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RESEARCH ARTICLE

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Enriching historical biologging datasets on seabirds using deep neural networks: A transformer-based approach to infer energy expenditure proxy from GPS and environmental data

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Abstract

1. Recent advances in biologging have led to the widespread use of accelerometers, which generate high-resolution movement data essential for understanding animal behaviour. Derived from tri-axial accelerometry, Overall Dynamic Body Acceleration (ODBA) serves as a proxy for energy expenditure that is less invasive and more cost-effective than alternative methods, contributing to a better understanding of individual survival and population dynamics. However, many long-term datasets lack accelerometry due to limitations in instrumentation or older technologies, thereby constraining their utility in multi-year ecological studies.
2. Marine top predators, particularly seabirds, are valuable ecosystem sentinels due to their foraging strategies, energy constraints and sensitivity to environmental conditions. Understanding energy use during at-sea travel is essential for forecasting colony viability under climate change, thus supporting long-term ecological research and conservation efforts. High-resolution biologging has facilitated data-driven approaches to monitor seabird behaviour, but gaps in accelerometry data remain a challenge.
3. New developments in deep neural networks (DNNs) offer opportunities to reconstruct missing biologging-derived metrics by capturing the complex spatiotemporal relationships between movement and environmental data. One way to model such dependencies is to use a transformer architecture, which processes all inputs jointly and produces representations that explicitly encode relationships between them.
4. In this study, we present ODBAFormer, a transformer-based model designed to infer ODBA from GPS trajectories and environmental covariates. We applied

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ODBAFormer to seabird tracking data to address gaps in proxy data for energy expenditure. We evaluated the model on unseen data and compared it with state-of-the-art machine-learning regression method XGBoost as a baseline. We also explored its sensitivity to data heterogeneity and different environmental covariates combinations. Overall, ODBAFormer accurately reconstructs ODBA time series and proxies for both energy budgets and spatial energy expenditure distribution, providing a scalable solution to enrich legacy datasets or for situations where the use of multisensor loggers is limited by cost or weight.

KEYWORDS
accelerometry, bioenergetics, biologging, deep learning, marine ecosystem monitoring, ODBA, seabirds, transformer models

1 | INTRODUCTION

As biologging technologies have advanced, accelerometers have become increasingly used, generating large volumes of high-resolution movement data. Yet significant challenges remain, as many existing datasets are incomplete or outdated. They often lack accelerometry data due to the use of older technologies, which limits their usefulness in long-term ecological studies despite accelerometers being especially valuable thanks to their ability to capture fine-scale behaviours (Brown et al., 2013; Conners et al., 2021). Additionally, triaxial acceleration serves as a proxy for energy expenditure through Overall Dynamic Body Acceleration (ODBA) (Wilson et al., 2006), which is less invasive, more cost-effective and easier to deploy compared with other techniques such as heart rate monitoring (Groscolas et al., 2010; Weimerskirch et al., 2002) or doubly labelled water (Bourne et al., 2019). When properly calibrated, ODBA is linearly related to true energy expenditure measured through oxygen consumption rates (Halsey et al., 2009) and consistent with the energy expenditure measures via other proxies (Hicks et al., 2020; Sutton et al., 2021, 2023; Van Oordt et al., 2024). This is fundamental in animal ecology, as understanding energy expenditure directly influences individual survival and, by extension, population and species dynamics (Grémillet et al., 2018; Harrington et al., 2020; Rotics et al., 2016), while also providing crucial information about space use through the construction of energy landscapes (English et al., 2024; Lambert et al., 2025; Masello et al., 2021; Wilson et al., 2012). As global change increasingly impacts ecosystems, deriving metrics such as energy expenditure from movement data is critical to supporting wildlife conservation and management. However, estimating energy expenditure in cases where direct measurements or proxies are not available is complex, as energy expenditure is influenced by a range of biological and environmental factors, especially since movement patterns can be heavily affected by context-specific behaviours (e.g. prey capture dives) or external conditions (e.g. wind) (Halsey et al., 2009).

With biologging entering a new era of high-resolution, multisensor data collection (Joo et al., 2022; Yoda, 2019), marine science has become increasingly data-driven (Malde et al., 2020; Nathan et al., 2022). In this context, marine top predators, especially seabirds, have gained prominence as ecosystem sentinels (Hazen et al., 2019). Their foraging behaviours, spatial distribution and physiological sensitivity make them ideal indicators of ecosystem health. Seabirds, which breed in colonies and use central-place foraging strategies during breeding, face increased energy constraints that reflect broader environmental conditions (Velarde et al., 2019). Their long lifespans, high mobility and position at upper trophic levels amplify their value for ecological monitoring. Seabird tracking data have therefore become central to efforts to inform marine spatial planning and conservation policies (Hays et al., 2019; Hindell et al., 2020).

Simultaneously, as more data become available, opportunities to apply data-intensive approaches have expanded. While machine-learning methods are well established in biologging (Malde et al., 2020; Nathan et al., 2022; Yoda, 2019), the use of deep neural networks (DNNs)-based methods (LeCun et al., 2015) is less widespread (Borowiec et al., 2022; Pichler & Hartig, 2023). Composed of multiple processing units, these methods show promising results in handling tasks involving data with complex, non-linear dependencies, such as animal movement data. Recent studies have demonstrated the potential of different DNN architectures to reconstruct biologging-derived metrics. For instance, DNNs have been used to infer diving behaviour from GPS in seabirds using fully connected or convolutional architectures (Browning et al., 2018; Roy et al., 2022) and to estimate ODBA from depth data in sharks using fully connected networks (Liu et al., 2019). However, existing models do not account for environmental covariates, despite their strong influence on animal behaviour and energy use. Also, most models are species- or individual-specific, limiting their generalizability across taxa or contexts. Building on recent advances in DNNs, transformer models offer promising solutions to these challenges. Originally developed for natural language processing (Vaswani et al., 2017), transformers have since been adapted for image classification (Dosovitskiy et al., 2020) and spatiotemporal applications, such as weather (Gao et al., 2022) and ocean forecasting (Liu et al., 2024). By modelling relationships between input elements through attention mechanisms, these models can learn complex dependencies across time and space, making them promising candidates for handling biologging data.

In this study, we present ODBAFormer, a transformer-based model that infers ODBA from GPS trajectories and environmental data, and we illustrate its application to seabird tracking data to address the frequent lack of energy expenditure proxies in biologging datasets. This approach is particularly valuable for enriching legacy datasets collected before multisensor platforms became widely available for animal tracking, but also in cases when the use of multisensor loggers is limited by high costs, increased device weight or when the need for remote data retrieval is made challenging due to the amount of data recorded by high-resolution devices. In the absence of an established benchmark, we compared ODBAFormer to XGBoost, a widely adopted method that provides a middle ground between model complexity and accessibility. We also evaluated ODBAFormer's sensitivity to different environmental covariates and its capacity to generalize across close species. Overall, it accurately reconstructs the spatial distribution of the ODBA, energy budget proxies and ODBA time series, providing a scalable solution to enrich legacy datasets and expand behavioural and energetic analyses in movement ecology.

2 | MATERIALS AND METHODS

2.1 | Sampling

This study was conducted on Masked Boobies (*Sula dactylatra*) and Brown Boobies (*Sula leucogaster*) at breeding colonies along the coast of Brazil. Fieldwork was carried out on Meio Island in the Fernando de Noronha Archipelago (−3.8195, −32.3929) in 2019 and 2022, in the Abrolhos Archipelago (−17.9631, −38.7010) in 2019 and from 2021 to 2024, and in the São Pedro and São Paulo Archipelago (0.9167, −29.3455) in 2023 and 2024 (see Table 1 for sampling dates). Data loggers (Axy-Trek by TechnoSmart), including a GPS, a tri-axial accelerometer and a pressure sensor, weighing 25 g, were attached to the central tail feathers for each individual using TESA 4651 tape. Loggers' weight represented less than 3% of the birds' body mass (respectively 1550 g for males, 1675 g for females on average for Masked Boobies and 1380 g for males, 1715 g for females on average for Brown Boobies), as recommended for flying seabirds (Bodey et al., 2018). Loggers were set to record GPS position every 10 s—1 min and tri-axial accelerometry every 20 ms (50 Hz). After 2 to 7 days, birds were recaptured for logger retrieval and released on the nest. Sampling was conducted after approval by the Ethics Committee (CEUA/UFRGS no. 37905 and CEUA/FURG no. 23116.001336/2020-40) and authorization under SISBIO (no. 64234 and no. 64261).

