ASSESSING SPATIOTEMPORAL RESOLUTION OF VARIABLES IN LANDSCAPE-SCALE SPECIES DISTRIBUTION MODELS

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1. INTRODUCTION & OBJECTIVES

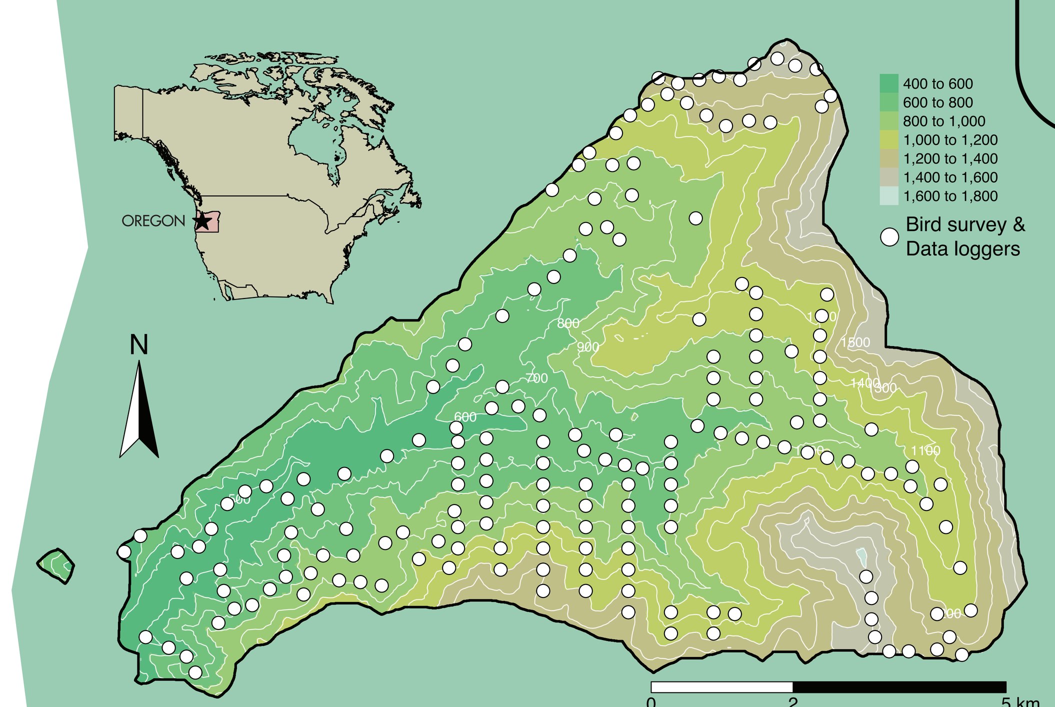
Species distribution models (SDM) are commonly used to predict the future of biodiversity under **global change**

However, frequently **only one year** or **a few years** of data are used in modeling

Finer spatiotemporal resolution and **long-term data** could be key **ecological goals** to improve reliability and predictions of SDMs

O1 Build landscape scale **SDMs** using 10-years **microclimate data**
O2 Compare 3 **modeling frameworks** based on the temporal resolution of predictors
O3 Assess the **intra-** and **inter-annual accuracy** of the frameworks

2. METHODS



HJ ANDREWS EXPERIMENTAL FOREST
6,478 ha | Old-growth temperate rainforest
Cascade mountains, Oregon, USA

SPECIES OCCURRENCE

29 bird species
182 annual obs. | 10 years
(2010-2019)

PREDICTORS

Vegetation (n = 10)
(LiDAR-derived)

Microclimate temperatures (n = 56)
monthly-seasonal (data loggers)

DYNAMIC SDMs

BARTs

3 FRAMEWORKS

Random-year = a ramdom year of observation
Weighted-year = sum of occurrences across the years & temporal occupancy (abundance) as weight
Long-term ensemble = ensemble of annual models (mean of the probability of presence)

