**Subject: Report on Myotis Bat Recovery and Population Crash Models**

I am writing to provide an update on the models we have been developing to study Myotis bat recovery and population crashes across hibernacula site in Michigan’s Upper Peninsula. The Myotis species in this region experienced significant population declines following the introduction of *Pseudogymnoascus destructans* (Pd) the fungus responsible for white-nose syndrome (WNS).

**Data and Modeling Approach**

We have survey data from sites across the Upper Peninsula dating back to 1996. While some sites were surveyed sporadically, others have more consistent data. Our analysis compares populations before and after WNS-induced population crashes, recognizing that the timing of these crashes varies depending on the year of survey and the year of initial infection at each site.

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

**Crash Rate Calculation**

The population **crash** rate at each site was calculated using the formula:

**Population Crash Rate**=1−(Minimum Survey Count / Mean Survey Count Before WNS)

This captures the overall population decline from a “steady state” before WNS to the minimum number of bats surveyed.

**Recovery Rate Calculation**

We calculated the **slope** of recovery by first normalizing the bat counts at each site to a range of [0, 1] using the following formula:

**Normalized Count** = (count – minimum count) / (maximum count - minimum count)

This ensures that the maximum count at each site is standardized to 1 and the minimum count to 0. We then fit a linear regression of normalized count against the relative year (where year 0 corresponds to the year of the minimum survey count) to derive the slope of recovery.

Lm = normalized count ~ relative year

**Initial Models and Results**

After processing the data, we constructed models using the `glm` function in R, where the response variables were population **crash** rate and recovery **slope**, and the explanatory variables included mean temperature, log-transformed passage length, standing water presence, recovery years, and various bat count metrics.

We fit three models to explore the relationship between environmental factors and population crash rate:

crash\_null\_model <- glm(crash ~ 1, weights = mean\_count, family = gaussian)

crash\_1 <- glm(crash ~ mean\_temp, weights = mean\_count, family = gaussian)

crash\_2 <- glm(crash ~ mean\_temp + log\_passage, weights = mean\_count, family = gaussian)

crash\_3 <- glm(crash ~ median\_temp + log\_passage + standing\_water, weights = mean\_count, family = gaussian)

The best model according to AIC was crash\_2, which included mean temperature and log-transformed passage length as predictors. The results are as follows:

**Coefficients Estimate Std. Error t-value P-value**

Intercept 0.30213 0.14092 2.144 0.0488

Mean\_temp 0.03467 0.01113 3.115 0.0071

Log\_passage 0.05141 0.01875 2.742 0.0151

This model suggests that both mean temperature and passage length are significant predictors of population crash, with higher temperatures and longer passages associated with greater crashes.

**Recovery Rate Models**

We then examined the slope of recovery rate, incorporating an offset variable (`recovery\_years`) to account for differences in the duration of recovery across sites. The models were:

null\_model <- glm(slope ~ 1 + offset(recovery\_years), family = gaussian, weights = last\_count).

slope\_1 <- glm(slope ~ mean\_temp + offset(recovery\_years), family = gaussian, weights = last\_count)

slope\_2 <- glm(slope ~ mean\_temp + log\_passage + offset(recovery\_years), family = gaussian, weights = last\_count)

slope\_3 <- glm(slope ~ mean\_temp + log\_passage + standing\_water + offset(recovery\_years), family = gaussian, weights = last\_count)

The best model according to AIC was `slope\_1`, which included only mean temperature:

**Coefficients Estimate Std. Error t-value P-value**

Intercept -3.08296 0.35650 -8.648 2.31e-08

Mean\_temp -0.30872 0.08055 -3.833 0.000969

This model indicates that higher temperatures are associated with slower recovery rates.

Questions and Concerns

1. Weighting the Response Variable in Bayesian Models:

When we attempted to incorporate weights into our Bayesian models using the `brms` package, we encountered issues 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 count variable (e.g., `crash \* sqrt(mean\_count)`), which allowed the model to run successfully. However, we are uncertain whether this is an appropriate method to apply weights in a Bayesian context. Could you please advise if this approach is valid, or suggest alternative strategies?

**CRASH MODEL using brms** with uninformative prior

Coefficients Estimate Est. Error l-95% u-95%

Intercept -139.11 84.59 -306.92 26.32

Mean\_temp **-0.02**  **0.99** **-1.95 1.87**

Log\_passage **21.01 12.67 -3.82 45.91**

**SLOPE MODEL using brms** with uninformative prior

Coefficients Estimate Est. Error l-95% u-95%

Intercept 1.54 1.60 -1.64 4.66

**Mean\_temp -0.65 0.26 -1.15 -0.14**

**Same models but using weighted responses using GLM**

**CRASH MODEL GLM**

Coefficients Estimate std. Error t-value p-value

Intercept -83.8891 54.0440 -1.552 0.1414

**Mean\_temp -0.9582 3.9573 -0.242 0.8119**

**Log\_passage 21.1142 7.1806 2.940 0.0101**

**SLOPE MODEL GLM**

Coefficients Estimate std. Error t-value p-value

Intercept 1.5713 1.5260 1.030 0.3149

**Mean\_temp -0.6466 0.2431 -2.659 0.0147**

1. Discrepancy Between Models:

We observed some discrepancies between the frequentist and Bayesian model results, particularly in the crash model estimates of mean temperature. What could be the cause of these differences, and should we be concerned about the robustness of our findings?