Building a better metaweb: predicting spatiotemporally explicit plant-pollinator networks

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Purpose: This template provides a series of scripts to render a markdown document into an interactive website and a series of PDFs.

Motivation: It makes collaborating on text with GitHub easier, and means that we never need to think about the output.

Internals: GitHub actions and a series of python scritpts. The markdown is handled with pandoc.

1 Abstract

- 2 Using a data set of [DESCRIBE EACH DATASET IN A NICE WAY], we predict a spatiotemporally explicit
- metaweb of interactions between bumblebees (Bombus) and wildflowers (within find clade). We integrate
- 4 this data with crowdsourced occurrence data and climate data to [best paint the picture of the Colorado
- 5 bumblebee-plant metaweb]. Using temporal climate data, we forecast how the spatiotemporal overlap of
- 6 interacting species will change under proposed climate scenarios. We use this to estimate what
- 7 interactions between bees and plants need the most attention to prevent the spatiotemporal decoupling of
- 8 an interactions from threatening ecosystem functioning or the persistence of a species.

9 Introduction

- 10 Species interactions are important. It is ultimately interactions between individuals of different species
- that drive the structure, dynamics, and persistence of ecosystems, and the abundance and diversity of the
- species within them. Plant-pollinator interactions specifically drive the function and persistence of
- "architecture of biodiversity" (Bascompte & Jordano 2007). However, we are far from a robust
- understanding of plant-pollinator networks. This is because sampling interactions is costly. Interactions
- vary in space and time (Poisot et al. 2015)—particularly relevent in this system (CaraDonna et al. 2014).
- 16 This is why there is interest in using models to predict interactions from sparse data (**Strydom2021?**). In
- this paper, we combine several datasets, each spanning several years, to produce spatially and temporally
- explicit predictions of the bumblebee (genus *Bombus*) and wildflower pollination network across the state
- 19 of Colorado.
- 20 We do this in two parts: (1) metaweb prediction and (2) conditioning our metaweb prediction on
- 21 co-occurrence probability. First, we build a model to predict the metaweb—the network of all
- 22 interactions, aggregated across all times and spatial locations—of *Bombus* and wildflower species across
- ²³ Colorado. (Why do this? The metaweb is more predictable than local interactions.) We do this using
- network embedding (cite?). Network embedding takes each node in the network (either a bumblebee or a
- ²⁵ wildflower) and represents it in a latent *n* dimensional space. Combination of running models on
- Temporal niche (T), Phylogenetic niche (P), Environmental niche (E), and relative abundance in
- 27 community (RA).

- 28 Second, we then use this metaweb to predict the structure of networks at specific locations and times of
- 29 year (Gravel et al. 2019). Finally we suggest a map of sampling priority, which suggests the locations to
- sample that will best improve our understanding of the Colorado *Bombus* pollination metaweb.
- 31 Why is this good for science, what does this contribute to our understanding of plant-pollinator ints,
- networks, Bombus, predictive models, etc., and how can these results be useful.

Data

34 We use three separate field datasets to estimate the Colorado *Bombus* metaweb.

35 Methods

36

[Figure 1 about here.]

37 Metaweb Model

- 38 Feature Embedding
- 39 Relative Abundance
- 40 Phylogenetic features
- Phylogeny Construction We construct phylogenies for both *Bombus* and wildflower species using
- barcode markers, mitochondrial COI and chloroplast rbcL, respectively. These sequences were obtained
- 43 from NCBI GenBank for all species. For species for which no sequence was available (only a handful of
- 44 plants), their was substituted with a barcode from a member of the same genus. Justify why this is fine
- 45 here.
- 46 These sequences were aligned using ClustalOmega v???, and then a posterior distribution of phylogenies
- and consensus tree was obtained via MrBayes v??, using XX substition model with gamma-distributed
- rates. Run until convergence, which here we define as the standard-deviation of splits falling below 0.1.

49 **Creating an embedding from phylogenies** We simulate traits.

50 Environmental niche features

- 51 We take the 19 BioClim layers from CHELSA (cite; 1km resolution) and a map of elevation and PCA them.
- A resulting 4 layers cover 99.5% of the variance. We use species occurrence data from GBIF, and consider
- each occurrence record as a point in environment space. Then we fit a multivariate normal distribution to
- these points in environmental space.

