Assessing Areas for Interactions between Tricolored Bats and Wind Energy Facilities

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INTRODUCTION

The tricolored bat (*Perimyotis subflavus*) was recently proposed for listing as endangered by the U.S. Fish and Wildlife Service primarily due to the disease, white-nose syndrome, however, impacts from wind energy developments were also considered to be a contributing factor. If the species is listed as endangered, then wind energy projects may be subject to mitigatory actions (e.g., curtailment). Currently, wind turbines are operating in a considerable portion of the species' range (**Figure 1**). To understand where areas with potential interactions between tricolored bats and wind turbines might occur, we modelled the distribution of the species

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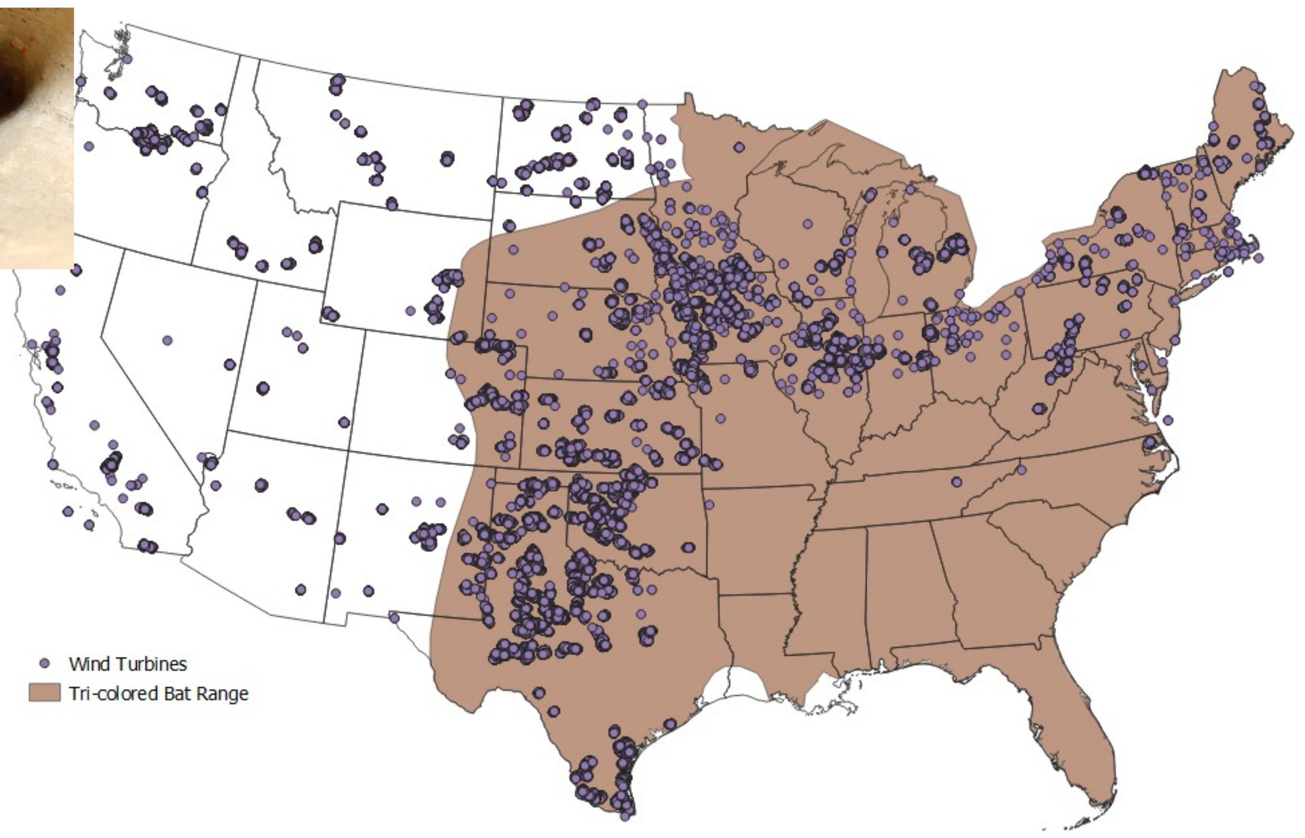

FIGURE 1. The range of the tricolored bat overlayed with currently installed wind turbines.

METHODS

Occurrence records were obtained from online biodiversity databases (Arctos 2023; GBIF 2023; iDigBio 2023; Vertnet 2023) and a database of acoustic detections from the North American Bat Monitoring Program (NABat 2023a; 2023b). Data were cleaned to obtain records that had associated coordinates and were 'thinned' to one presence record per predictor grid cell (~4km²) to remove pseudo-replication based on areas of increased sampling activity.

Environmental predictor variables were obtained from authoritative sources; elevation (USGS 2021), land cover (LP DAAC 2023a), precipitation (USFS 2023), average temperature (LP DAAC 2023b), distance to water source (Matti et al. 2017), and wind speed (Fick et al. 2017). These predictors were resampled to the coarsest resolution (~4km²) and masked to the known range of the species, plus a 150km buffer.

