Building a better metaweb: predicting spatially and temporally explicit alpine plant-pollinator interaction networks

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0.1. Abstract 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 this data with crowdsourced occurrence data and climate data to [best paint the picture of the Colorado bumblebee-plant metaweb]. Using temporal climate data, we forecast how the spatiotemporal overlap of interacting species will change under proposed climate scenarios. We use this to estimate what interactions between bees and plants need the most attention to prevent the spatiotemporal decoupling of an interactions from threatening ecosystem functioning or the persistence of a species.

1 ─────────────────────────────

Introduction

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)—particularlly relevent in this system (CaraDonna *et al.* 2014). 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 of Colorado.

We do this in two parts: (1) metaweb prediction and (2) conditioning our metaweb prediction on co-occurrence probability. First, we build a model to predict the metaweb—the network of *all* interactions, aggregated across all times and spatial locations—of *Bombus* and wildflower species across Colorado.
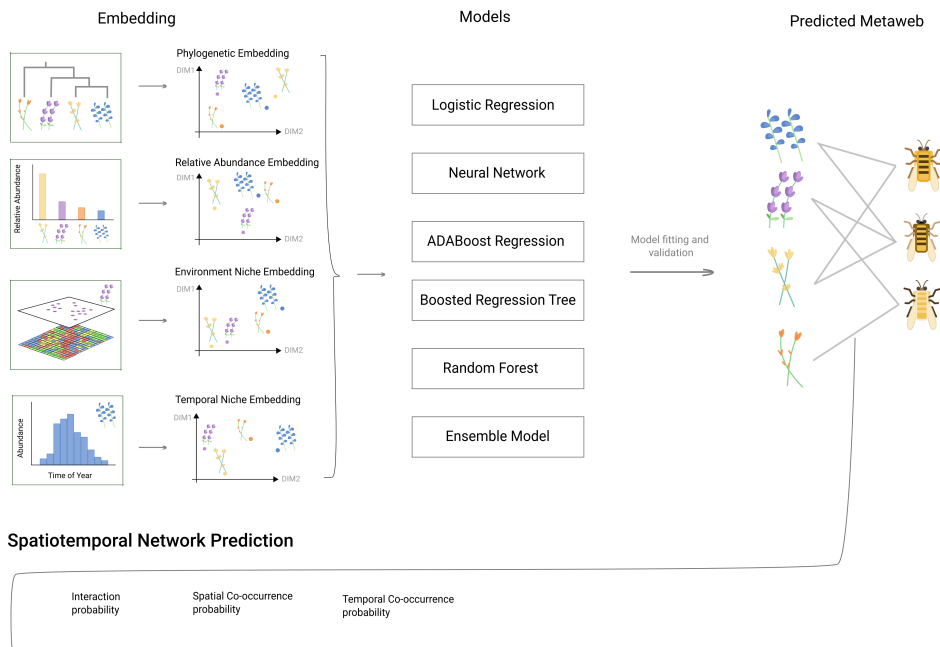
Metaweb Prediction

Embedding

Models

Predicted Metaweb

Phylogenetic Embedding

Relative Abundance Embedding

Environment Niche Embedding

Temporal Niche Embedding

Logistic Regression

Neural Network

ADABoost Regression

Boosted Regression Tree

Random Forest

Ensemble Model

Model fitting and validation

Figure 1 todo

Spatiotemporal Network Prediction

Interaction probability

Spatial Co-occurrence probability

Temporal Co-occurrence probability

(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 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 community (RA).

Second, we then use this metaweb to predict the structure of networks at specific locations and times of 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.

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.

2
Data

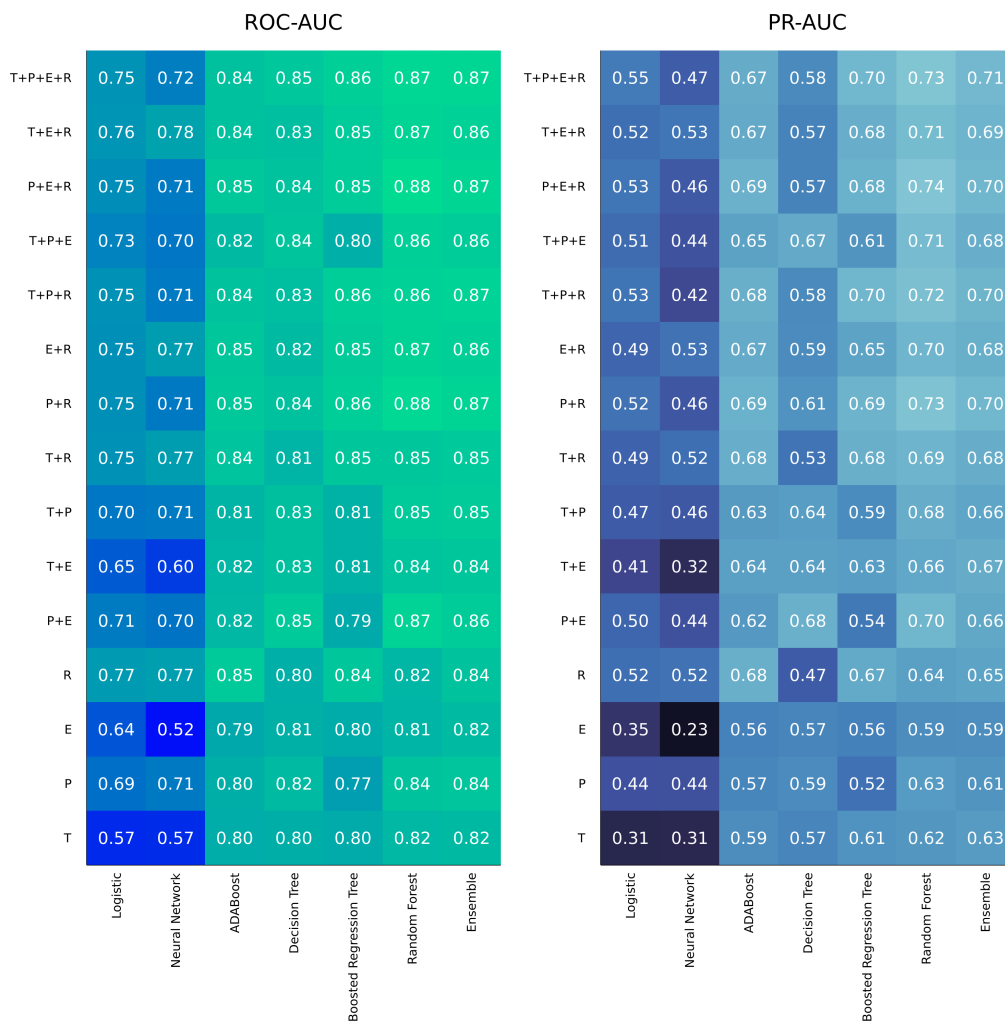We use three separate field datasets to estimate the Colorado *Bombus* metaweb.