2.2 | Data preprocessing

To prepare data for model training, GPS and accelerometry signals were processed as follows: each GPS track was regularized to a 10 s time resolution and split into individual foraging trips by only selecting points more than 2 km away from the colony for a given minimal duration of 20 min. Trips within 10 km of the colony were removed from the dataset, because it was difficult to determine with certainty that they were actual foraging trips. Plots of all the trajectories are

TABLE 1 Summary of the data used for model training and evaluation.

Species	Location	Dates	Trips	Duration (h)	Length (km)	Max dist. (km)
Masked Booby	Abrolhos	03 December 2019–10 December 2019	11	15.4 ± 18.3	290.3 ± 202.9	88.0 ± 54.6
Masked Booby	Abrolhos	11 August 2021–19 August 2021	66	7.2 ± 4.6	213.0 ± 107.8	82.7 ± 44.6
Masked Booby	Abrolhos	22 September 2022–27 September 2022	59	10.9 ± 11.1	261.2 ± 175.5	95.7 ± 53.0
Masked Booby	Abrolhos	08 October 2023–10 October 2023	16	10.9 ± 8.3	300.2 ± 121.9	116.7 ± 44.9
Masked Booby	Abrolhos	18 September 2024–25 September 2024	73	6.5 ± 4.8	200.0 ± 110.2	75.7 ± 38.4
Masked Booby	Fernando de Noronha	16 April 2019–26 April 2019	23	7.9 ± 5.4	176.8 ± 78.8	57.0 ± 28.3
Masked Booby	Fernando de Noronha	27 April 2022–29 April 2022	73	4.1 ± 1.9	108.0 ± 44.9	40.8 ± 17.7
Brown Booby	Abrolhos	26 June 2019–05 July 2019	36	5.17 ± 4.1	142.5 ± 81.8	52.4 ± 32.6
Brown Booby	São Pedro e São Paulo	23 June 2023–27 June 2023	108	2.0 ± 1.1	56.3 ± 25.3	21.2 ± 8.7
Brown Booby	São Pedro e São Paulo	04 February 2024–15 February 2024	118	2.5 ± 1.3	57.3 ± 26.8	16.6 ± 6.2

Note: Each row details a deployment period, including species, location, date range, number of recorded trips, trip duration, trip length and maximum distance to the nest. Values are reported as mean ± standard deviation where applicable. The underlined rows indicate the data specifically used for model evaluation in this paper.

displayed in the Supporting Information. We obtained dynamic acceleration by removing the median value of the time series and filtering the acceleration data with a high-pass Butterworth filter (Brown et al., 2013) with a cut-off frequency empirically set to 0.8 Hz. We then computed Overall Dynamic Body Acceleration (ODBA) by summing the absolute values of dynamic accelerations across all three spatial dimensions and resampled to the same frequency as the GPS data. GPS and accelerometry data cleaning and processing were made using the Python package `cpforager`. The bathymetric maps were recovered from the GEBCO database (GEBCO Bathymetric Compilation Group, 2024) (resolution 15 arc seconds ≈0.004°), and wind data were collected from the ERA5 dataset (C3S, 2018) (0.25°; 1 h) for the duration of each fieldwork.

Trajectories are recorded as time series of GPS positions, but ODBAFormer relies on spatial structure rather than temporal order, so we summarized each trajectory as a density of points in space. For each trip, a spatial domain was defined by the maximal trip length. A fixed-size grid, here set to 100 × 100, was then overlaid onto this domain, centred on the trajectory's spatial barycenter. The resulting input matrix was a 100 × 100 array, where each element contains the number of GPS data points falling within that cell (see Figure 1). By construction, the fixed grid size combined with trip-specific spatial domains resulted in varying spatial resolution across input data. A similar matrix was created to represent ODBA values, which serve as the target for inference, with each element holding the sum of ODBA values across all data points within the corresponding grid cell. Bathymetry maps were normalized by the maximum depth around the colony, cropped to the trajectory domain bounds and rescaled to a size of 100 × 100. Wind data for both directions (u-wind and v-wind) was averaged over the trip duration, then interpolated and rescaled before cropping. These preprocessing steps, especially the interpolation, can be aggressive and may limit interpretability, but they were the most practical solution to align datasets of differing resolutions.

2.3 | ODBAFormer overview

Inferring ODBA from GPS data and environmental covariates requires a way to compute long-range dependencies and non-linearities from the data. One way to model such dependencies is using a transformer architecture (Vaswani et al., 2017), which

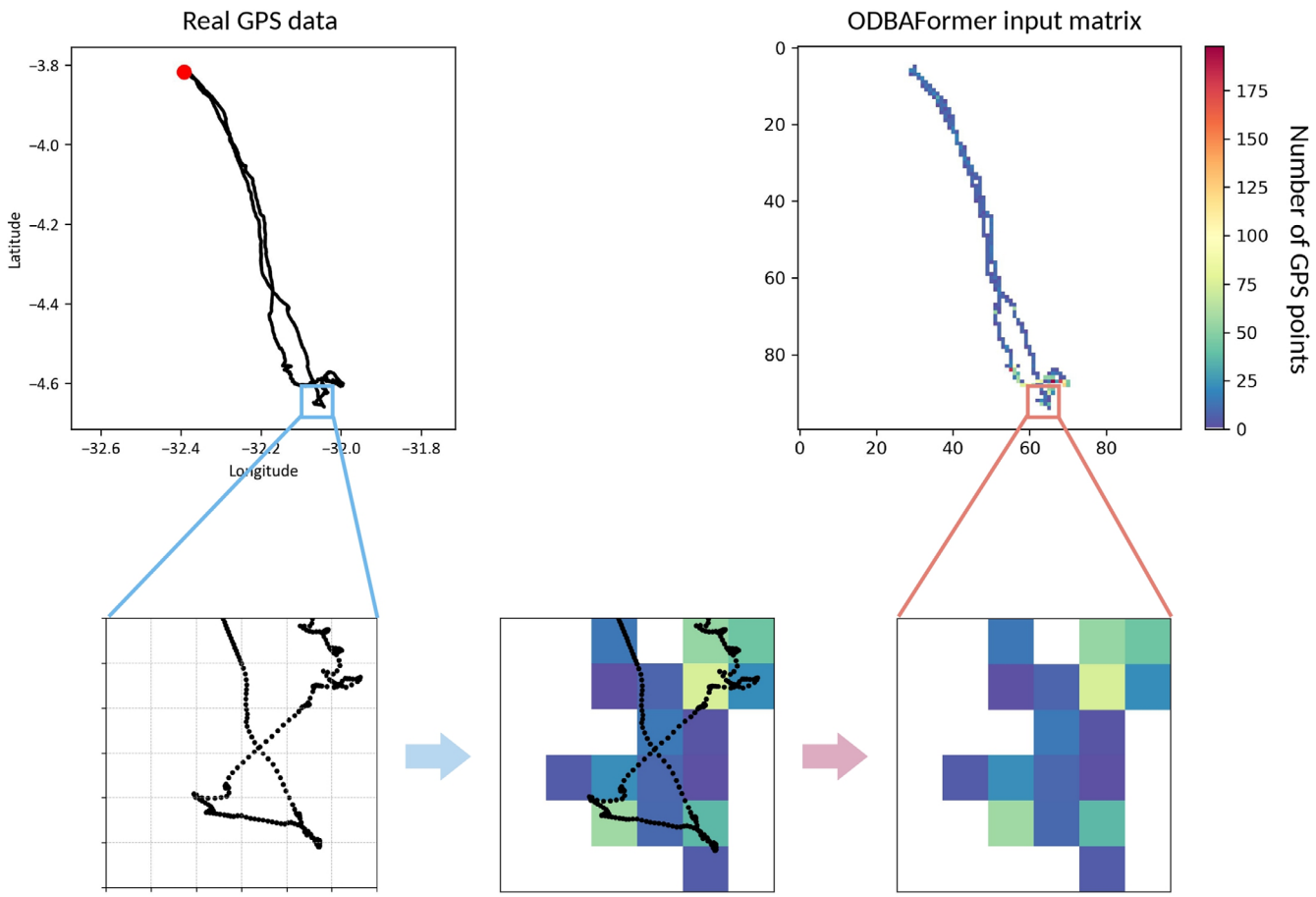

FIGURE 1 Seabird movement trajectory and spatial use estimation from GPS data. Top left: GPS-based trajectory of a tracked seabird, with the nest location marked in red. Top right: Input data for ODBAFormer. Bottom panels: Illustration of the data processing workflow. We superimposed a spatial grid on the trajectory (bottom left), and the number of GPS points falling within each grid cell was counted to produce a spatial density map (bottom right).

