitigation actions, particularly during periods of higher stranding incidence.

One of the most important results of this study was the strong spatial structure exhibited by strandings throughout the Santos Basin. Our model adequately reproduced the observed heterogeneity, indicating that strandings are not randomly distributed along the coastline but are organized into persistent aggregations whose structure remains relatively stable even when temporal variability is considered. Our results coincide with the anthropogenic activity hotspots identified by Fuentes et al. (2020), particularly the Paranaguá Estuarine Complex region, in Paraná, and the central-northern region of São Paulo, from Itanhaém to Ubatuba. These areas have the highest concentration of overlapping anthropogenic activities, including maritime traffic, ports, and artisanal and industrial fishing. The estimated mean spatial range of approximately 33 km adds a dimension that studies of marine turtle strandings have explored little. This parameter indicates that coastal segments separated by distances smaller than this value tend to share similar stranding intensities, showing that the spatial structure of strandings extends across a regional scale, with relatively close coastal segments sharing similar intensity patterns. In practical terms, this result suggests that coastal hotspots represent relatively broad areas of influence, in which different ecological and oceanographic mechanisms may act in an integrated manner.

Although hotspots identify segments where stranding intensity is consistently high, they should not be directly interpreted as areas of higher marine turtle mortality. Stranding represents only the final stage of a chain of processes involving mortality occurring in the marine environment, carcass residence time in the water column, buoyancy, transport by currents and winds, and, finally, deposition and retention along the coastline (Santos et al. 2018; Tagliolatto et al. 2020; Cook et al. 2021). Therefore, the observed spatial intensity may reflect areas where mortality is higher and regions that serve as preferential concentration zones for carcasses originating from different locations.

Carcass drift dynamics may help explain why simple coastal geography was insufficient to explain the distribution of strandings. Immediately after death, a turtle typically sinks in the water column and returns to the surface as gases generated by decomposition accumulate (Epperly et al. 1996). From this point on, physical processes transport the carcass. Experiments conducted by Santos et al. (2018) demonstrated that wind speed and the location of animal death can significantly influence the drift trajectory of marine turtle carcasses. Temperature may also play a significant role in the duration of drift and, therefore, in the probability that an animal strands on the beach. At higher temperatures, the carcass will probably decompose faster and remain buoyant for a shorter period. In other words, the lower the water temperature, the greater the probability that a carcass will reach land and strand. Depending on the rate of decomposition, it is also possible that, in warmer waters, only animals that died closer to shore will reach land, whereas animals that died farther offshore will decompose before doing

so. In addition to temperature and drift conditions, depth at the location of death may also determine the probability that a carcass will acquire and maintain sufficient buoyancy to reach the coast. When a carcass becomes buoyant at depths greater than 30 m, it frequently remains at the surface for less than 24 hours before sinking again, because pressure prevents the production of sufficient gases for buoyancy (Schultz et al. 2022).

The movement of floating objects results from a complex interaction among ocean currents, direct wind forcing on the emerged structure, and wave- and swell-induced motion, including Stokes drift (Breivik et al. 2011; Santos et al. 2018). For turtle carcasses, the relative importance of these mechanisms will depend on their physical characteristics and the oceanographic conditions encountered along the trajectory. Consequently, the distance between the mortality location and the stranding location may substantially modify the probability of carcass detection: the minimum estimate is that only 7–20% of carcasses strand on the coast (Hart et al. 2006; Koch et al. 2013; Nero et al. 2013; Cook et al. 2021). This relationship also means that the absence of an association between a particular geomorphological characteristic and stranding occurrence does not necessarily indicate that coastal configuration is irrelevant. Small-scale hydrodynamic processes, such as local circulation, wave exposure, coastline orientation, and convergence and retention zones, may be more directly related to carcass deposition than the geomorphological classes used in the present study.

Temperature, currents, waves, and primary productivity may influence both turtle distribution and carcass drift, but these effects may occur at temporal and spatial scales different from those used in the analysis. In addition, the time between mortality and stranding creates a temporal mismatch between the observed environmental conditions and when the animal actually reaches the beach. Thus, a direct relationship between oceanographic conditions at the time of stranding and stranding occurrence may be weak even when oceanographic processes are important for carcass transport. The absence of an effect of the evaluated oceanographic variables should therefore be interpreted with caution and does not mean these processes do not contribute to the observed patterns.

