Modeling Long-Term Trends in Wild Bee Abundance: Results of a Seven-Year Study Using a Generalized Additive Mixed Model Approach

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Introduction

- Concern for the decline of wild bees has grown in the scientific community, but few long-term monitoring studies are available to model and track changes in the pollinator community (Goulson et al. 2015, Hallman et al 2017, Seibold et al. 2019, Didham 2020).
- The cyclic nature of insect abundance and other environmental variables complicate the collection and interpretation of wild bee abundance (Daskalova et al. 2021).
- Weather conditions during sampling efforts, as well as changes in insect behaviors (e.g. foraging patterns), may change the number of bees collected per sampling event but not represent a real change in local bee abundance.
- Generalized Additive Mixed Models (GAMMs) are a type of regression analysis thought to be well-suited for modelling insect abundance over time (Zuur et al. 2007).
- The aim of this study was to use GAMMs to model wild bee abundance trends over time, while accounting for said environmental variables and other random sampling variability.

Methods

- Bees were sampled biweekly from thaw to frost, using pan traps and sweep netting, from 2016 to 2023, at six sites in Plymouth County, MA (Popic 2013).
- Weather data was gathered from the database Visual Crossing.
- Individual models for pan trap and sweep net abundances were created using R Statistics.
- Pan trap and sweep net abundance data were modeled separately as response variables. Predictor variables are listed in Table 1.

Predictor	Definition/Explanation
Time	Month, Sample Date, and Year
Temperature (°C)	Difference between avg. daily temperature on day of placement and retrieval of pan traps
Windspeed (kph)	Avg. wind speed on day of retrieval of pan traps
Atmospheric Pressure (mb)	The atmospheric pressure at a location that removes reduction in pressure due to altitude
Humidity & Cloud Cover (%)	Tensor product of the mean percent humidity and percent cloud cover
Dew Point (°C)	Dew point on day of retrieval of pan traps
Visibility (km)	Distance seen in daylight on day of retrieval of pan traps

Table 1. List of predictor variables used for pan trap and sweep net models.

Results

Predictor variables ranked by *p*-values

Pan Trap (62.6%)	Sweep Net (35.3%)
Temperature (C°) ($p < 0.01$)	Temperature (C°) ($p < 0.001$)
Time (Days since Start) ($p < 0.01$)	Time (Days since Start) ($p < 0.01$)
Atmospheric Pressure (mb) ($p > 0.05$)	Humidity & Cloud Cover (%) ($p < 0.05$)
Visibility (km) ($p > 0.05$)	Atmospheric Pressure (mb) ($p > 0.05$)
Humidity & Cloud Cover (%) ($p > 0.05$)	Windspeed (kph) ($p > 0.05$)
Dew Point (C°) ($p > 0.05$)	Visibility (km) ($p > 0.05$)
Windspeed (kph) ($p > 0.05$)	Dew Point (C°) ($p > 0.05$)

Table 2. Predictor variables from Pan Trap and Sweep Net models, ranked from highest to lowest *p*-value to reflect individual statistical significance. The deviance explained for each model is beside the respective sample method.