processes all inputs jointly and produces representations that explicitly encode relationships between them. More precisely, the model generates a weighted representation of the input values, where the weights encode the relationships between different elements in the input sequence though the self-attention mechanism. It fist derives from the data three internal projections used to compute similarities (query (*Q*), key (*K*) and value (*V*)), then compute its representation weighted by its internal similarities *Attention* (Q, K, V) (Equation 1, where d_k is the dimension of the *K* matrix used as a scaling factor).

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{1}$$

While self-attention can capture long-range and context-dependent interactions, it becomes computationally expensive as input size increases, and thus, variants like cuboid attention have been proposed to handle high-dimensional data. The core idea is to decompose the input into non-overlapping sections (or cuboids), apply self-attention within each section and merge them back into a unified representation (see Figure 2). In this work, we adopted the version introduced in the Earthformer architecture, developed by Gao et al. (2022), designed to process high-dimensional Earth observation data, that we adapted here to a static spatial context. As to further capture interactions in the data, the model also integrates global vectors, which act as a cross-channel information summary to better inform internal representations of the data. Finally, to better capture multi-scale dependencies, attention is computed at different scales throughout the model by progressively downsampling then upsampling the data.

ODBAFormer follows a hierarchical encoder–decoder architecture based on transformers, whose exact structure is summarized in Figure 3 and training parameters are reported in the Supporting Information. In this architecture, the encoder maps the input sequence into hierarchical latent representations that capture contextual dependencies across scales by progressively downsampling the input data. These are passed to the decoder, which selectively extracts relevant information from the encoder's output to generate predictions at different scales by progressively upsampling coarse representations back to finer resolutions. ODBAFormer was trained on a single NVIDIA RTX 2000 Ada Generation Laptop GPU

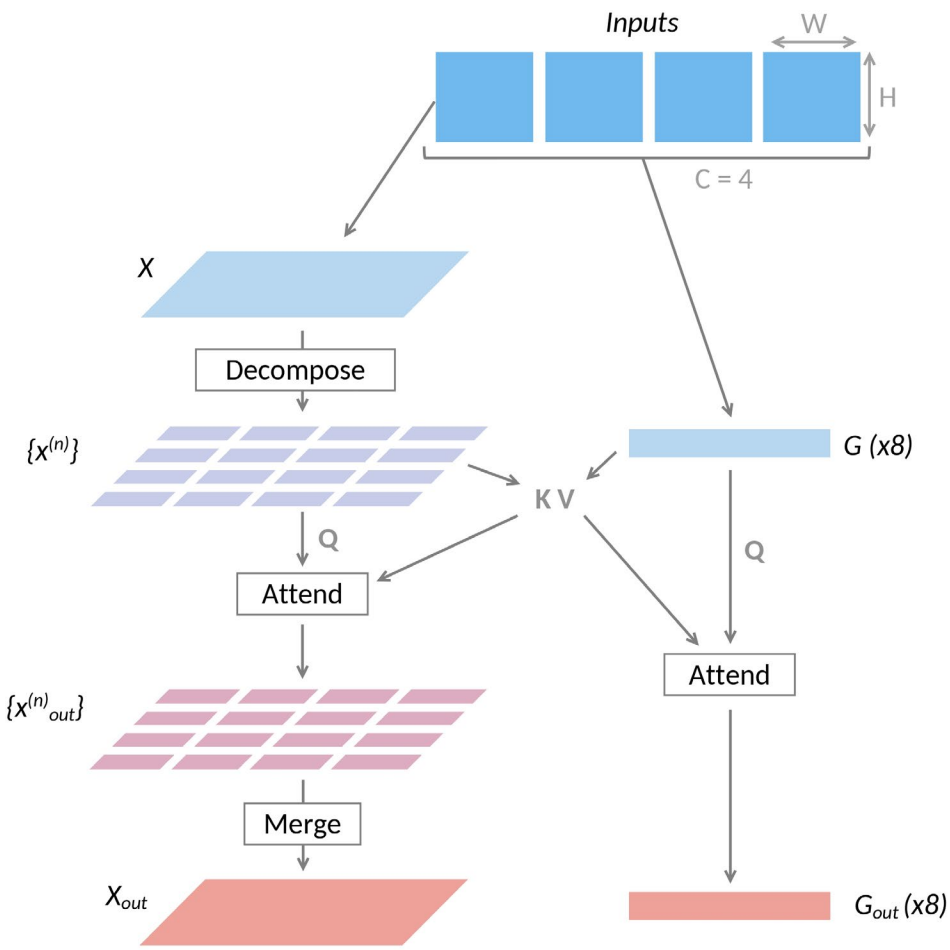

FIGURE 2 Cuboid attention with global vectors. The input data of size (H,W) with C = 4 channels is split into two branches: a local branch (X) and a global vector branch (G). In the local branch, each individual channel X is decomposed into non-overlapping cuboids $x^{(n)}$. From G and $x^{(n)}$ are derived the Q, K and V matrices used in the attention mechanism. After applying attention, cuboids $x^{(n)}_{out}$ are merged to produce the output tensor X_{out}. Simultaneously, globally informed representations of the data G_{out} are produced.

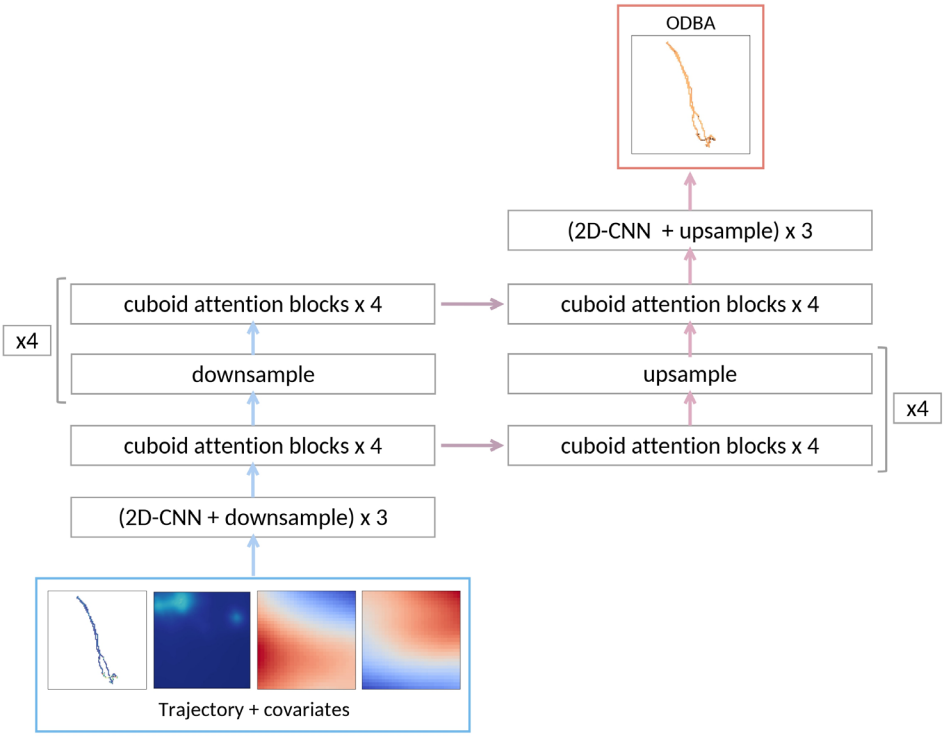

FIGURE 3 ODBAFormer architecture.

with 8 GB of memory. Its checkpoint from the final training epoch was used for evaluation. We provided the loss curves for training and validation in the Supporting Information.

