









# Towards predicting temporal biodiversity change from static data

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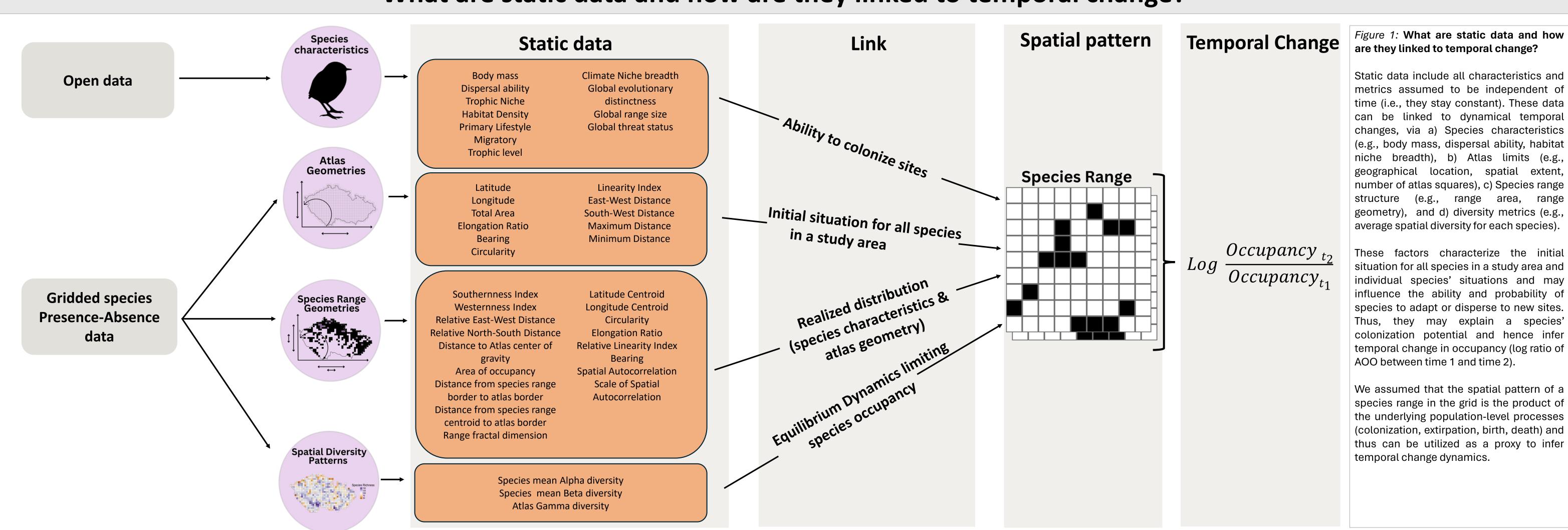
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#### **Objective** Background

The world is experiencing significant environmental transformations, impacting biodiversity and ecosystem functions. Obtaining temporal biodiversity data is challenging due to cost and monitoring limitations. We aim to predict temporal trends in species occupancy using static data, which are considered fixed once recorded, unlike dynamic data requiring continuous updates.

We analyzed static snapshots of species spatial distributions and their covariates from four breeding bird atlases sampled in two time periods (pre-2000 and post-2000). Our goal was to determine the predictive strength of static covariates and the overall predictive ability of the model.

## What are static data and how are they linked to temporal change?



### Methods

#### Data:

We used high-quality breeding bird atlas data from Czech Republic, Japan, New York State, and Europe (N = 841). Data were aggregated over several years for each sampling period. We calculated predictors characterizing species range geometry and structure, diversity metrics, and atlas coverage. External data from various sources were integrated to extract species traits. Temporal change was defined as the log ratio of the area of occupancy (AOO) between the two sampling periods.

#### **Model:**

We developed two complex random forest models to predict the log ratio of AOO. Each model utilized 54 covariates (83 predictors) derived from the two sampling periods for both past and future changes. We used ten resampling splits and k-fold repeated crossvalidation with 10 folds and 5 repeats to ensure robust model results. We identified the top predictors based on their importance across resampling runs, using variable permutation and mean squared error (MSE) decrease (Figure 4). The models' predictive performance was then evaluated against new data (Figure 5).

#### **Occupancy** Turnover (++)stable extinct Athene noctua Emberiza citrinella Corvus corax Vanellus vanellus colonized (Little owl) (Common raven) (Yellowhammer) (Northern lapwing) Figure 2: Examples of temporal change trends. We can differentiate constant occupancy Figure 2: Examples of temporal change trends turnover. Those very different processes are both of Species 100 masked by a stable occupancy trend. Figure 3: Regional occupancy trends by category for birds in Czechia, Europe,