A similar result was observed for variables related to fishing activity and maritime traffic. Although these activities constitute important potential sources of negative impacts on marine turtles, the indicators used in this study did not contribute substantially to explaining the spatiotemporal structure of strandings. One possible explanation is gaps in activity-monitoring data. Participation in the PREPS is mandatory only for vessels with a Gross Tonnage of 50 or more and a total length of 15 m or more, which limits this tracking to large industrial vessels. Although fish production in the Santos Basin region is predominantly industrial, approximately 70% of regional catches (Gherardi and Cabral 2007), 14 601 small and medium-sized vessels are currently registered in the four states comprising the region (Ministério da Pesca e Aquicultura 2026). Similarly, tracking data available through Global Fishing Watch (GFW) shows a strong bias toward larger vessels: less than 1% of vessels shorter than 12 m are detected by the Automatic Identification System (AIS), whereas up to 90% of vessels longer than 24 m are represented. This limitation is particularly relevant when interpreting interactions with marine turtles, as an important proportion of coastal fishing effort may occur outside the tracking systems used in this

analysis. These findings highlight the information gap regarding fishing activity not only in the study area but also worldwide. Although small-scale fisheries have a lower impact on the marine environment, systematic monitoring would provide access to essential information. The lack of an association between fishing activity and the effect of maritime traffic on strandings should therefore be interpreted as an absence of evidence for a detectable relationship with the available indicators, rather than as evidence of an absence of interaction.

Thus, our results demonstrate that marine turtle strandings in the Santos Basin exhibit a robust temporal and spatial structure, characterized by strong seasonality, persistent spatial aggregation, and dependence at tens of kilometers. At the same time, the lack of consistent associations with fishing and maritime traffic indicators highlights the need to expand data coverage on anthropogenic activities, particularly those poorly represented by the available tracking systems. Rather than directly reflecting the distribution of mortality sources, the observed patterns likely result from factors not directly included in our analyses, such as interactions among turtle habitat use, mortality processes, carcass drift dynamics, and other coastal-environment characteristics. This complexity does not diminish the value of strandings as a conservation tool; rather, it shows how to use this information more effectively. The seasonal predictability of strandings allows monitoring and response efforts to focus on periods of higher occurrence, while the spatial persistence of aggregations allows priority areas to be identified at a regional scale. The predominance of juvenile *Chelonia mydas* further reinforces the importance of actions to reduce mortality at this life stage, particularly in coastal areas used for feeding and development.

In this context, the hotspots identified by the model should be considered priority areas for monitoring and investigation, rather than necessarily locations of higher mortality. Integrating stranding data, causes of death, habitat use, fishing activity, and maritime traffic with carcass drift models offers an important pathway to transform stranding patterns into information more directly applicable to identifying and mitigating mortality sources. In this sense, understanding strandings as the final product of a chain of processes, rather than as a direct measure of local mortality, constitutes an important perspective for interpreting stranding patterns and improving marine turtle conservation strategies along the Brazilian coast.

Declarations

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Competing Interests

The authors declare no competing interests.

Author Contributions

Conceptualization: Elizabeth S. Araújo, Guarino R. Colli; Methodology: Elizabeth S. Araújo, Gabriel H. O. Caetano, Guarino R. Colli, Heitor C. Sousa, Ticiane L. Costa; Formal analysis and investigation: Elizabeth S. Araújo, Guarino R. Colli; Writing - original draft preparation: Elizabeth S. Araújo; Writing - review and editing: Elizabeth S. Araújo, Gabriel H. O. Caetano, Guarino R. Colli, Heitor C. Sousa, Ticiane L. Costa; Funding acquisition: Guarino R. Colli; Resources: Guarino R. Colli; Supervision: Guarino R. Colli.