55 Temporal niche features

- We take the mean and variance of the distribution of number of observations per week of year in the
- 57 interaction field data.

58 Metaweb Model Fitting and Validation

- 59 We fit a bunch of models using MLJ.jl.
- 60 Some of them are bagged, some are not bagged.
- 61 AUC-ROC and AUC-PR values below in fig. 2

[Figure 2 about here.]

63 Spatiotemporally Explicit Networks

- Now that we have a metaweb.....
- 65 Figure 3: Maps over time figure and Prob(Connectance) vs. Month figure

66 Sampling Prioiritization

67 Figure 4: Uncertainty and sampling priority map

68 Discussion

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- through space and time. Oikos, 124, 243–251.

Embedding Models Predicted Metaweb Phylogenetic Embedding Logistic Regression Relative Abundance Embedding Neural Network **₹** Model fitting and validation ADABoost Regression Environment Niche Embedding **Boosted Regression Tree** Random Forest Temporal Niche Embedding Ensemble Model Time of Year **Spatiotemporal Network Prediction** Interaction probability Spatial Co-occurrence probability Temporal Co-occurrence probability

Metaweb Prediction

Figure 1: todo

	ROC-AUC									PR-AUC						
T+P+E+R	0.75	0.72	0.84	0.85	0.86	0.87	0.87	T+P+E+R	0.55	0.47	0.67	0.58	0.70	0.73	0.71	
T+E+R	0.76	0.78	0.84	0.83	0.85	0.87	0.86	T+E+R	0.52	0.53	0.67	0.57	0.68	0.71	0.69	
P+E+R	0.75	0.71	0.85	0.84	0.85	0.88	0.87	P+E+R	0.53	0.46	0.69	0.57	0.68	0.74	0.70	
T+P+E	0.73	0.70	0.82	0.84	0.80	0.86	0.86	T+P+E	0.51	0.44	0.65	0.67	0.61	0.71	0.68	
T+P+R	0.75	0.71	0.84	0.83	0.86	0.86	0.87	T+P+R	0.53	0.42	0.68	0.58	0.70	0.72	0.70	
E+R	0.75	0.77	0.85	0.82	0.85	0.87	0.86	E+R	0.49	0.53	0.67	0.59	0.65	0.70	0.68	
P+R	0.75	0.71	0.85	0.84	0.86	0.88	0.87	P+R	0.52	0.46	0.69	0.61	0.69	0.73	0.70	
T+R	0.75	0.77	0.84	0.81	0.85	0.85	0.85	T+R	0.49	0.52	0.68	0.53	0.68	0.69	0.68	
T+P	0.70	0.71	0.81	0.83	0.81	0.85	0.85	T+P	0.47	0.46	0.63	0.64	0.59	0.68	0.66	
T+E	0.65	0.60	0.82	0.83	0.81	0.84	0.84	T+E	0.41	0.32	0.64	0.64	0.63	0.66	0.67	
P+E	0.71	0.70	0.82	0.85	0.79	0.87	0.86	P+E	0.50	0.44	0.62	0.68	0.54	0.70	0.66	
R	0.77	0.77	0.85	0.80	0.84	0.82	0.84	R	0.52	0.52	0.68	0.47	0.67	0.64	0.65	
Е	0.64	0.52	0.79	0.81	0.80	0.81	0.82	Е	0.35	0.23	0.56	0.57	0.56	0.59	0.59	
Р	0.69	0.71	0.80	0.82	0.77	0.84	0.84	Р	0.44	0.44	0.57	0.59	0.52	0.63	0.61	
Т	0.57	0.57	0.80	0.80	0.80	0.82	0.82	Т	0.31	0.31	0.59	0.57	0.61	0.62	0.63	
	Logistic	Neural Network	ADABoost	Decision Tree	Boosted Regression Tree	Random Forest	Ensemble		Logistic	Neural Network	ADABoost	Decision Tree	Boosted Regression Tree	Random Forest	Ensemble	

Figure 2: todo