Stable (0): Constant

Figure 3: Regional occupancy trends

Strong decrease

Strong increase

# Results

Birds of New York

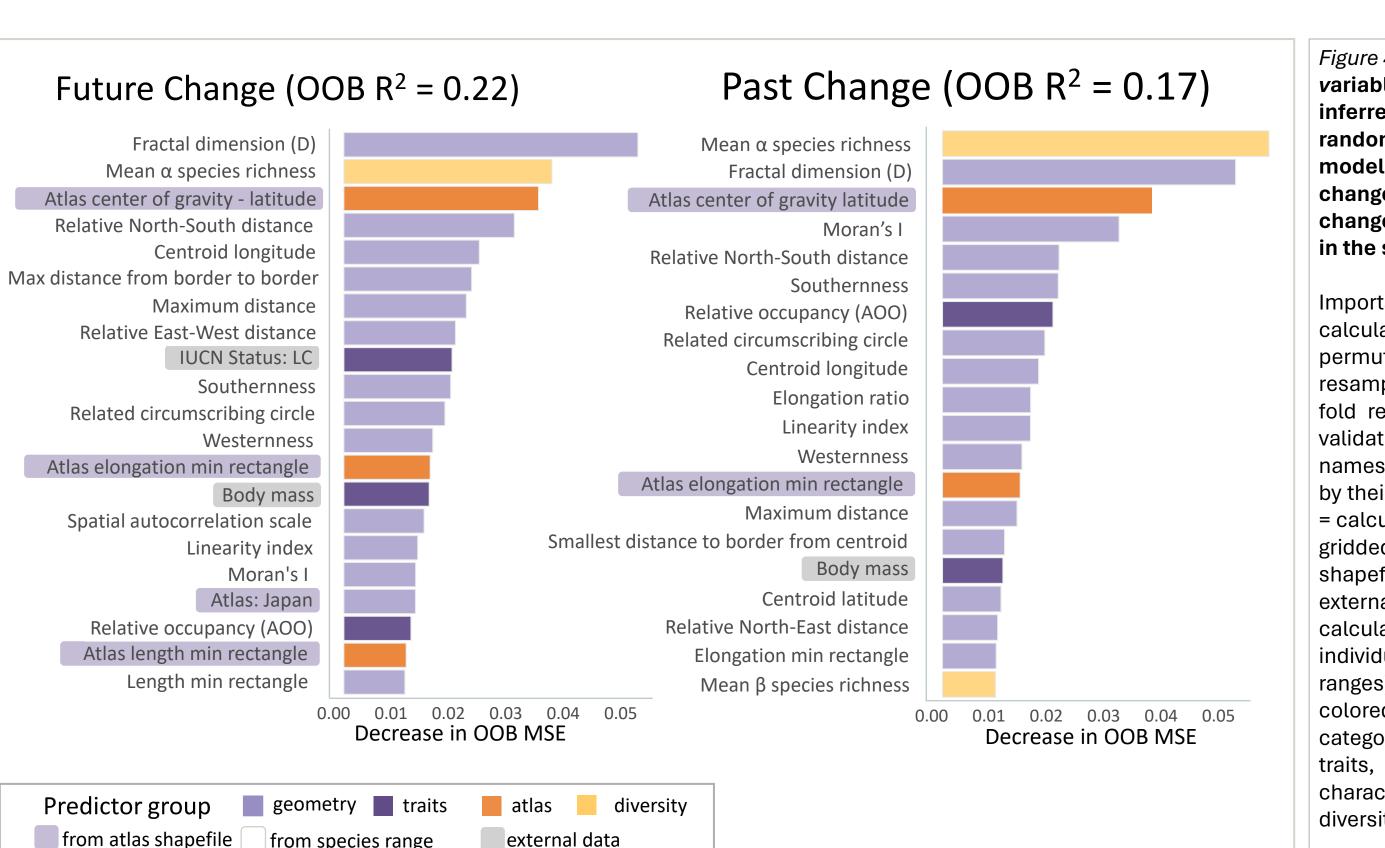


Figure 4: Average variable importance inferred from the random forest model for a) future change and b) past change for all birds in the study.

Japan and New York

state for the first

sampling periods.

Local

Occupancy

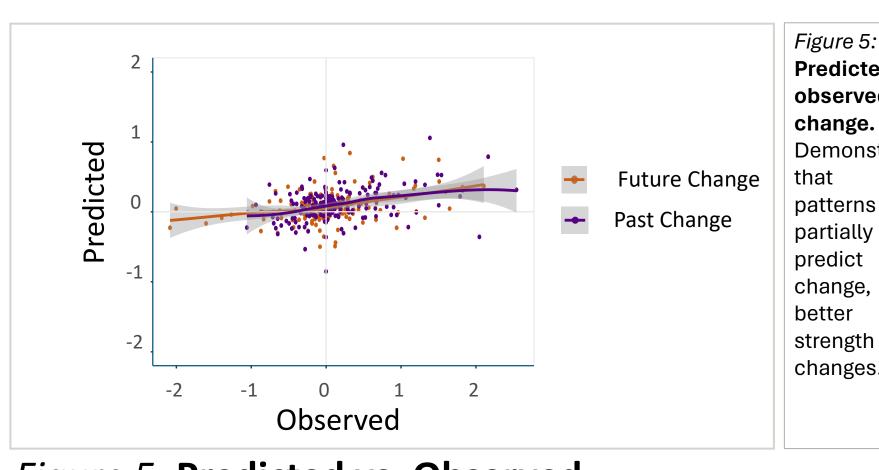
balanced

underlying

Stable (0): Balanced

Importance calculated based on permutation across resamples with kfold repeated crossvalidation. Predictor names are colored by their origin (purple = calculated from the atlas gridded shapefiles, grey = external data, white = calculated individual species ranges) and bars are colored by predictor category (geometry, characteristics, diversity).

## **Discussion & Conclusions**



**Predicted versus** observed change. Demonstrating partially able to temporal predict change, with predictive strength for future changes.

Although static patterns are only partially able to predict temporal change,

we found that the predictive strength lower predicting past change as compared to future change.

Figure 5: Predicted vs. Observed

Interestingly, geometric constraints of the study area and the species distribution enhance model performance significantly, suggesting that processes of temporal change leave signals in static data. Reasons for the weak model performance are potentially the diverse underlying and patterns of stable species (Figure 2), which may be diluting the spatial imprints of temporal change.

Further investigations will involve exploring stable species and adapting the model for the integration of unstructured species range data.



Figure 4: Predicting change from static data: Top Predictors