Data Availability

The data and R code required to reproduce the analyses will be deposited in a public repository upon acceptance of the manuscript. The repository accession number and permanent link will be added to the published article. Access to original records or precise locations may remain subject to data-owner authorization and sensitivity restrictions.

Ethics Statement

The study involved analysis of existing monitoring records and no new animal handling.

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Figures

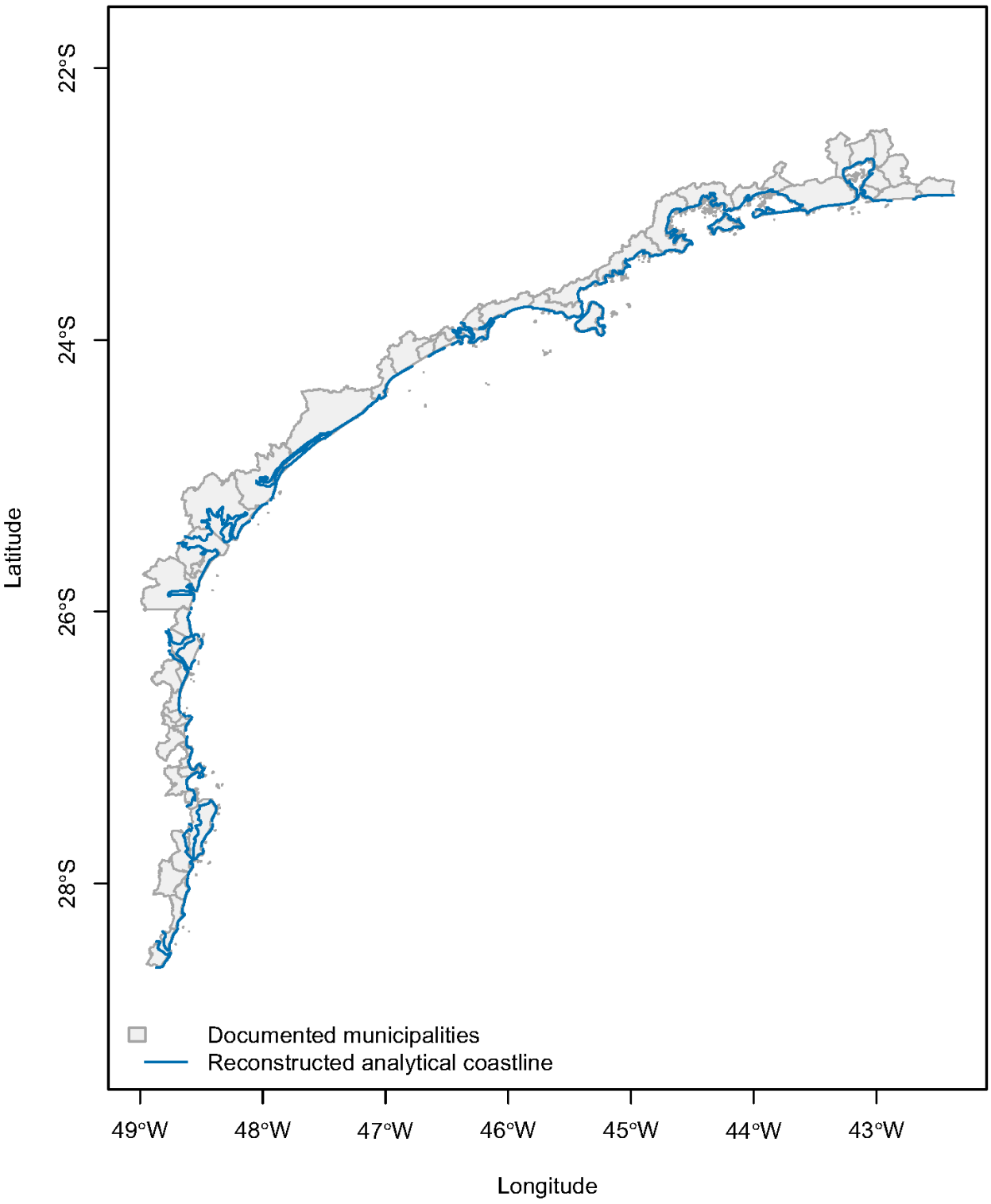

Figure 1

Study area and independently reconstructed spatial support for observed marine turtle strandings along the southeastern Brazilian coast. The mapped coastline is an integration support, not a measure of daily patrol effort.