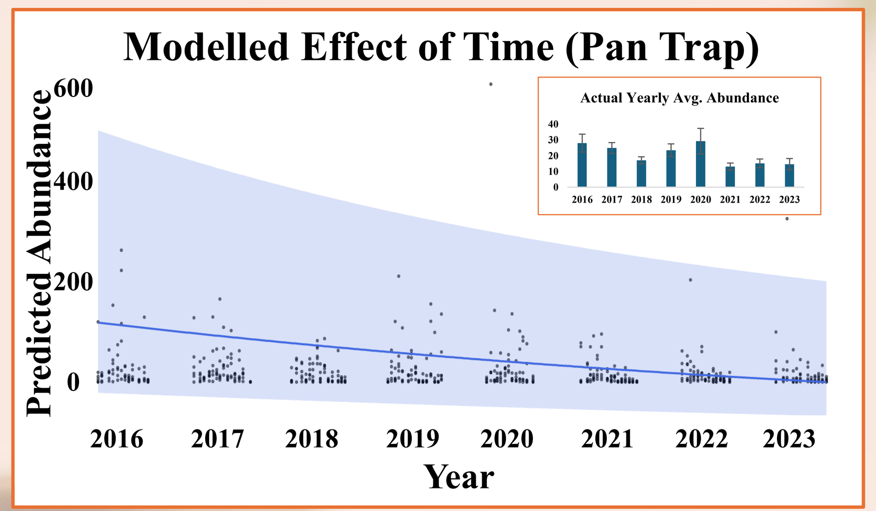

Fig 1. Predicted pan trap abundance with actual yearly averages embedded. Error bars represent S.E.M. The trendline is in blue, and the shaded area is the 95% confidence interval. Data points are bees per sampling event per study site.

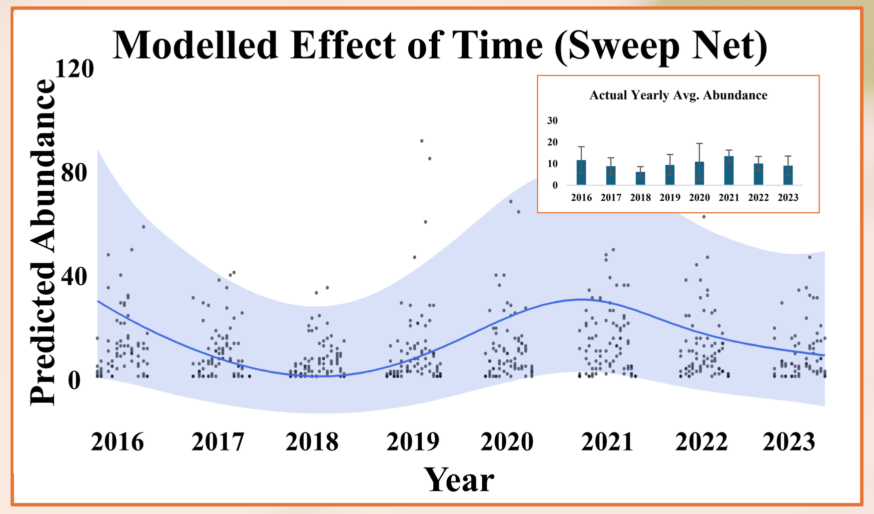

Fig. 2. Predicted sweep net abundance with actual yearly averages embedded. Error bars represent S.E.M. The trendline is in blue, and the shaded area is the 95% confidence interval. Data points are bees per sampling event per study site.

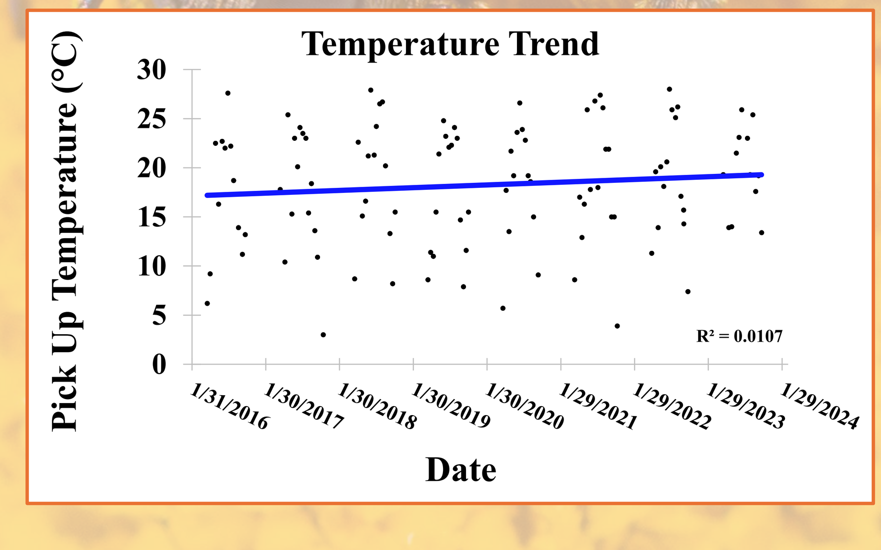

Fig. 3. Linear regression for daily average temperature across retrieval dates, with the trendline for predicted temperature in blue. The R-squared is 0.0107.