ODBAFormer was trained from scratch under two configurations (single-species and two-species model). The single-species model was trained on Masked Booby (MB) data only (298 trips) and evaluated on an independent MB dataset from Fernando de Noronha (2019; 23 trips) withheld from training. The two-species model was trained on the same MB data plus additional Brown Booby (BB) data (524 trips total). Its performance was evaluated on both the MB evaluation dataset and an independent BB dataset from Abrolhos (2019; 36 trips), which were also excluded from training (see underlined rows in Table 1). From the training data, 5% was randomly selected as the test set to assess model performance after training. The remaining 95% was split into 80% for training (to optimize the model's parameters) and 20% for validation (to tune the model's hyperparameters).

2.4 | Processing ODBAFormer outputs

2.4.1 | Direct calculation of ODBA density maps

We calculated a proxy map of total expanded energy for a collection of trajectories, which inform on space use and could, in principle, be converted into an energy landscape. Here, we present the raw maps without further normalization, allowing for flexibility in their application depending on study-specific requirements. We first inferred ODBA for each trajectory individually, then the inferred ODBA matrices were rescaled to a real 0.05° resolution, aligned to their correct spatial location and finally summed to obtain the resulting field. The quality of ODBA field reconstruction was assessed using four evaluation metrics computed on non-zero elements of the fields only: mean error (bias), mean absolute error (MAE), root mean squared error (MSE) and structural similarity index measure (SSIM). They measure, respectively, how much the predictions systematically over- or underestimate the true field, the average magnitude of deviations regardless of direction, the magnitude of larger deviations, with greater emphasis on outliers, and how well the spatial patterns of the predicted field match those of the true field.

2.4.2 | Reconstruction of ODBA time series

To recover the ODBA time series from the density matrix, each trajectory point was assigned the predicted ODBA ($\widehat{\text{ODBA}}$) of its corresponding matrix cell, distributed equally among all points in that cell. Model performance was assessed using the Earth Mover's Distance (EMD) (Pele & Werman, 2009) between true and predicted ODBA distributions. To quantify the performance of energy budget proxy inference, we introduced the relative error in cumulated ODBA, Δ, computed on the recovered ODBA time series (Equation 2).

$$\Delta = \frac{\sum_{t=0}^{N} \widehat{\text{ODBA}}(t) - \sum_{t=0}^{N} \text{ODBA}(t)}{\sum_{t=0}^{N} \text{ODBA}(t)} \tag{2}$$

We evaluated behaviour-specific energy budget proxies using first a two-state Hidden Markov Model (HMM) fitted to step lengths and turning angles to segment behavioural states using the R package `moveHMM`. Its parameters, fitted distributions and plots of the segmented trajectories are reported in the Supporting Information. The two inferred states broadly correspond to 'travelling' (high step length and low turning angle) and 'foraging' (low step length and high turning angle) behaviours. The foraging behaviour is defined here as both area-restricted search and plunge-diving, with most of the birds' foraging activity being the area-restricted search. For example, in our evaluation dataset on Masked Boobies, the average foraging bout duration per trip is 5.1 min, with a total time spent foraging on average of 3.9 h per trip, whereas the total diving time is around 1.3 min per trip. We calculate relative error in cumulated ODBA per inferred behavioural state on the inferred ODBA time series, noted $\Delta_{\text{traveling}}$ and Δ_{foraging} (Equation 3). The complete workflow from from data preparation to model outputs is summarized in Figure 4.

$$\Delta_{\text{state}} = \frac{\sum_{t \in \text{state}} \widehat{\text{ODBA}}(t) - \sum_{t \in \text{state}} \text{ODBA}(t)}{\sum_{t \in \text{state}} \text{ODBA}(t)}, \quad \text{state} \in \{\text{traveling}, \text{foraging}\} \tag{3}$$

2.5 | Machine-learning baseline

Because no established state-of-the-art method currently exists for predicting ODBA from positional and environmental data, we compared ODBAFormer performances with a well-established statistical learning approach by also estimating ODBA using the gradient boosting regression model XGBoost (Chen & Guestrin, 2016) (XGBRegressor, `xgboost` package, Python). This baseline serves as a reasonable compromise, as XGBoost offers a relevant benchmark capable of performing effective inference on complex data without relying on other DNN-based models that are not yet represented in the literature. It was configured with 100 estimators, a learning rate of 0.1, a maximum tree depth of 3 and a fixed

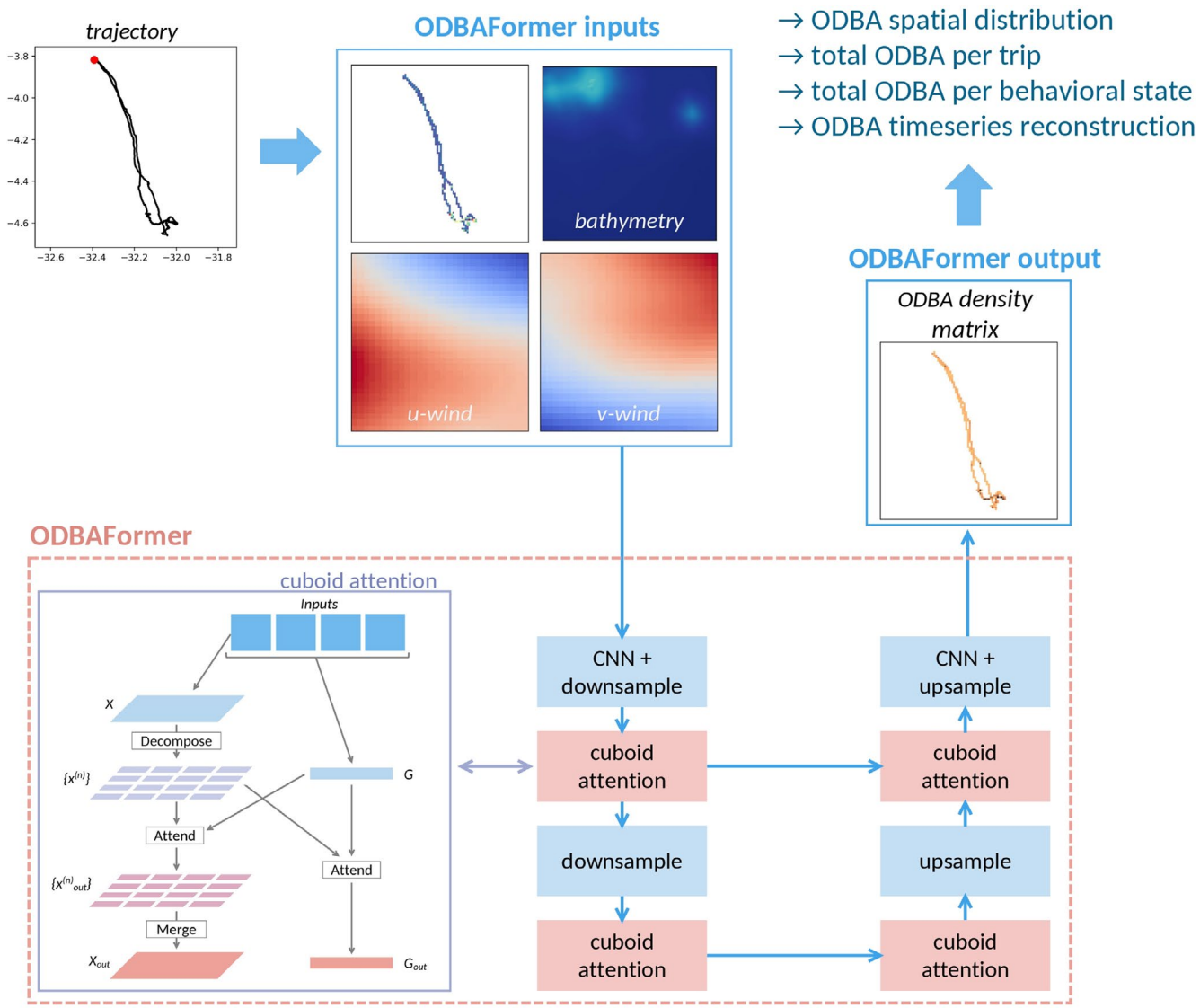

FIGURE 4 Workflow from data preparation to model outputs.

random seed for reproducibility. It was trained and evaluated on the same datasets as ODBAFormer to ensure consistency. However, since XGBoost only handles tabular data, the most effective input representation was not the raw GPS trajectory but a derived time series composed of step length between successive GPS points, turning angle between points and normalized bathymetry at each location.

