Subject: Seeking advice on Myotis bat recovery and population crash Bayesian models

Hi Jeremy,

I hope this message finds you well. My team and I are working on Bayesian statistical models for ecological data, and I am reaching out to seek your advice.

We are studying Little Brown Bat population recovery in relation to *Pseudogymnoascus destructans* (Pd), the fungus responsible for white-nose syndrome (WNS). Our dataset consists of survey data from hibernacula sites across Michigan’s Upper Peninsula, dating back to 1996. While some sites were surveyed sporadically, others have more consistent data. Our analysis compares bat populations before and after WNS-induced population crashes, recognizing that the timing of these crashes varies by site depending on the year of initial infection and survey timing.

Our hypothesis is that environmental conditions conducive to Pd growth, particularly mean temperature, correlate with both population decline (crash) and recovery rates. Specifically, we predict that sites with cooler mean temperatures, which inhibit fungal growth, will exhibit lower population crash rates and steeper population recovery slopes.

Key Metrics:

Population crash rate:

Calculated as 1 – (minimum survey count / mean survey count before WNS). This captures the overall population decline from the “steady state” prior to WNS to the minimum bat count observed after Pd was introduced.

Recovery slope:

To calculate recovery slope, we first normalized the bat counts at each site using the formula:

Normalized count = (count−minimum count) / (maximum count - minimum count).

We then performed a linear regression of normalized count against the relative year (where year 0 corresponds to the year of the minimum count) to determine the recovery slope. The model formula is: normalized count ~ relative year

Models and Approach:

We constructed Bayesian models using the `brms` package in R. The response variables were population crash and recovery slope, while the explanatory variables included mean temperature, log-transformed passage length, the presence of standing water, and recovery years (the number of years the site had to recover). We also weighted the recovery slope models using the last survey count to account for larger populations being more influential.

The best models based on LOO-CV were:

Crash\_model <- brm(

Formula = crash ~ mean\_temp,

Prior = normal(0,1), class = “b”, coef = “mean\_temp”,

Family = gaussian(),

Chains = 4,

Iter = 4000,

Warmup = 1000,

Control = list(adapt\_delta = 0.99)).

And

Slope\_model <- brm(

Formula = slope\_weighted = mean\_temp + I(mean\_temp^2) + offset(recovery\_years),

Prior = normal(0,1), class = “b”, coef = “mean\_temp”,

Family = gaussian(),

Chains = 4,

Iter = 4000,

Warmup = 1000

Questions and concerns:

1. Posterior predictive checks:

We used pp\_check to compare the simulated (predicted) data with the posterior predicted observed data. However, the dens\_overlay plots indicate that the model potentially does not fit well (see graph for reference). Could you suggest any potential reasons for this and how we might improve the model fit?

1. Weighting and response variable:

We encountered issues when attempting to directly incorporate weights into the Bayesian models using `brms`, where the model returned a standard error of 0.00. As a workaround, we pre-weighted the response variable by multiplying it with the square root of the survey count (e.g., slope \* sqrt(last\_count)), which allowed the model to run and converge. Is this an appropriate way to handle weights in Bayesian models, or is there a better alternative approach you would recommend?

Your expertise would be greatly appreciated, and I’d be grateful for any suggestions or insights you might have.

Thank you for your time, and I look forward to hearing from you,

Best regards,

Tanner Barnes or Jared Wolfe