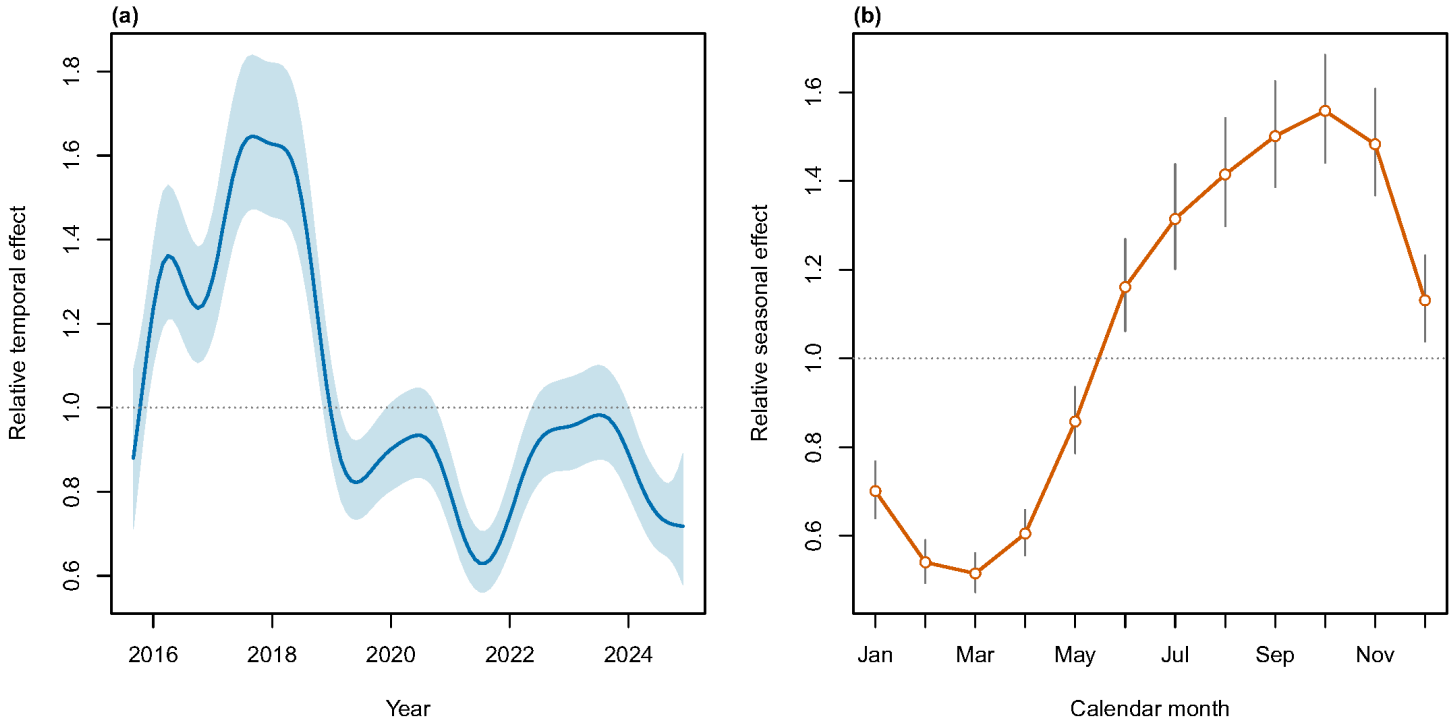

Figure 2

Estimated (a) nonlinear long-term and (b) cyclic calendar-month patterns in observed strandings under regular monitoring, September 2015 to December 2024. Effects are model-centered relative intensities with 95% confidence intervals.