2.6 | Simulation setup

A series of simulation experiments was conducted to evaluate ODBAFormer's ability to infer ODBA from movement trajectories and environmental covariates, and to assess its flexibility and generalizability. First, the model was trained exclusively on MB data using bathymetry as the sole covariate and evaluated on a withheld dataset to generate spatial maps of cumulated energy expenditure proxy, which provide a first approximation of energetic space use and a first step towards the calculation of an energy landscape. The inferred ODBA was then converted into time series, and these predictions were compared with ones given by XGBoost trained and evaluated on the same datasets as ODBAFormer. Model flexibility was then assessed by varying the number and type of covariates used in the inference process (bathymetry, wind, both or none). Finally, to examine generalizability across species with similar movement behaviour, performance was compared between the single-species model and a two-species model trained on both MB and BB data. Evaluation was conducted on withheld datasets for each species.

3 | RESULTS

3.1 | Spatial and temporal inference of ODBA

3.1.1 | Direct inference of ODBA density map

We used ODBAFormer to infer the spatial distribution of the total ODBA in the area surrounding Fernando de Noronha for the individuals tracked in April 2019 (23 trips), unseen in model training. The trajectories used as model inputs, the true ODBA density map and the inferred ODBA density map by ODBAFormer are displayed in Figure 5. The predicted map closely matches the real one, with an average MAE of 73.95 g (standard acceleration due to gravity) (about 1.33% of the maximum observed value, which is 5571.0 g). RMSE is 153.97 g (2.76%). Overall, the average bias is −2.60 g, indicating the model slightly underestimates the spatial ODBA density. The SSIM is 0.97, which is very close to 1, indicating a great overall understanding of the map's spatial structure.

3.1.2 | Inference of ODBA time series

We assessed ODBAFormer's capacity to infer broad energy metrics from reconstructed ODBA time series by benchmarking the model against a similar task performed by XGBoost. Results on the evaluation dataset are summarized in Table 2. Across all metrics, ODBAFormer significantly ($p < 0.05$) outperforms XGBoost, demonstrating lower errors and improved predictive accuracy. Overall, these results indicate that ODBAFormer provides more accurate and reliable results across both global and behaviour-specific metrics than a strong baseline model such as XGBoost. The corresponding

TABLE 2 Comparison of ODBAFormer and XGBoost in predicting cumulated ODBA. Metrics include relative error in cumulated ODBA (Δ), relative error in cumulated ODBA per inferred behavioural state ($\Delta_{traveling}$, $\Delta_{foraging}$), and Earth Mover's Distance (EMD) between inferred and real ODBA values distributions. Values are reported as mean ± standard deviation.

Evaluation metric	ODBAFormer	XGBoost
Δ (%)	3.3 ± 15.8	16.9 ± 12.0
$\Delta_{traveling}$ (%)	2.9 ± 16.3	14.4 ± 12.6
$\Delta_{foraging}$ (%)	3.8 ± 27.2	22.6 ± 23.7
EMD	30.3 ± 11.3	66.6 ± 9.9

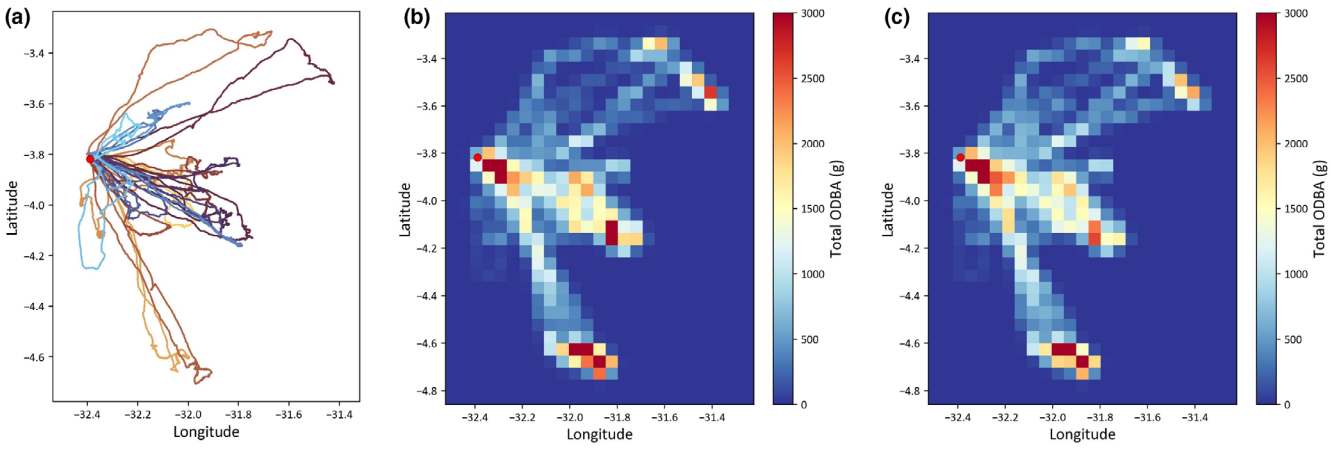

FIGURE 5 Spatial Overall Dynamic Body Acceleration (ODBA) distribution inference results. (a) Trajectories used in the inference process. (b) True ODBA density map. (c) Inferred ODBA density map by ODBAFormer. Colony position is represented by the red dot.

box plots, histograms of errors and plots of the predicted energy budget proxies against their real values (Figure 6) further illustrate these differences, highlighting not only the reduced error variance but also the closer alignment between predicted and observed data distributions.

The box plots show that the error distributions for ODBAFormer are more centred around zero than those for XGBoost, indicating that the total ODBA estimation per trajectory is closer to the ground truth. For Δ and $\Delta_{traveling}$, the interquartile range lies within the −15% to +15% error interval, meaning that half of the evaluation dataset is inferred with less than 15% error relative to the ground truth. $\Delta_{foraging}$ shows a wider spread, with the interquartile range contained within −20% to +20%. Regarding the distributions, both models tend to underestimate low ODBA values. However, ODBAFormer captures a broader range of variability, particularly for ODBA values in the 100–200 g range that are not well represented by XGBoost, even though it tends to average-out the distribution of values. Finally, plots of the predicted energy budget proxies against their real values show closer alignment for the ODBAFormer prediction, especially in the high-ODBA sum range.

3.2 | Comparative effect of covariate combinations

We evaluated ODBAFormer's performance when trained with different covariate combinations to assess the influence of environmental predictors: GPS input only (no covariates), GPS with bathymetry, GPS with wind fields, and GPS with both bathymetry and wind. The resulting metrics across these configurations are summarized in Table 3 and the distributions of Δ, $\Delta_{traveling}$ and $\Delta_{foraging}$ are shown in Figure 7.

