Satellite-derived ecosystem functional variables and temporal transferability of bird species distribution models

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SPECIES DISTRIBUTION MODELS AND TEMPORAL TRANSFERABILITY

Species distribution models (SDMs) are today mainly used to predict the impacts of global environmental change on species distribution. However, temporal transferability of SDMs (i.e., the ability of accurately predict species distributions in time) is rarely evaluated prior to predicting species distribution to a different time.

MATERIAL AND METHODS

In this study, we tested if ecosystem functioning variables derived from remote sensing can improve our ability to predict the distribution of 27 bird species (Table 1) within the model calibration period (year 2000), and in a different time frame (year 2010) in a highly dynamic landscape of NW Iberia (Gerês-Xurés Mountains; Fig. 1). To do so, we compared the predictive accuracy of models based on:

1) **Climate variables** were created using the function '*biovars*' available from R-based package '*dismo*' from monthly air temperature and total precipitation.

2) **Land use/cover (LCT) variables** were extracted from optical and thermal multispectral bands of Landsat TM and ETM + images using a hybrid classification procedure.

3) **Ecosystem Functional variables (EFAs)** were derived from the Enhanced Vegetation Index (EVI) obtained from monthly images captured by the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor at a spatial resolution of 0.05◦ × 0.05◦ (approx. 230 meters).

A new set of models were developed by combining the environmental suitability predicted from the trivariate models as predictors to integrate **all possible combinations of these three dimension of the ecological niches of species** within the modelling framework: 4) Climate + Land cover, 5) Clim + EFAs; 6) Land cover + EFAs, and 7) Clim + Land cover + EFAs.

Acronym	Scientific name
CPAL	*Columba palumbus*
CCAN	*Cuculus canorus*
AARV	*Alauda arvensis*
TTRO	*Troglodytes troglodytes*
PMOD	*Prunella modularis*
ERUB	*Erithacus rubecula*
STOR	*Saxicola torquata*
TMER	*Turdus merula*
SUND	*Sylvia undata*
SCOM	*Sylvia communis*
SATR	*Sylvia atricapilla*
PIBE	*Phylloscopus ibericus*
RIGN	*Regulus ignicapilla*
PCRI	*Parus cristatus*
PATE	*Parus ater*
PMAJ	*Parus major*
LCOL	*Lanius collurio*
GGLA	*Garrulus glandarius*
FCOE	*Fringilla coelebs*
SSER	*Serinus serinus*
CCANN	*Carduelis cannabina*
ECIA	*Emberiza cia*
STUR	*Streptopelia turtur*
CBRA	*Certhia brachydactyla*
OORI	*Oriolus oriolus*
CCHL	*Carduelis chloris*
PVIR	*Picus viridis*

Table. 1. List of target bird species.