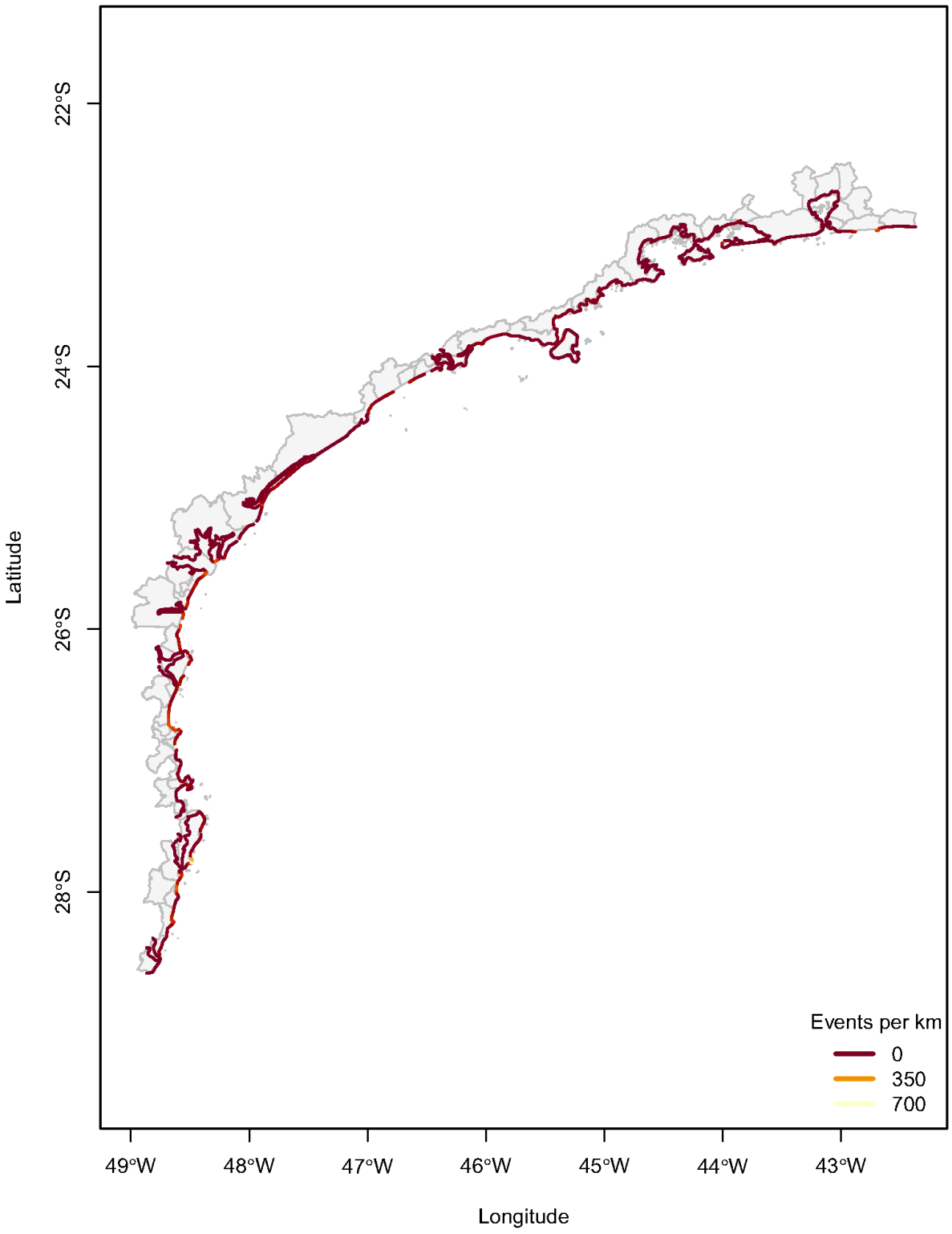

Figure 3

Relative fitted spatial pattern of observed strandings per kilometer of reconstructed coastline from the negative-binomial Cox-process approximation. Values represent observation intensity on the analytical support, not effort-adjusted mortality or turtle abundance. Coordinates are displayed as longitude and latitude (WGS84); spatial analyses were conducted in SIRGAS 2000 / Brazil Polyconic (EPSG:5880).

