# Template to prepare preprints and manuscripts using markdown and github actions

Michael D. Catchen 1,2

 $^1$  McGill University  $^2$  Québec Centre for Biodiversity Sciences

# **Correspondance to:**

Michael D. Catchen — michael.catchen@mail.mcgill.ca

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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.

# **Introduction**

2 This document is for brainstorming the Colorado bumblebee metaweb prediction project.

#### 3 1 Data

- 4 The data consists of two parts, the field data collected at three stations across Colorado, and the GBIF
- 5 metaweb data aggregated and cleaned by Julian R. and a student.

#### 6 1.1 Field data

- 7 This data consists of nearly-daily records of visits between bee and flower species for the months
- 8 August-October. Data is collected from three field sites: 1) Rocky Mountain Biological Lab (RMBL) 2)
- 9 Niwot Ridge 3) Pikes Peak
- each with tens of plots each across an elevational gradient, collected for 7/4/3 summers total.
- 11 To be determined: specific number of plots per site and years per site

#### 1.2 GBIF metaweb

- 13 This data of a network of bee/flower species which have a record of both occurring on GBIF for locations
- at some spatial grain
- To be determined: how does the scale of spatial aggregation affect properties of metaweb, how much
- taxonomic overlap is there with field data?—We have a lot of field data on interactions, but we can't
- validate predictions on taxa that aren't present in field data. As a result validation can only be done on
- interactions for which both species appear in field data.

#### 19 Methods

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[Figure 1 about here.]

#### 21 A predictive model to make spatially explicit network prediction

- 22 The goal is two have two predictive models: interaction-predictor model and a distribution-predictor
- model (a la Strydom & Catchen et al. 2021, figure 2).
- The interaction-predictor model,  $f_i(s_i, s_j, \theta_i)$  predicts interaction based on species-level features  $(s_i, s_j)$ ,
- 25 and is trained on the field-data.
- 26 These features could include Phylogeny (to be determined: how available are genomes or trees for these
- species) Environment/Climate Traits (to be determined: what trait data is available, how annoying is it to
- clean) Time (only for the phenology model, see 3.2 and 3.3)
- The distribution-predictor model,  $f_s(s_i, \vec{x}, t)$  is trained on GBIF data to predict the occurrence of species
- with features si at a location in space x, and time t. Many options here. Here the species level features
- could be Climatic variables derived from remote sensing products. Co-occurence to make a JSDM
- Potentially weighted by phenology information from field data. Time (only for the phenology model, see
- 33 3.2 and 3.3)

## Combining distribution-predictor and interaction-predictor models

- $_{35}$  Can split this into two based on how the distribution-predictor works. If  $f_s$  predicts co-occurrence, then
- draw the species pool first and predict interactions between the species in that pool. If  $f_s$  is a
- single-species SDM, get the occurrence probability for each species p\_s and compute the probability of
- observing interaction as function of the product of occ. prob.

### 39 Results

- 40 After comparing different combinations of features/model structures and finding the 'best' performing
- 41 model on validation data.

### 42 Figure one: spatial species pool and network prediction

- Figure that is two panels: a map of total species richness and a map of network properties across Colorado.
- This model doesn't consider time, only other predictors.

## Figure two: Phenology

- Same as figure one but consists of maps but at different times of the year (e.g. March, June, August) and
- uses both an interaction-predictor and distribution-predictor that incorporate time into predictions

### 48 Figure three: Climate

- Much as climate change has shifted temperature gradients to get warmer toward the poles, it has also
- 50 moved temperature gradients up in elevation.
- We can get a CMIP6 forecast of temperature and precipitation, and then predict how many observed
- interactions in the field data will no longer have their composing species' distributions overlap.
- Decompose temporal component of overlap from spatial component.

# Discussion

## 55 Acknowledgements

# 56 References

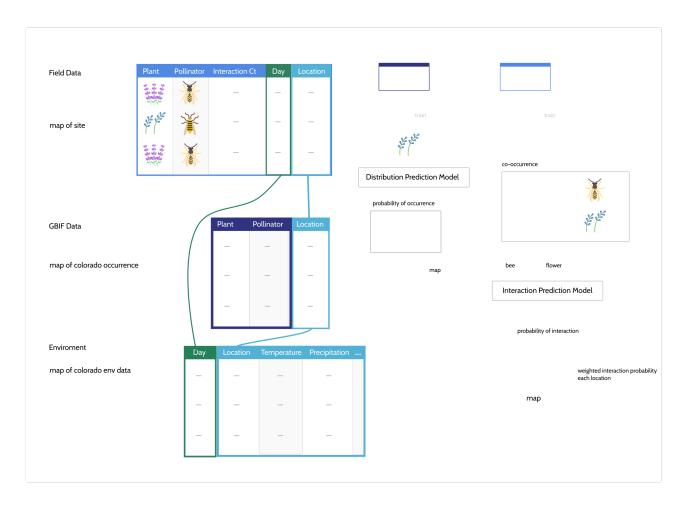


Figure 1: todo