

# Towards predicting temporal biodiversity change from static data

Friederike J.R. Wölke<sup>1</sup>, Carmen D. Soria<sup>1</sup>, Gabriel R. Ortega Solís<sup>1</sup>, Karel Šťastný<sup>2</sup>, Vladimír Bejček<sup>2</sup>, Ivan Mikuláš<sup>2</sup>, Mutsuyuki Ueta<sup>3</sup> & Petr Keil<sup>1</sup>

<sup>1</sup>Department of Spatial Sciences, Faculty of Environmental Sciences, Czech University of Life Sciences Prague, Praha-Suchdol, Czech Republic  
<sup>2</sup>Department of Ecology, Faculty of Environmental Sciences, Czech University of Life Sciences Prague, Praha-Suchdol, Czech Republic  
<sup>3</sup>Japan Bird Research Association, Fuchu-shi, Tokyo, Japan



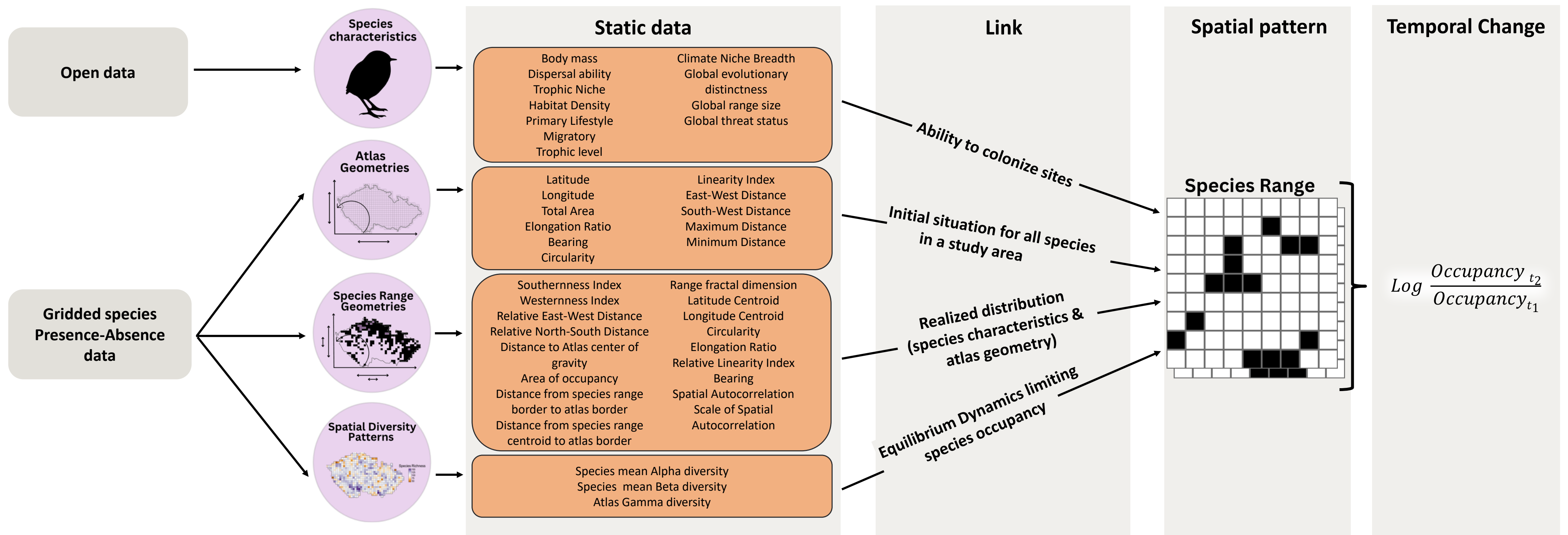
## Background

The world is undergoing significant environmental transformations, impacting biodiversity and ecosystem functions. Since obtaining temporal biodiversity data is challenging due to cost and monitoring limitations, we aimed at predicting temporal trends of species occupancy from static data, which could circumvent the growing need for temporally replicated biodiversity data.