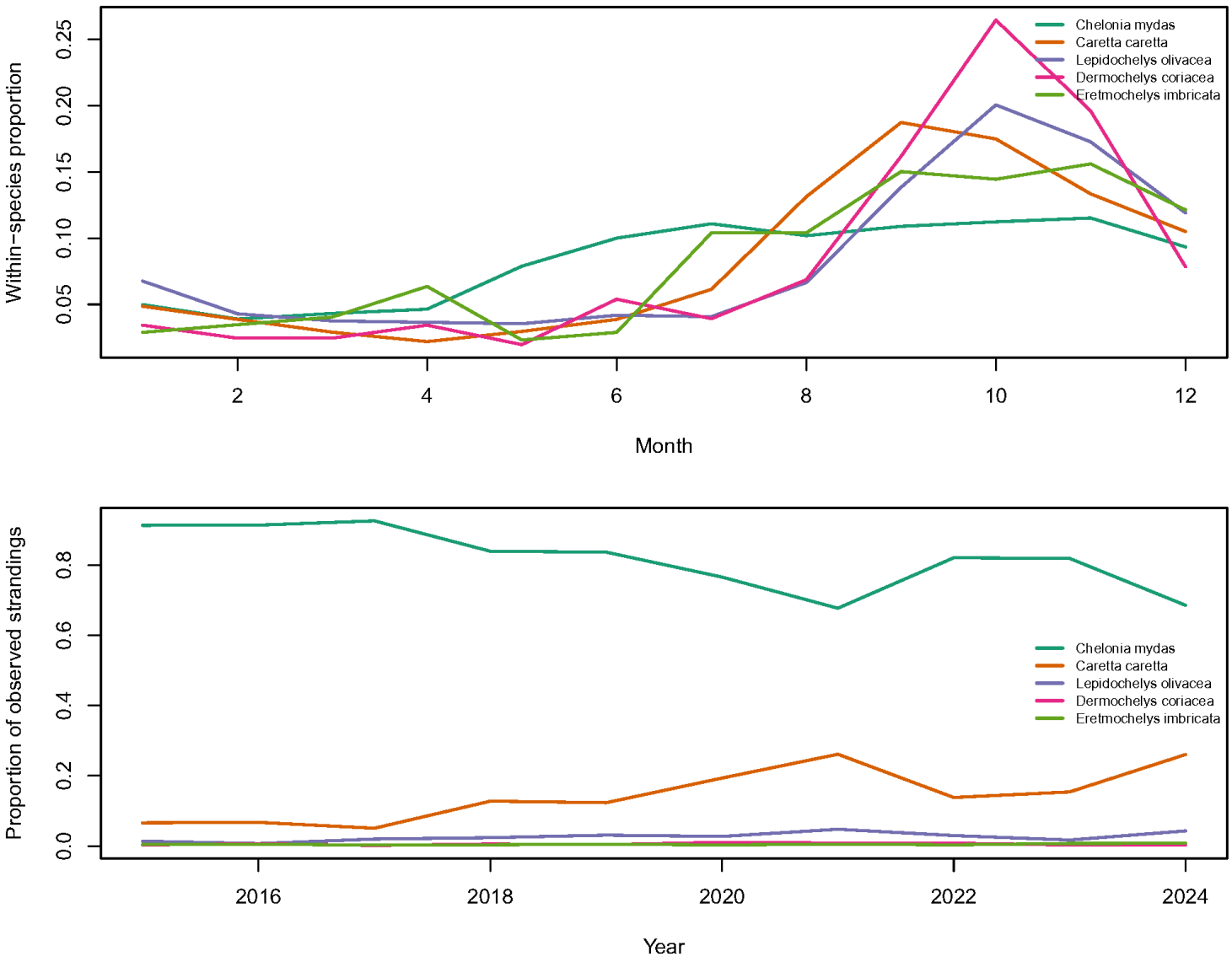

Figure 4

Annual and calendar-month composition of identified, regular-monitoring strandings. Composition is conditional on an observed stranding and does not estimate at-sea abundance or habitat use.

Supplementary Files

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- SupplementaryMaterial.docx