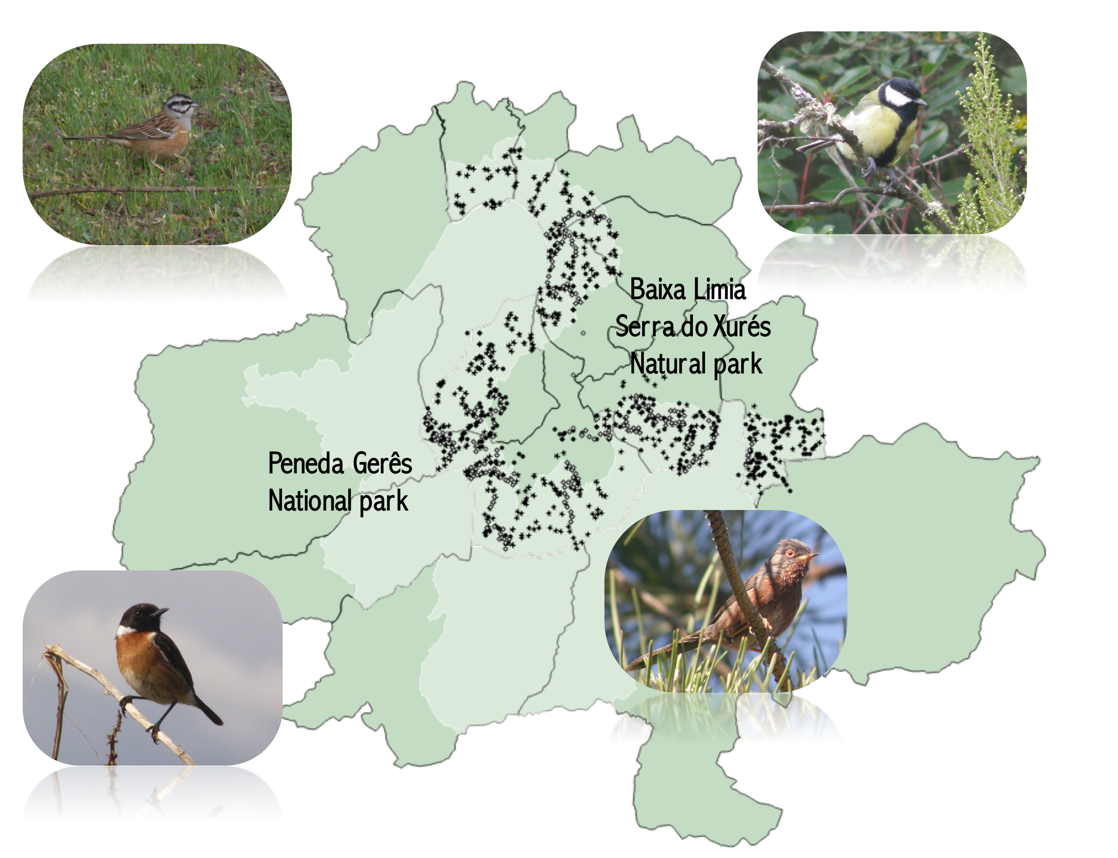


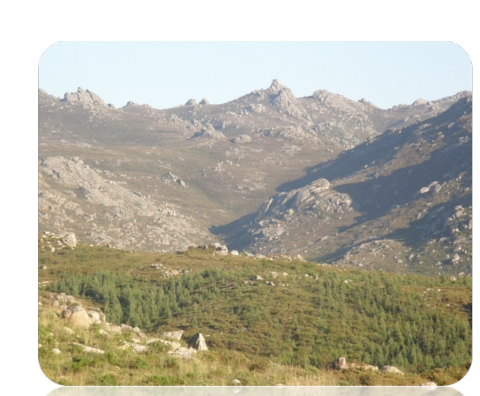
Fig. 1. Transboundary Biosphere Reserve Gerês – Xurés. Spatial distribution of the bird surveys carried out in year 2000 and 2010.

Type		Predictors
Climate		Maximum temperature of warmest month
		Total (annual) precipitation
		Precipitation seasonality (coefficient of variation)
Ecosystem functioning		Productivity indicator: EVI annual mean, a estimator of annual primary production.
		Seasonality indicator: EVI seasonal standard deviation, a descriptor of the difference in carbon gains between season.
		Phenological indicator: the date of the maximum EVI value, a indicator for the peak of the growing season, i.e. indicates the more productive month during the year.
Land use/cover		Percentage of forest
		Percentage of shrublands
		Percentage of croplands

Table. 2. Brief description of predictors used for species distribution modelling.

Bird community in the study region was surveyed in 2000 and 2010 (Fig. 1, and Table 1) using two different sampling methodologies:

1) a set of 344 5-min point counts with unlimited distance carried out in year 2000 ('crossvalidation'). This initial dataset was partially replicated in 2010 by re-sampling a subset of 204 5-min point counts to evaluate temporal transferability (TT) of SDMs ('TT internal'); simultaneously,
2) another set of 384 20-min point counts with a limited distance of 80 meters was surveyed two times along the spring of 2010 to form spatiotemporal independent samples ('TT external').