ACCURACY ASSESSMENT

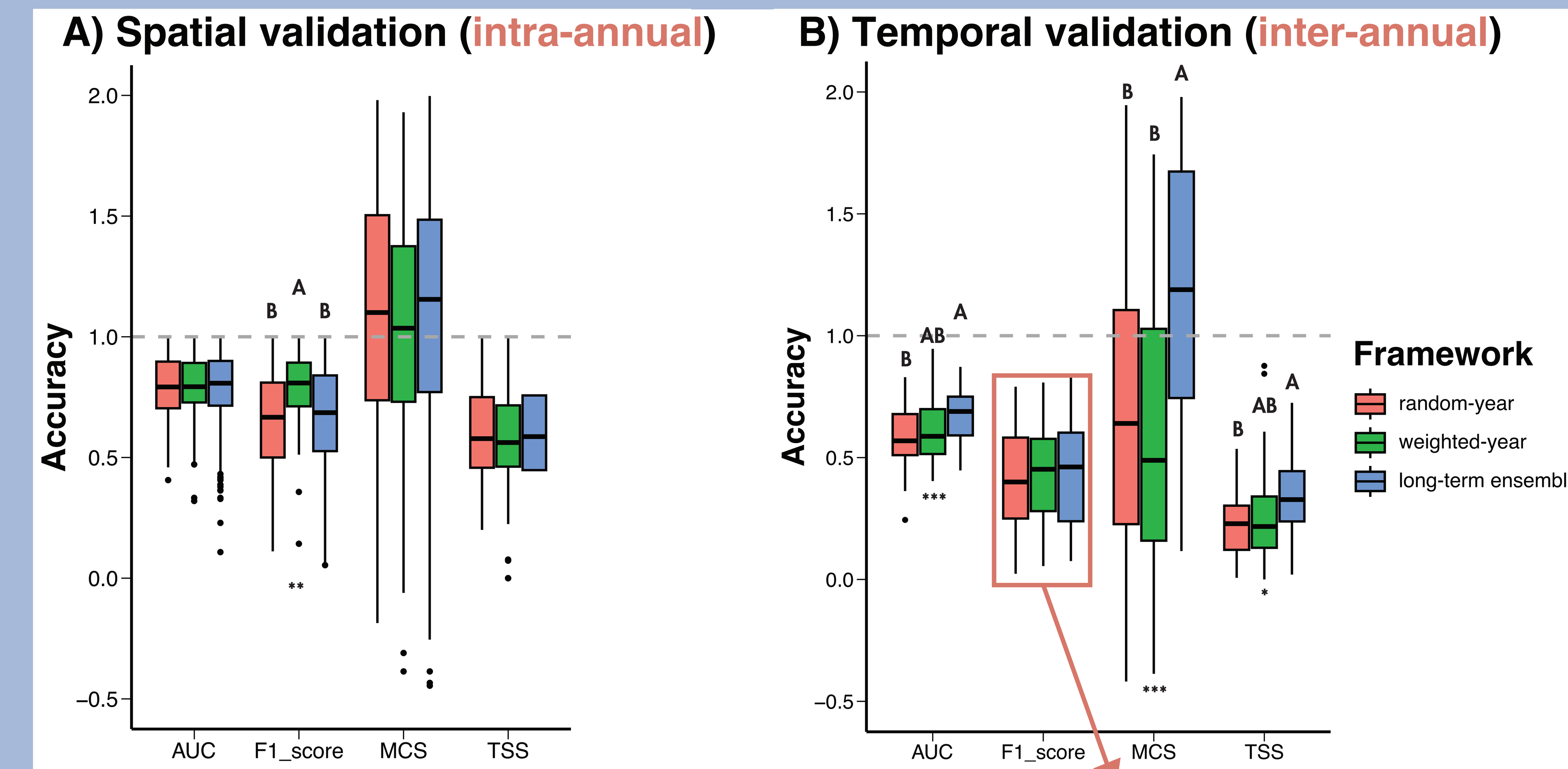
(spatial & temporal)

Generalized linear mixed models:
accuracy ~ framework * size * migration
Random effects = species, family