The GPS + bathymetry model achieved the lowest Δ and EMD, though these improvements were not statistically significant compared with other models ($p < 0.05$). $\Delta_{traveling}$ was consistently small and did not differ significantly across covariate sets. For $\Delta_{foraging}$, however, the inclusion of bathymetry in the covariates had a significant effect on performance ($p < 0.05$), as the GPS + bathymetry model substantially reduced $\Delta_{foraging}$ compared with all other covariate combinations. This result indicates that bathymetry provides critical explanatory power for estimating total ODBA for foraging behaviour, whereas neither wind fields alone or in combination with bathymetry did improve performance. Box plots of errors show

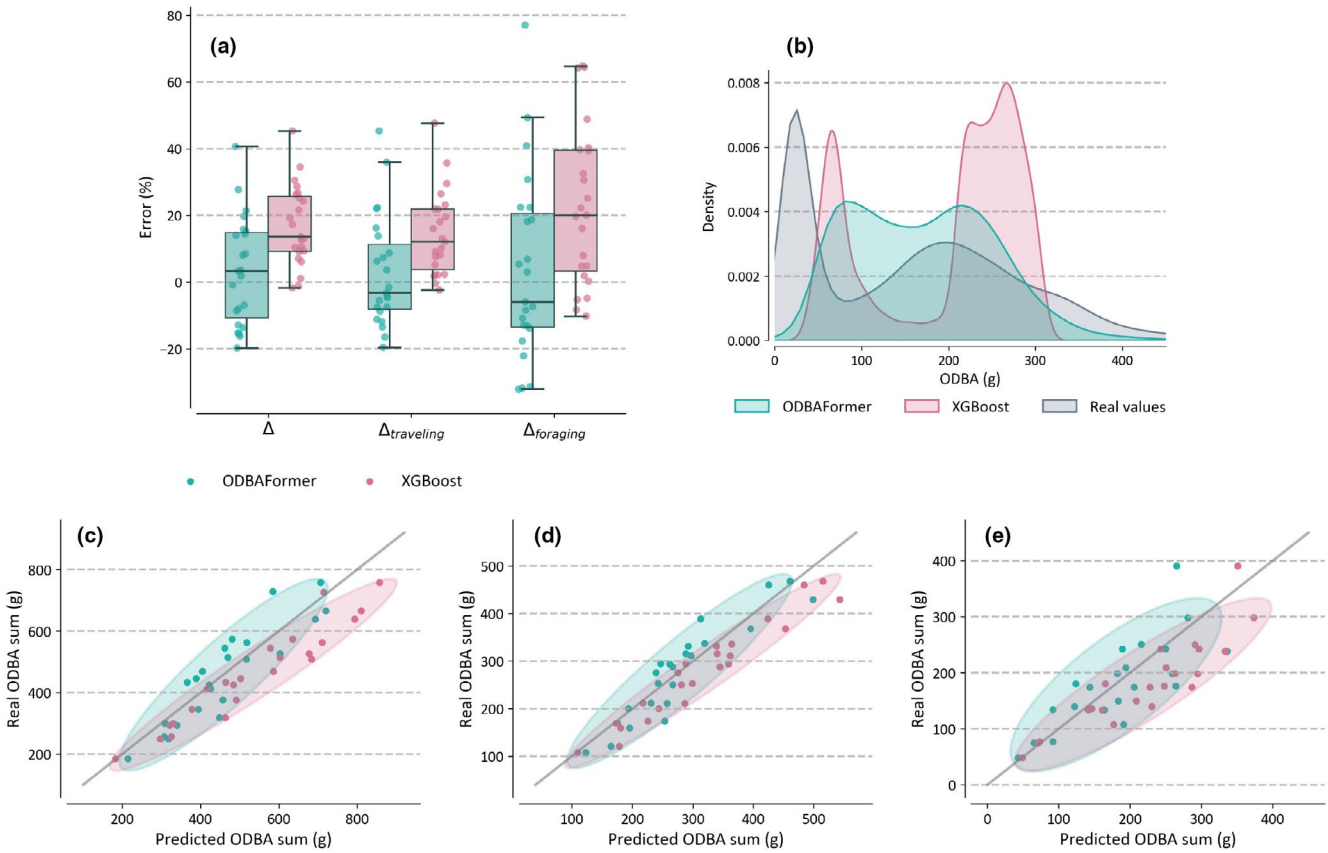

FIGURE 6 Distributions of Overall Dynamic Body Acceleration (ODBA) prediction performances for both ODBAFormer and XGBoost. (a) Relative error in cumulated ODBA (Δ) and relative error per inferred behavioural state ($\Delta_{traveling}$, $\Delta_{foraging}$). (b) Distributions of predicted ODBA values and real values. (c) Predicted vs. real plot of total energy budget proxy. (d) Predicted vs. real plot of energy budget proxy for the travelling state. (e) Predicted vs. real plot of energy budget proxy for the foraging state. Coloured ellipses for the three bottom plots show the 95% confidence region of the points' distribution.

TABLE 3 Comparison of ODBAFormer performance for different covariate combinations as inputs.

Evaluation metric	GPS only	GPS + bathymetry	GPS + wind	GPS + wind + bathymetry
Δ (%)	11.5 ± 18.2	**3.3 ± 16.1**	10.5 ± 18.0	10.9 ± 19.4
$\Delta_{traveling}$ (%)	3.0 ± 17.6	2.9 ± 16.7	**1.9 ± 16.7**	8.0 ± 119.7
$\Delta_{foraging}$ (%)	24.8 ± 34.7	**3.8 ± 27.8**	24.1 ± 33.1	14.8 ± 35.2
EMD	34.8 ± 17.7	**30.3 ± 11.5**	36.7 ± 13.6	34.0 ± 16.3

Note: Metrics include relative error in cumulated ODBA (Δ), relative error in cumulated ODBA per inferred behavioural state ($\Delta_{traveling}$, $\Delta_{foraging}$), and Earth Mover's Distance (EMD) between inferred and real ODBA values distributions. Values are reported as mean ± standard deviation. Bold values indicate the best-performing covariate combination for each metric.

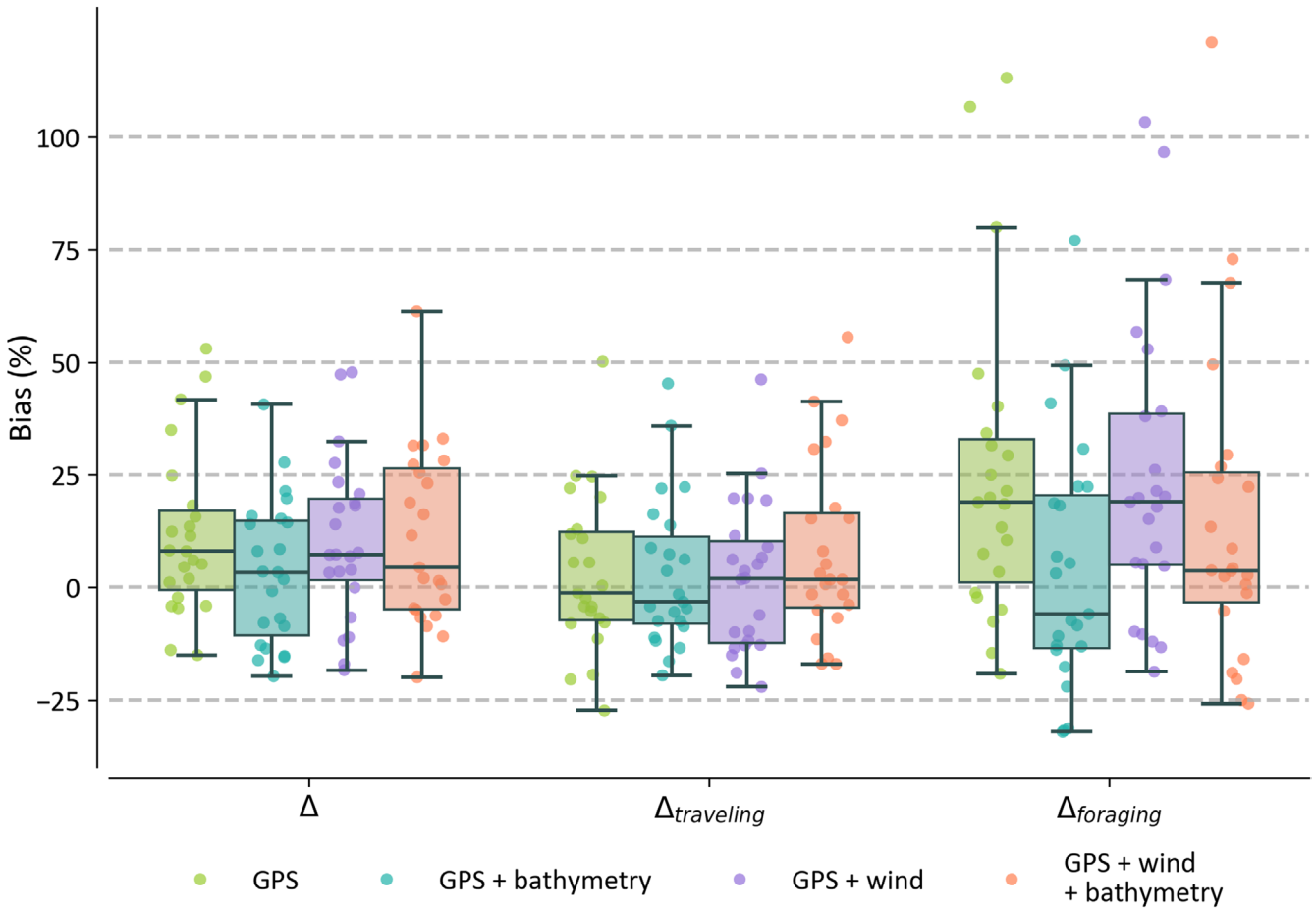

FIGURE 7 Distributions of Overall Dynamic Body Acceleration (ODBA) prediction performances for each covariate combination.

similar trends, with the inclusion of bathymetry as a covariate consistently centring the error spread around 0%.