RESULTS

Our results showed that models developed with the three sets of predictors were all useful for describing the distribution of our target species ($AUC_{Climate}$ = 0.889 ± 0.104; AUC_{EFA} = 0.867 ± 0.117; AUC_{LCT} = 0.873 ± 0.071; Figs. 2 and 3). The combination of climate, land cover and ecosystem functional variables increased substantially the model performance within the calibration time frame (AUC_{mean} up to 0.98).

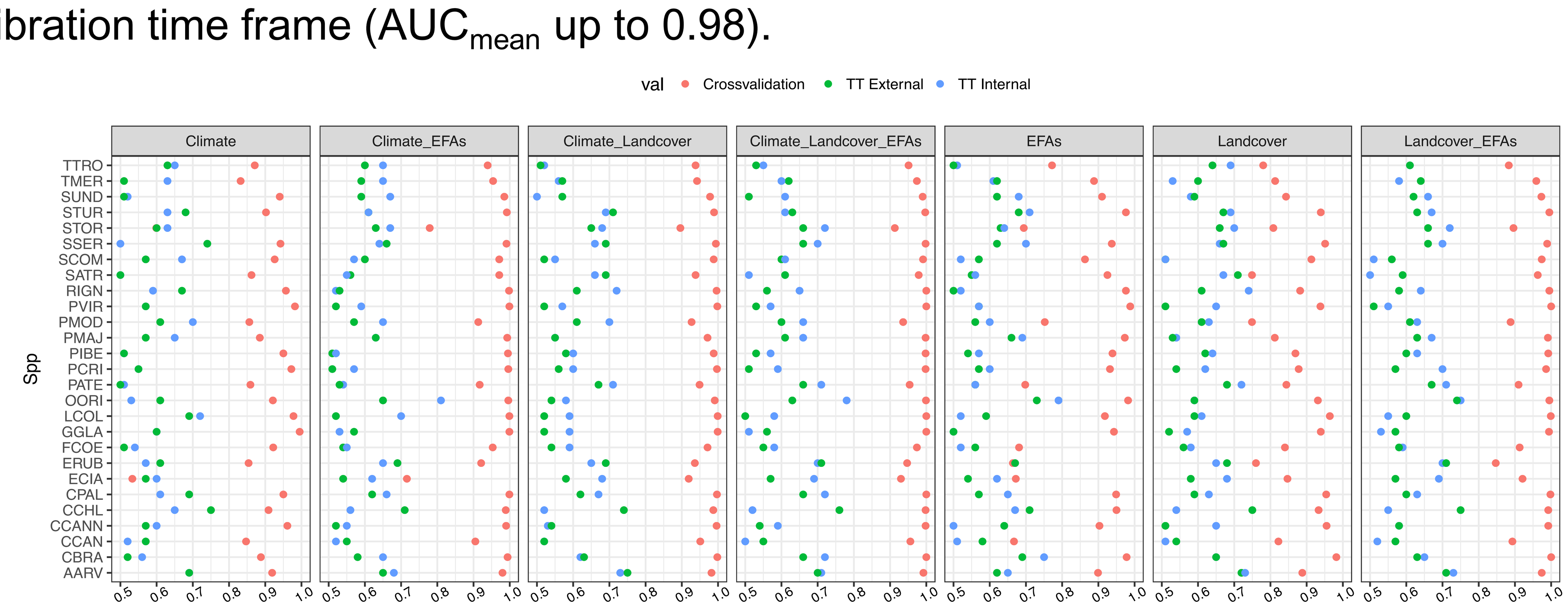


Fig 2. AUC value for each species and each model (single-predictor models and combined models) obtained for crossvalidation ('Crossvalidation'), internal ('TT internal') and external temporal transferability ('TT External').