SPATIAL PREDICTIONS

Visual comparison of predictions

3. RESULTS



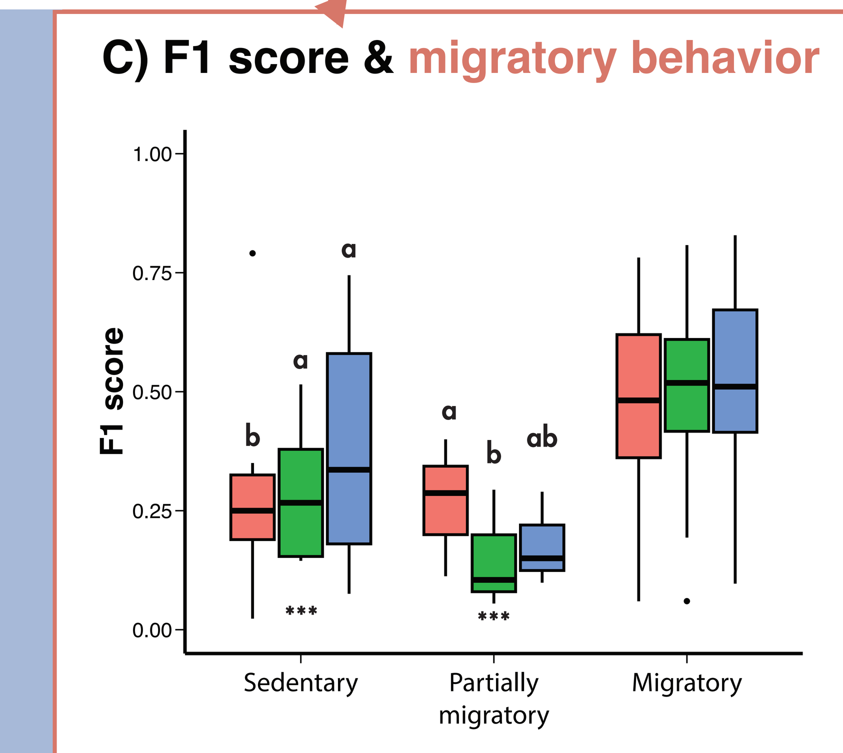


Fig. 1 - Results of GLMM on different accuracy metrics for **(a)** spatial (intra-annual) validation and **(b)** temporal (inter-annual) validation. Letters indicate significant differences among the groups according to a Tukey post-hoc test with Bonferroni adjustment. **(c)** F1 score for the temporal validation tested on different migratory behaviors of the species.

Small differences among the frameworks for **spatial (intra-annual) validations**

Differences in **accuracy** (AUC, TSS) and **calibration** (MCS) for the **temporal (inter-annual) validation**

Long-term ensemble performs better for inter-annual interpolations

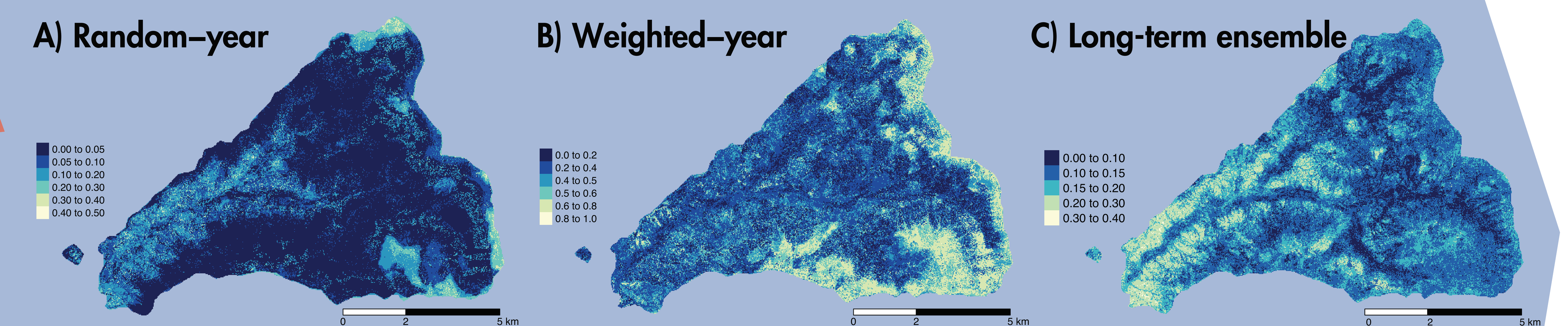


Fig. 2 - Spatial predictions on the HJ Andrews forest of the probability of presence of the Black-headed grosbeak for **(a)** the random-year approach (2017), **(b)** the weighted-year approach (2010-2019), and **(c)** the long-term ensemble framework.

Some species show **very different spatial predicions** of probability of presence among the 3 frameworks (e.g., black-headed grosbeak)

Binary maps!!

4. CONCLUSION

Accuracies = long-term ensemble seems to be **the most accurate** modeling framework

Predictions = **binary maps** need to be created, calculate e.g. the **distance** between probability distribution

To-do = integrate **more species** (~70 spp.), **ecological interpretation** of predictions

Fine spatiotemporal predictors are essential to monitor and predict changes in the distribution of species **at the landscape scale** according to future global changes (i.e., climate change)

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