3.3 | Comparative effect of single-species and two-species training approaches

ODBAFormer was trained on two different dataset compositions: a single-species dataset and a two-species dataset, to evaluate the trade-off between specialization and generalization. Two independent evaluation sets, held out from training, were used: MB data (23 trips) and BB data (36 trips). Mean evaluation metrics are summarized in Table 4.

The single-species model, trained on only MB data, performed better on the MB evaluation set (Δ = 3.7 ± 15.9%) that the two-species model (Δ = 11.2 ± 19.7%), with greater variability indicated by higher standard deviations. However, median and interquartile range, illustrated in Figure 8, show only minor differences, indicating that the performance loss is mostly due to outliers. Additionally, the two-species model shows good results on inferring ODBA on the BB evaluation dataset despite the presence of two species' data indistinctively used at training.

TABLE 4 Comparison of ODBAFormer performance with a single-species training dataset (SS) and a two-species training dataset (TS).

Evaluation metric	SS model, MB	TS model, MB	TS model, BB
Δ (%)	3.3 ± 16.1	10.2 ± 19.7	6.8 ± 15.9
$\Delta_{traveling}$ (%)	2.9 ± 16.7	6.2 ± 18.5	10.7 ± 18.5
$\Delta_{foraging}$ (%)	3.8 ± 27.8	16.0 ± 36.4	−1.9 ± 25.6
EMD	30.3 ± 11.5	33.5 ± 17.0	33.6 ± 19.3

Note: Metrics on the evaluation dataset for Masked Boobies (MB) and Brown Boobies (BB) are reported. Metrics include relative error in cumulated ODBA (Δ), relative error in cumulated ODBA per inferred behavioural state ($\Delta_{traveling}$, $\Delta_{foraging}$), and Earth Mover's Distance (EMD) between inferred and real ODBA values distributions. Values are reported as mean ± standard deviation.

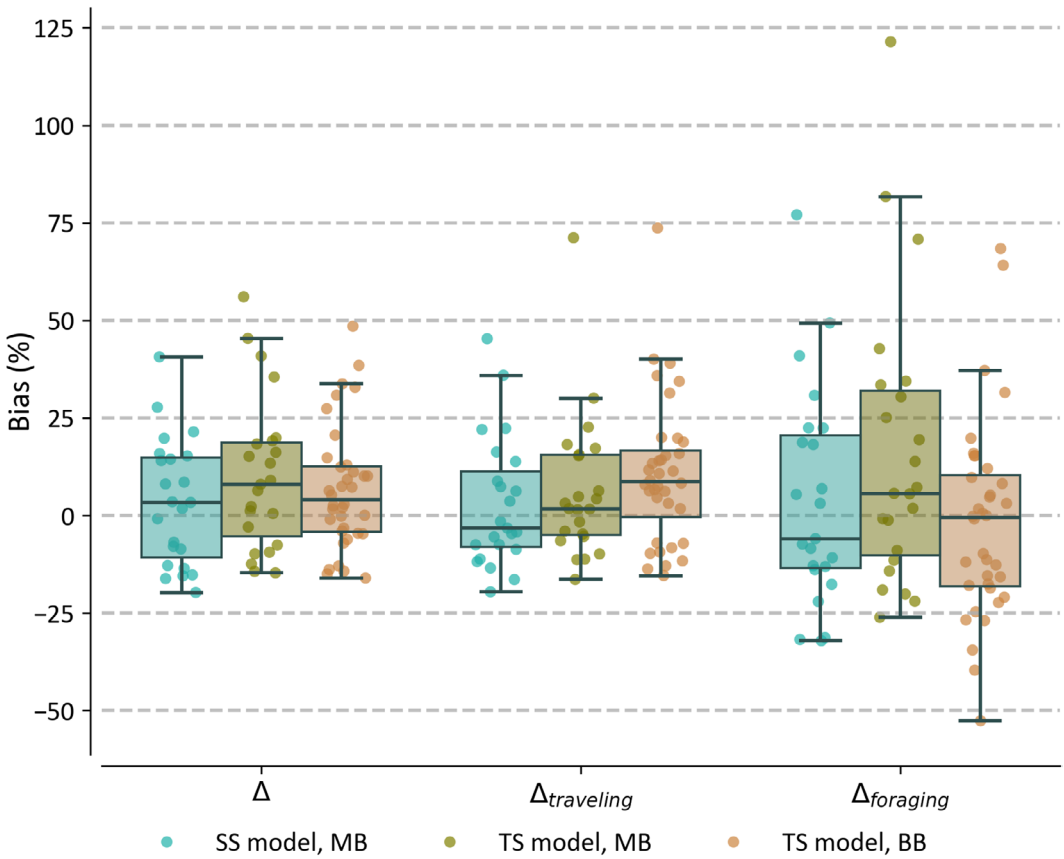

FIGURE 8 Distributions of Overall Dynamic Body Acceleration (ODBA) prediction performance across both evaluation datasets (Masked Boobies (MB) and Brown Boobies (BB)) for the single-species model (SS) and the two-species model (TS).

4 | DISCUSSION

ODBAFormer provides a practical and implementable framework for movement ecology data augmentation by inferring ODBA from GPS data and environmental covariates, enabling the prediction of proxy maps of energy expenditure distribution and energy budget proxies and ODBA time series with minimal error. This opens new possibilities for reanalysing historical datasets where ODBA was not previously measurable, providing a more comprehensive perspective for long-term studies. One of ODBAFormer's key strengths is its ability to operate effectively despite being trained on a relatively small database of a few hundred trajectories, making it a suitable tool for ecological research where data may be scarce, as supported with proper model evaluation conducted on held-out independent datasets (Wilson et al., 2025). Our approach innovates in treating trajectories as spatial distributions rather than purely temporal sequences. By representing GPS points as a spatial density and considering their local neighbourhoods, the model uses transformer architectures' capacity to capture contextual spatial dependencies, allowing it to extract information not only from individual points but also from nearby points in space and their environmental covariates. ODBAFormer thus produces accurate estimates of ODBA distribution in space, allowing the estimation of total expanded energy proxies and then the calculation of the corresponding time series.

In the current literature, there is no established baseline method for the task, aside from the work done by Liu et al. (2019), who used a feed-forward neural network to infer ODBA from temporal depth data in sharks. We selected XGBoost due to its simplicity, widespread use and sufficient predictive power, providing a fair point of comparison. While this is somewhat imperfect, as XGBoost operates on tabular data and uses metrics derived from GPS data rather than the GPS data itself, treats covariates as additional information per GPS position rather than as spatial fields and outputs directly in tabular form, it nevertheless provides valuable insight. The fact that ODBAFormer outperforms XGBoost despite an additional step of linearizing the ODBA density matrix into a time series underscores the strength of our spatially aware approach. Moreover, while we could refine the transformation from ODBA density matrices back to time series using more advanced methods, even a naive reallocation yields great results for global energy budget proxies.