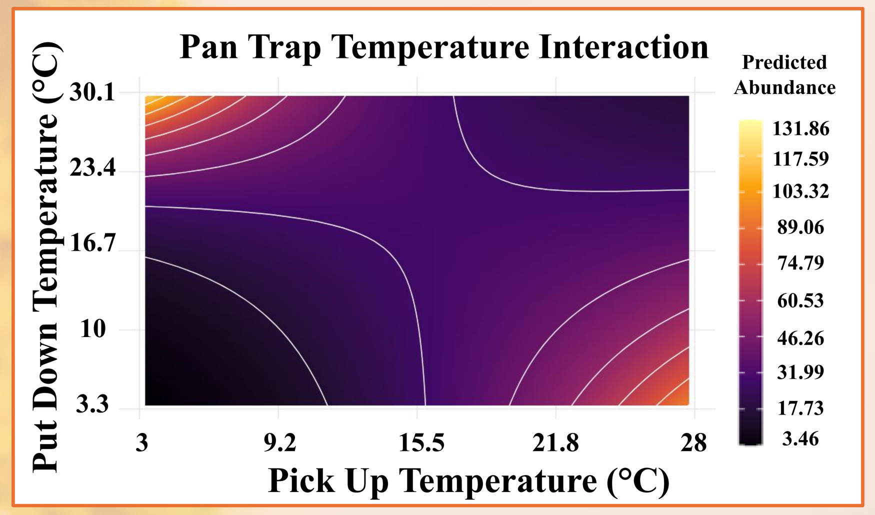

Fig. 4 Contour plot of the interaction between daily avg. temperature for pan trap placement and retrieval date. Predicted pan trap abundance is represented by color.

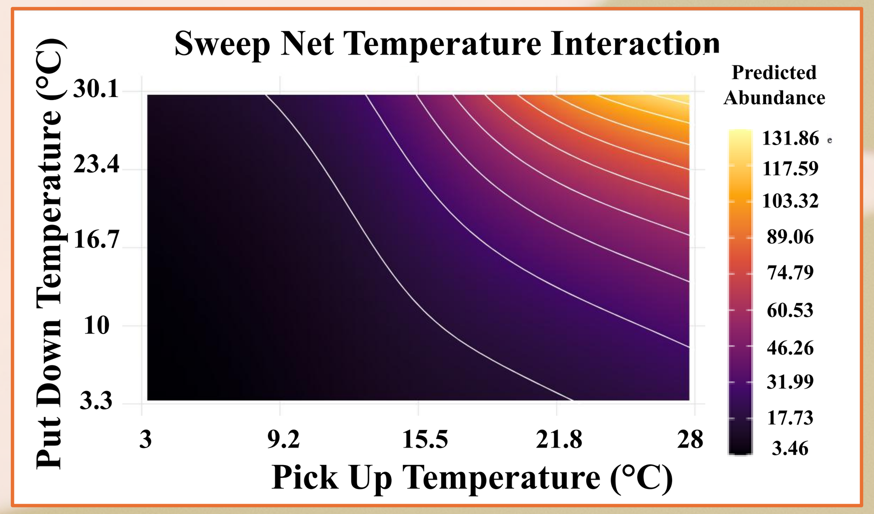

Fig. 5. Contour plot of the interaction between daily avg. temperature for pan trap placement and retrieval date. Predicted sweep net abundance is represented by color.

Discussion and Conclusions

- Progression of study date had a statistically significant effect on both pan trap (Fig. 1) and sweep net (Fig. 2) abundance with only pan trap showing a clear decline over time.
- Comparison of pan trap deviance explained (62.6%) vs sweep net (35.3%) suggests that the pan trap model is superior (Table 2).
- The predicted decline in wild bee pan trap results is consistent with concerns about downward pressure on wild bee abundance; sweep net results suggest no clear trend and require model refinement.
- However, it is important to note that the predicted decline may be influenced by confounding factors that impact sampling efficiency (Fig. 3, 4, & 5).

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