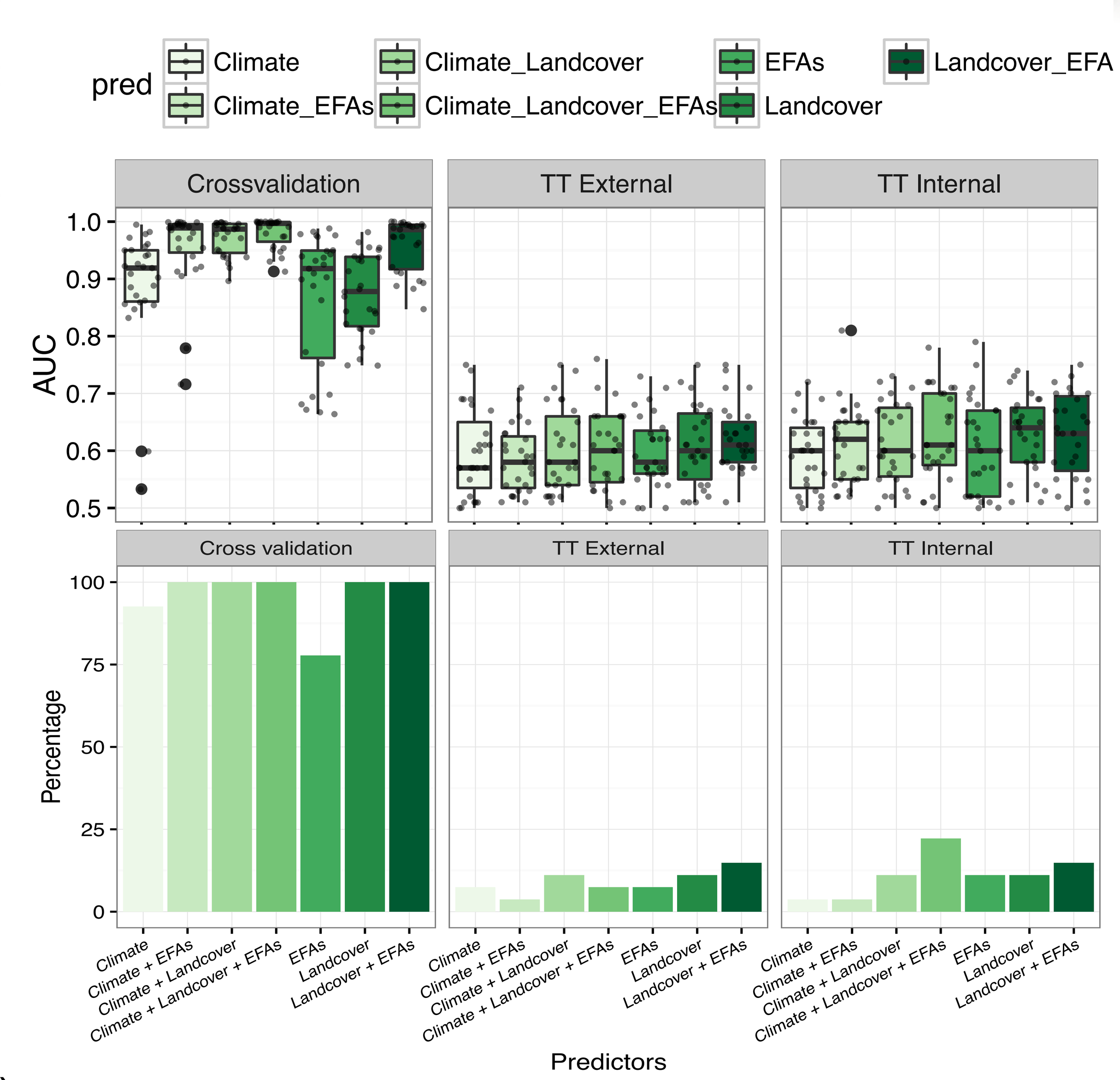


Fig. 3. Model performance (AUC value and number of species with AUC up 0.7) of each models (single-predictor models and combined models) for crossvalidation ('Crossvalidation'), internal ('TT internal') and external temporal transferability ('TT External').

However, the low temporal transferability (AUC higher than 0.7 for less than 25% of species; Fig. 3) indicates that our ability to predict distributional shifts is limited.

CONCLUSIONS

We strongly emphasize the need for caution when using SDMs to predict shifts in bird distributions since a high discriminative power within the calibration timeframe does not guarantee a model's ability to predict the future.

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