## Objective

Analyzing static snapshots of species spatial distributions and their covariates from four breeding bird atlases that were sampled in two time periods (pre-2000 and post-2000). Determining the predictive strength of static covariates and the predictive ability of the model.

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



## Methods

Figure 2: Examples of temporal change trends

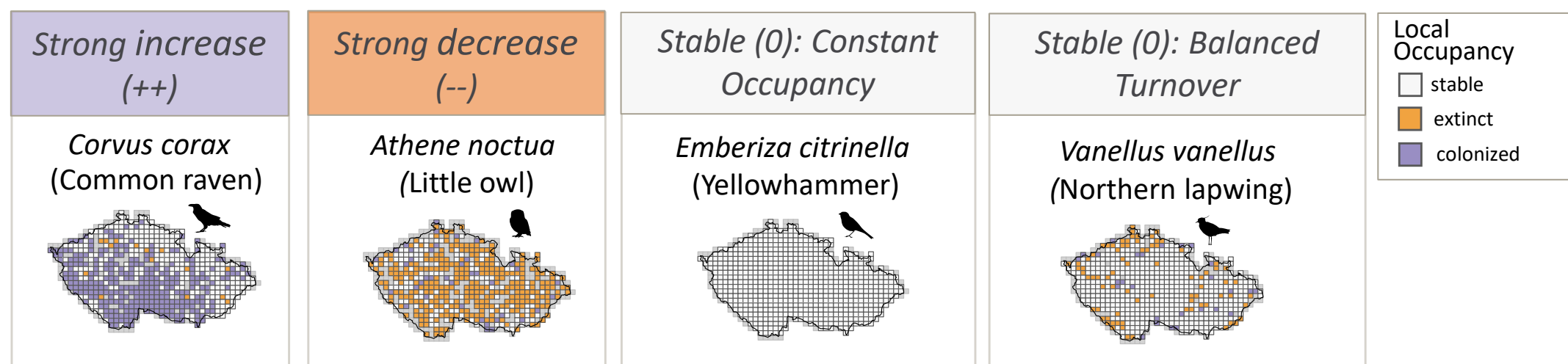
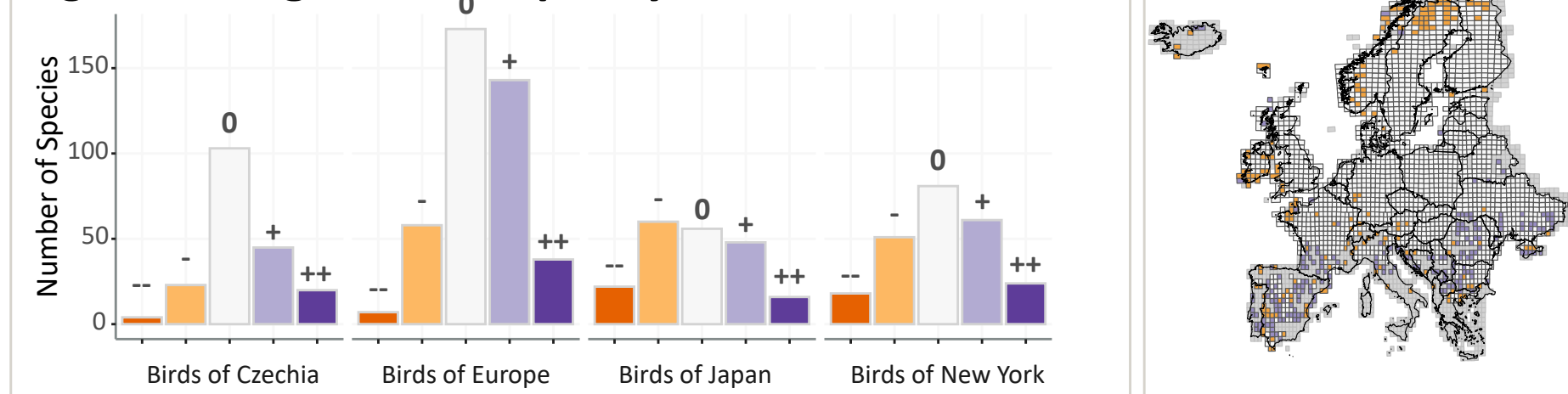


