**Statistical Methods**

As an initial exploration of how these data could inform status and trend assessments, we estimated temporal variation in occurrence of each species, measured as the proportion of routes on which a species is detected. Since not every route was surveyed every year, we used a Bayesian model to estimate the expected proportion of routes on which the species occurred each year.

We considered each of the routes as independent units of observation. The response variable in our model was denoted by , and represents the observed species occurrence (i.e., the “population state”) on route in year . The variable takes a value of 1 if the species was detected the route, or 0 otherwise.

Temporal variation in occurrence was modeled using a process analogous to dynamic occupancy models (Royle and Kéry 2007). The initial occurrence probability in year is denoted by , and the initial occurrence state of each route were assumed to be distributed as:

Changes in species occurrence on routes through time were described by two time-varying parameters: persistence probability and colonization probability . For routes where the species occurred in year (i.e., where the occurrence state in year was modeled as:

For routes where the species did not occur in year (i.e., where the occurrence state in year was modeled as:

The overall occurrence probability in each year was then estimated as derived parameter, calculated as:

The parameters and were modeled as time-varying random effects, drawn from logit-normal distributions:

We fit the statistical model in a Bayesian framework using JAGS version 4.3.0 (Plummer 2003), interfaced with the R programming language version 4.0.2 (R Core Team 2024) using the jagsUI library version 1.5.2 (Kellner 2021). We specified vague priors on all model parameters. After a burn-in of 10,000 iterations, we stored every 100th iteration until we accumulated 1000 posterior samples from each of three MCMC chains. We assessed chain convergence by visual examination of MCMC traceplots and by evaluating that the Gelman–Rubin convergence statistic was close to 1 for all model parameters. Code to repeat these analyses is available at https://github.com/davidiles/BeeBS.

We did not attempt to estimate detection probabilities because routes were only visited once per season. Occurrence estimates should therefore be considered an index of occupancy in the same way that estimates from the BBS are considered an index of abundance, and we caution that unmodeled variation in detection probabilities could lead to biased trend estimates if detection probabilities change systematically over time.

We also note that BeeBS data could potentially be used to study trends in bumble bee abundance in addition to occurrence (e.g., using methods similar to the North American Breeding Bird Survey; Smith et al. XXXX). However, the majority of detections in the BeeBS dataset are of sterile workers rather than reproductive queens which are the fundamental unit of bumble bee population dynamics. Thus, trends in abundance from the BeeBS could be partially confounded with changes in colony size (number of workers per colony) rather than changes in the number of colonies.

**Precision Analysis**