3
Methods

4
Metaweb Model

4.1. Phylogeny Construction

4.2. Feature Embedding

ROC-AUC

	Logistic	Neural Network	ADABoost	Decision Tree	Boosted Regression Tree	Random Forest	Ensemble
T+P+E+R	0.75	0.72	0.84	0.85	0.86	0.87	0.87
T+E+R	0.76	0.78	0.84	0.83	0.85	0.87	0.86
P+E+R	0.75	0.71	0.85	0.84	0.85	0.88	0.87
T+P+E	0.73	0.70	0.82	0.84	0.80	0.86	0.86
T+P+R	0.75	0.71	0.84	0.83	0.86	0.86	0.87
E+R	0.75	0.77	0.85	0.82	0.85	0.87	0.86
P+R	0.75	0.71	0.85	0.84	0.86	0.88	0.87
T+R	0.75	0.77	0.84	0.81	0.85	0.85	0.85
T+P	0.70	0.71	0.81	0.83	0.81	0.85	0.85
T+E	0.65	0.60	0.82	0.83	0.81	0.84	0.84
P+E	0.71	0.70	0.82	0.85	0.79	0.87	0.86
R	0.77	0.77	0.85	0.80	0.84	0.82	0.84
E	0.64	0.52	0.79	0.81	0.80	0.81	0.82
P	0.69	0.71	0.80	0.82	0.77	0.84	0.84
T	0.57	0.57	0.80	0.80	0.80	0.82	0.82

PR-AUC

	Logistic	Neural Network	ADABoost	Decision Tree	Boosted Regression Tree	Random Forest	Ensemble
T+P+E+R	0.55	0.47	0.67	0.58	0.70	0.73	0.71
T+E+R	0.52	0.53	0.67	0.57	0.68	0.71	0.69
P+E+R	0.53	0.46	0.69	0.57	0.68	0.74	0.70
T+P+E	0.51	0.44	0.65	0.67	0.61	0.71	0.68
T+P+R	0.53	0.42	0.68	0.58	0.70	0.72	0.70
E+R	0.49	0.53	0.67	0.59	0.65	0.70	0.68
P+R	0.52	0.46	0.69	0.61	0.69	0.73	0.70
T+R	0.49	0.52	0.68	0.53	0.68	0.69	0.68
T+P	0.47	0.46	0.63	0.64	0.59	0.68	0.66
T+E	0.41	0.32	0.64	0.64	0.63	0.66	0.67
P+E	0.50	0.44	0.62	0.68	0.54	0.70	0.66
R	0.52	0.52	0.68	0.47	0.67	0.64	0.65
E	0.35	0.23	0.56	0.57	0.56	0.59	0.59
P	0.44	0.44	0.57	0.59	0.52	0.63	0.61
T	0.31	0.31	0.59	0.57	0.61	0.62	0.63

Figure 2 todo

4.2.1 Relative Abundance

4.2.2 Phylogenetic features

4.2.3 Environmental niche features

4.2.4 Temporal niche features

4.3. Metaweb Model Fitting and Validation

5

Spatiotemporally Explicit Networks

Now that we have a metaweb…..

Figure 3: Maps over time figure and Prob(Connectance) vs. Month figure

6 _____

Sampling Prioiritization

Figure 4: Uncertainty and sampling priority map

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Discussion

Bascompte, J. & Jordano, P. (2007). Plant-Animal Mutualistic Networks: The Architecture of Biodiversity. *Annual Review of Ecology, Evolution, and Systematics*, 38, 567–593.

CaraDonna, P.J., Iler, A.M. & Inouye, D.W. (2014). Shifts in flowering phenology reshape a subalpine plant community. *Proceedings of the National Academy of Sciences*, 111, 4916–4921.

Gravel, D., Baiser, B., Dunne, J.A., Kopelke, J.-P., Martinez, N.D., Nyman, T., *et al.* (2019). Bringing Elton and Grinnell together: A quantitative framework to represent the biogeography of ecological interaction networks. *Ecography*, 42, 401–415.

Poisot, T., Stouffer, D.B. & Gravel, D. (2015). Beyond species: Why ecological interaction networks vary through space and time. *Oikos*, 124, 243–251.