Figure 3: Regional occupancy trends



### Data:

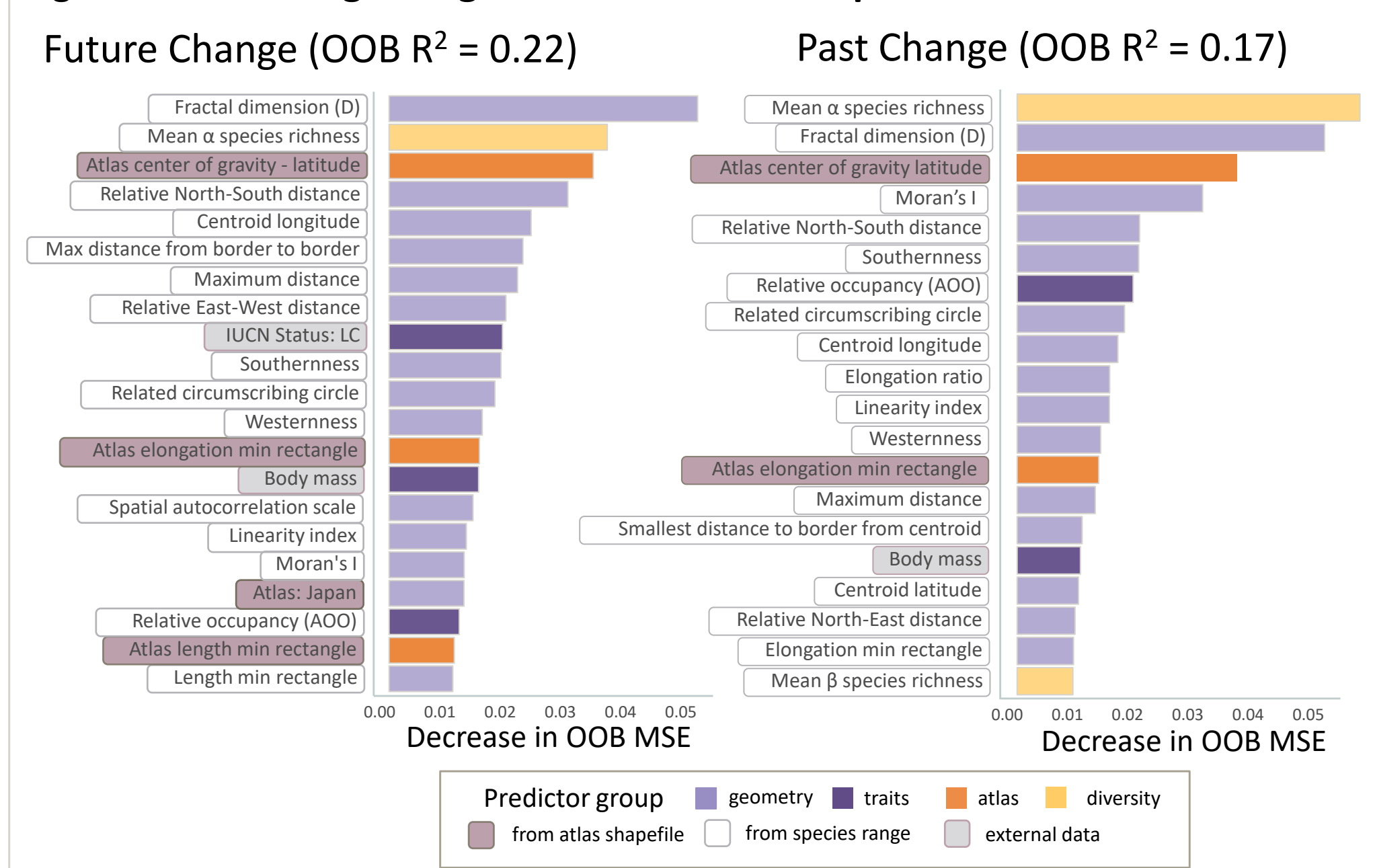
We used high-quality temporally replicated breeding bird atlases for species in Czech Republic, Japan, New York state, and the whole of Europe (N = 841). Atlas data is aggregated to several years each. We calculated predictors characterizing species range geometry, diversity metrics and atlas geometry, and integrated external data to extract species traits (*BirdLife International*, *IUCN*, *AVONET*, *BirdTree* and *CHELSA*). Change was defined as the log ratio of the area of occupancy (AOO) between sampling periods (Figures 2 and 3).

