Appendix I: Development of a Habitat Suitability Model for the Indiana Bat (*Myotis septentrionalis*) and Northern Long-eared Bat (*M. sodalis*) in Michigan

In 2018, the Michigan Ecological Services Field Office (MIFO) contracted with Dr. Eric McCluskey of Grand Valley State University to develop a habitat model for the Indiana bat in Michigan. In 2021, MIFO again contracted with Dr. McCluskey to develop a habitat model for the northern long-eared bat in Michigan, which we combined with the Indiana bat model. A shapefile of the combined habitat model is available here: Michigan Listed Bat Habitat Model

Indiana Bat Model

To develop the model, we compiled all available Indiana bat summer capture (foraging) and roost occurrence data for Michigan and applied a 500-m spatial filter as a minimum distance between occurrence records to minimize overemphasis of habitat importance based on clusters of individuals. After filtering the occurrence data, 44 locations remained (20 capture and 24 roost locations). We developed models using capture and roost occurrences separately as well as with all occurrences combined to determine which model was best suited for identifying foraging and roost habitat.

Due to the small number of occurrences, we used an ensemble of small models (ESM) approach that permits more predictor variables to be used by running each pairwise combination of variables and then weighting these final models in an ensemble. The ESMs were run in the R package ecospat. Presence only modeling requires the selection of background area from which background points will be randomly sampled to compare to the occurrence data. The background area should represent parts of the landscape that are accessible to the focal organism. We created a convex hull around our occurrence data using ArcMap, a polygon formed by connecting straight lines between points. We then buffered this convex hull by 25 km to include areas beyond the known core distribution of Indiana Bat in southern Michigan that should be physically accessible and may have undetected presences. We set background point selection for this entire buffered area except for within 5 km of Indiana Bat occurrences where background points are most likely to unintentionally represent true presences.

We selected predictor variables by removing the worse performing variable from highly correlated pairs (>0.75) using the 'corSelect' function from the fuzzySim R package. Then we then used Maxent's internal variable importance (permutation importance) and jackknife measures to determine which of the remaining variables were important to retain for separate capture and roost models. We selected two model types, Artificial neural network (ANN) and Maxent, for the ESMs. We compared five runs for each model type with the capture, roost, and combined datasets using area under the ROC curve (AUC) and true skill statistic (TSS). We then calculated the Boyce Index value using ecospat to compare the ANN and Maxent models from each dataset in their ability to identify capture and roost locations. We used Boyce Index as the primary assessment metric as it allowed for comparisons across all three model types for capture and roost data.

Based on the Boyce Index assessment, we selected the Maxent presence-only roost model as the strongest fit model. Using the 10th percentile threshold, we converted the model output to a binary raster. The binary raster was then converted to a shapefile using non-simplified shapes. Because considerable portions of the modeled habitat contained clearly non-suitable cover types, particularly near highly developed urban areas, we further refined the model by clipping the binary shapefile by the most recent available National Land Cover Database (NLCD 2019) data. Land cover categories excluded ("Clipped") from modeled habitat included open water, perennial ice/snow, developed (low, medium, and high intensity), and barren land (sand, rock, clay).

Northern Long-eared Bat Model

To develop the model, we compiled all available northern long-eared bat summer capture (foraging) and roost occurrence data for Michigan's Lower Peninsula and applied a 1-km spatial filter as a minimum distance between occurrence records to reduce the potential for biased results from over-represented sites. After filtering the occurrence data, 56 locations remained.

We screened a diverse set of candidate variables (30 m resolution) representing different habitat elements, including land cover, hydrology, and elevation. First, we identified and removed highly correlated variables (>0.75) with the 'corSelect' function in the fuzzySim R package, keeping the better performing variable from each correlated pair. We further evaluated the remaining variables using the jackknife of variable importance and training gain output in Maxent. The final northern long-eared bat variables were mean canopy at 100 m, canopy range at 500 m, percentage of emergent wetland at 50 ha, percentage of forested wetland at 5 ha, wetland diversity index at 25 ha, and wetland diversity index at 1,000 ha.

Once the occurrence data were thinned, we used a buffered region to clip the selected variable rasters to serve as the area for background point selection by ecospat. We used a 25-km buffer for background point selection (10,000 random points). The sample size was low enough (n=56) that we opted to use the R package ecospat, that was developed for datasets with few occurrences. Ecospat uses an ESM approach where separate models are produced with each pair of variables before an ensemble is created under a weighting scheme. We used Maxent and ANN for the ecospat ESMs. The ecospat models used five-fold cross validation (80% training partitions). We used Boyce Index implemented in ecospat as the primary model selection metric using the 'ecospat.boyce' function for the ESMs. Finally, we converted the continuous habitat suitability values from each species SDM to a binary raster of habitat and non-habitat to represent the distribution of habitat patches. We used the maximum sum of sensitivity and specificity (MSSS) threshold for the ecospat ESM models (equivalent to the maximum true skill statistic (TSS)).

Combined Listed Bat Model

To combine and further refine the habitat models, we created a grid of five-acre hexagons for Michigan using the "Generate Tessellation" tool in ArcPro 2.9. Five acres was selected as the patch size based on available literature and data suggesting that Indiana and northern long-eared bats are unlikely to occupy an isolated forest stand of less than five acres. The total acres of modeled habitat were summarized by hexagon using the "Summarize Within" tool. Hexagons with less than one acre of either bat's habitat were then removed. These small model fragments were typically isolated from other modeled hexagons, likely artifacts of imprecise raster data, and were considered unlikely to provide sufficient habitat to support roosting listed bats. Hexagons containing more than one acre of modeled habitat of either species were retained, helping to fill gaps and buffer edges among smaller but closely connected modeled patches and increasing the overall acreage of modeled habitat across the state.

The remaining hexagons were then aggregated using the “Dissolve” tool allowing for multipart features. The “Summarize Within” tool was run again to obtain acres of modeled habitat within each hexagon cluster. We then ran a “Near Neighbor” analysis to identify forest patches that were greater than 1,000 feet from forested areas to remove isolated patches unlikely to be used by roosting listed bats. We removed hexagons that were more than 1,000 feet from their nearest neighbor and that contained less than five acres of modeled habitat. These isolated forest patches are considered unlikely to support roosting listed bats due to their insufficient size and distance from other suitable, modeled areas. The final layer was then checked against known listed bat roosting areas and detections. An additional three hexagons were added to the model to capture locations that fell outside of the modeled habitat.