We evaluated ODBAFormer using different combinations of covariates: wind fields, bathymetry maps and a no-covariate scenario to illustrate cases where covariate data is unavailable. The best results were obtained when bathymetry was included as a unique covariate, showing that a simple high-resolution environmental covariate like bathymetry is seemingly enough to provide practical explanatory power that improves inference results. This result also aligns with previous research showing that tropical boobies tend to forage over deep oceanic waters or over continental shelf slopes (Correia et al., 2021; Gilmour et al., 2018; Mendez et al., 2017; Trevail et al., 2024; Weimerskirch et al., 2005), where high-energy density areas are thus located. Interestingly, including covariates that should have a strong explanatory power on ODBA, like wind (Elliott et al., 2014; Gibb et al., 2017; Thorne et al., 2023), does not necessarily improve inference performances. This likely reflects the resolution mismatch between the GPS data and the wind field: the wind dataset used, which was the best available in that geographic area, has a coarse resolution of 0.25° which is on the order of magnitude of the shorter trajectories in our dataset. Although we rescaled the wind fields to preserve as much information as possible, the lack of fine-scale data can lead to poor model performance. This observation emphasizes the importance of accounting for scale mismatch when analysing animal movement relative to environmental fields (Scales et al., 2017), and is also reflective of a known issue in DNNs where a noisy but slightly explicative covariate tends to decrease model generalization performances (Ye et al., 2024). Finally, the covariate ablation study highlights the flexibility of ODBAFormer: any covariates can be introduced as long as their resolution is compatible with the movement data, making the approach transferable to other species and ecological contexts, using covariates, such as for example terrain or vegetation cover that are known to affect energy expenditure of land species (Jonasson et al., 2024; Mosser et al., 2014). Additionally, the no-covariate option, which performs reasonably well, is promising for cases where suitable covariates are unavailable.

Beyond covariate flexibility, cross-species generalization is another key aspect of model performance. For some species, biologging data are sparse, but more complete datasets may exist for a behaviourally similar species. We thus considered a two-species model using Masked Boobies and Brown Boobies because both species are central-place foragers with behaviour differing mainly in the distance they forage from the coast. Their behavioural similarity justified integrating them both indistinctively into a multi-species model. In our study, the single-species model tends to perform better for the species of interest but it requires sufficient data to train separate models if the inference is needed for several, which can be limiting in specific contexts. The multi-species model shows slightly lower performance than specialized single-species models but offers the advantage of allowing inference across multiple species with just one trained model. Overall, these results highlight the trade-off between generalization and specialization, suggesting that the choice between single- and multi-species models should be guided by data availability and the intended scope of inference.

Despite this, generalization remains inherently data-dependent: the evaluation dataset used heavily influences the performance of the model it is evaluated on, so any predictions on completely unseen locations or behaviours should be approached with caution. In our case, we think the trained models can be applied to Masked Booby or Brown Booby data; however, we still recommend evaluating them on independent data where the true ODBA is known before complete application. This provides a realistic estimate of the errors and highlights characteristics of data points that the model may not infer well. For other central-place foraging birds or animals, the model would need to be retrained, potentially including additional covariates relevant to the species, and evaluated before use. For non-central-place foraging animals, the model could still perform reasonably well, although careful validation is advised to ensure generalizability. Beyond transfer to other species, ODBAFormer could estimate true energy expenditure if trained on calibrated ODBA data. Similarly, it can be adapted to VeDBA or other continuous covariates varying across space with appropriate retraining. Finally, the temporal resolution of the GPS data must be considered before applying the model, but this depends on the species and the behaviours being observed. For lower temporal resolutions, the lack of detail in the movement data is expected to increase prediction uncertainty, and at resolutions too coarse to properly distinguish behaviours (in our case, this threshold can be estimated as the average duration of a foraging bout, around 5 min), performance is expected to decrease significantly.

Moreover, ODBAFormer has some limitations by design that should be considered. First, raw model outputs provide information about energy-dense areas, but they do not distinguish between areas of high activity and areas where an animal has lingered for extended periods. While this limitation is minor in our case study data, it may be more relevant in other applications. With appropriate post-processing, more informative maps corresponding to a closer energy landscape proxy can be generated, though this is beyond the scope of the present study. Also, ODBAFormer struggles

to capture extreme ODBA values, whether in the spatial ODBA distributions or in the time series that are reconstructed from it. A contributing factor is that the current approach of converting spatial data into a time series is handled in a relatively naive manner. While this is enough for recovering global energy budget proxies, it lacks accuracy for reconstructing the fine-scale variations in the time series. It is possible that ODBAFormer's performance could improve by using larger input matrices, though this raises additional challenges related to covariate resolution mismatches and significantly increases computational demands. Hence, the input size used in this study (100 × 100) represents a practical compromise between resolution and feasibility. Also, performance in a multi-species model could be improved by introducing label conditioning to distinguish between species during training, which was not implemented in the present study.

Looking ahead, ODBAFormer contributes to a broader effort to rehabilitate legacy datasets, which opens opportunities for multi-year studies and potentially overcoming fieldwork limitations. In the context of biodiversity erosion, the ability to reference decades-old datasets and infer missing data is particularly valuable for long-term ecological comparisons. For Masked and Brown Boobies, a brief examination of the Seabird Tracking Database suggests that at least 12 research teams could benefit from using ODBAFormer as is in its current trained state. There are 1561 Brown Booby trips and 721 Masked Booby trips for which energy expenditure could be inferred, substantially increasing the available data for ecological studies. This approach is also valuable for estimating ODBA for species tracked with remotely downloaded GNSS receivers that cannot transmit accelerometry data due to their high sampling frequency (50–100 Hz), and for researchers who need to rely on low-cost GNSS-only devices because they lack funding for multisensor platforms, although it does not subsidize real-life data acquisition. Altogether, ODBAFormer provides a practical way to make better use of existing tracking data to study animal energetics, serving as a valuable tool for advancing movement ecology research.

AUTHOR CONTRIBUTIONS

Noémie Muquet contributed to the conceptualization of the study, developed the methodology and model, implemented software, carried out the investigation and validation and wrote the original draft of the manuscript. Adrien Brunel was responsible for data curation and database preparation, provided resources, contributed conceptual insights throughout the project, and participated in reviewing and editing the manuscript. Christophe Barbraud, Leandro Bugoni and Karine Delord contributed to data collection and reviewed and edited the manuscript. Guilherme Tavares Nunes contributed to data collection, offered conceptual insights and participated in reviewing and editing the manuscript. Jean-Daniel Zucker and Sophie Lanco supervised the work, provided conceptual guidance and valuable insights, contributed to project administration and funding acquisition, and participated in reviewing and editing the manuscript, while Sophie Lanco also contributed to data collection.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

PEER REVIEW

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1111/2041-210x.70336.

DATA AVAILABILITY STATEMENT

Trained models' weights are archived in Zenodo https://doi.org/10.5281/zenodo.20271369, and the tracking data used to train the models can be provided upon request. This model is built on the Earthformer architecture, available on their GitHub repository https://github.com/amazon-science/earth-forecasting-transformer. The code used in this study is accessible on this GitHub repository https://github.com/noemie-muquet/ODBAFomer-paper, also archived in Zenodo https://doi.org/10.5281/zenodo.19663263.

STATEMENT OF INCLUSION

Our study brings together authors from a number of different countries, including scientists based in Brazil where all the tracking data were gathered. All authors were engaged early on with the research and study design to ensure that the diverse sets of perspectives they represent were considered from the onset.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Figure S1. Plot of GPS trajectories over bathymetry for every data used in this study, separated by fieldwork.

Table S1. Summary of model hyperparameters and training configuration.

Figure S2. Training dynamics for the single-species dataset with bathymetry as covariate.

Figure S3. Histograms and HMM fitted distributions for the Masked Booby evaluation dataset.

Figure S4. Trajectories with segmented states for the Masked Booby evaluation dataset.

Table S2. HMM parameters values for the Masked Booby evaluation dataset.

Figure S5. Histograms and HMM fitted distributions for the Brown Booby evaluation dataset.

Figure S6. Trajectories with segmented states for the Brown Booby evaluation dataset.

Table S3. HMM parameters values for the Brown Booby evaluation dataset.

Figure S7. Distributions of ODBA prediction performances for each covariate combination, including distance to colony.

Table S4. Comparison of ODBA Former performance for different covariate combinations as inputs, including distance to colony.

Figure S8. Distributions of ODBA prediction performances for all the Masked Booby evaluation dataset and partitioned by individual.

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