### Model:

We fit two complex random forests with log ratio of AOO as response (Ntree = 1000, Mtry = 42, node size = 5) and 54 covariates (83 predictors) calculated from each of the two sampling periods for past and future change, respectively. We extracted top predictors based on variable permutation and MSE decrease (Figure 4) and assessed the prediction against new data (Figure 5).

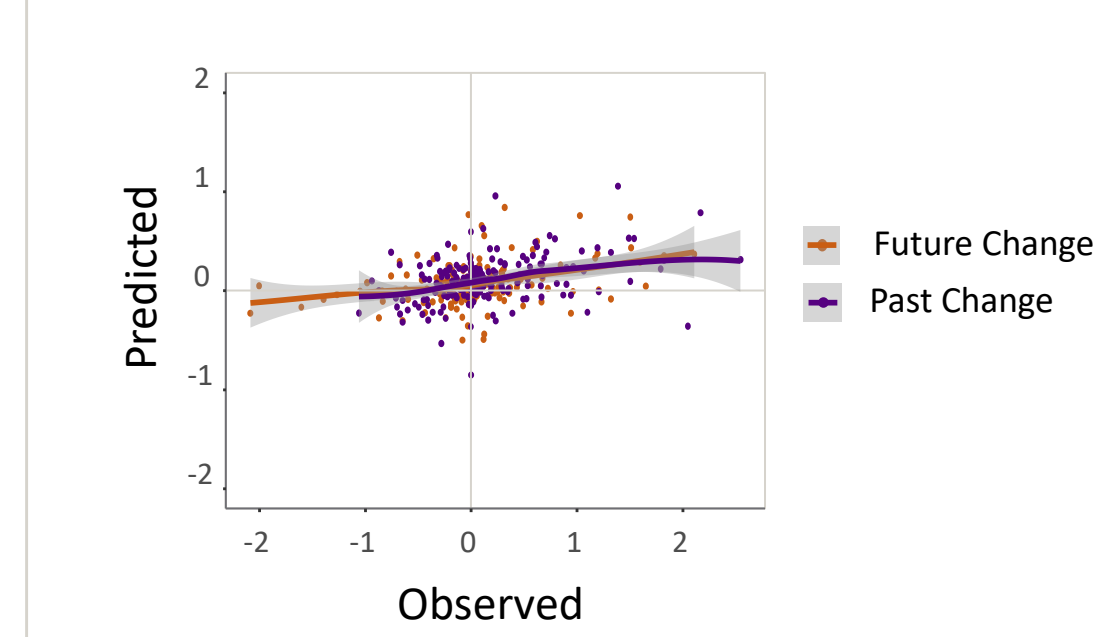
## Results

Figure 4: Predicting change from static data: Top Predictors



## Conclusions

Figure 5: Predicted vs. Observed



Although static patterns are only partially able to predict temporal change (Figure 5), we found that the predictive strength of static patterns is lower when predicting past change as compared to future change (Figure 4).

Interestingly, geometric constraints of the study area and the species distribution explain a high proportion of the predicted change in occupancy. Reasons are probably the diverse underlying processes and patterns of stable species (for examples see Figure 2), which may be diluting the spatial imprints of temporal change. Further investigations will involve exploring those stable species and adapting the model for the integration of unstructured occupancy data.