To develop predictions of tricolored bat distribution, two regression-based models (Generalized Additive Models [GAM] and Generalized Linear Model [GLM]) and two machine learning models (Random Forest [RF] and Boosted Regression Tree [BRT]) were used within the SDM package (Naimi & Arujo 2016) in R statistical environment (R Core Team 2023). Fitted models were assessed on predictive power using the Area Under the Receiver Operator Curve (AUC), True Skill Statistic (TSS) and the Pearson correlation between the predicted likelihood of presence and the presence data in the test dataset (COR). From these four models, an ensemble was calculated by combining predictions across the covariate space, weighted by each of their TSS, so that better performing models received a higher weighting for their prediction.

To compare predicted tricolored bat occurrence to current and future wind energy buildout, modeling results were overlayed with current turbine locations from the US Wind Turbine Database (Hoen et al. 2018) and possible suitable areas for wind energy development from the Geospatial Energy Mapper (ANL 2023).

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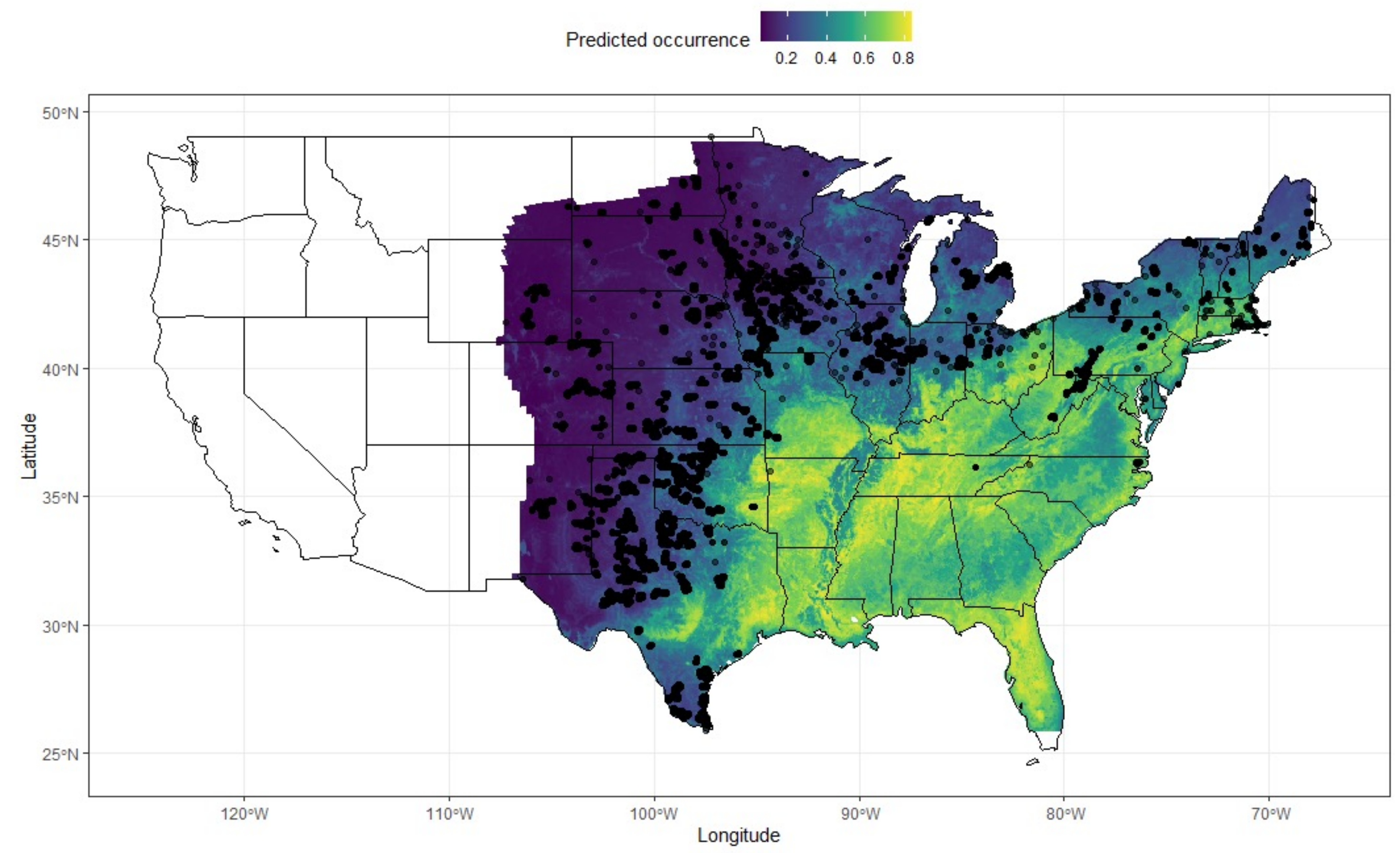

FIGURE 3. Predicted occurrence of the tricolored bat with currently installed wind turbines.

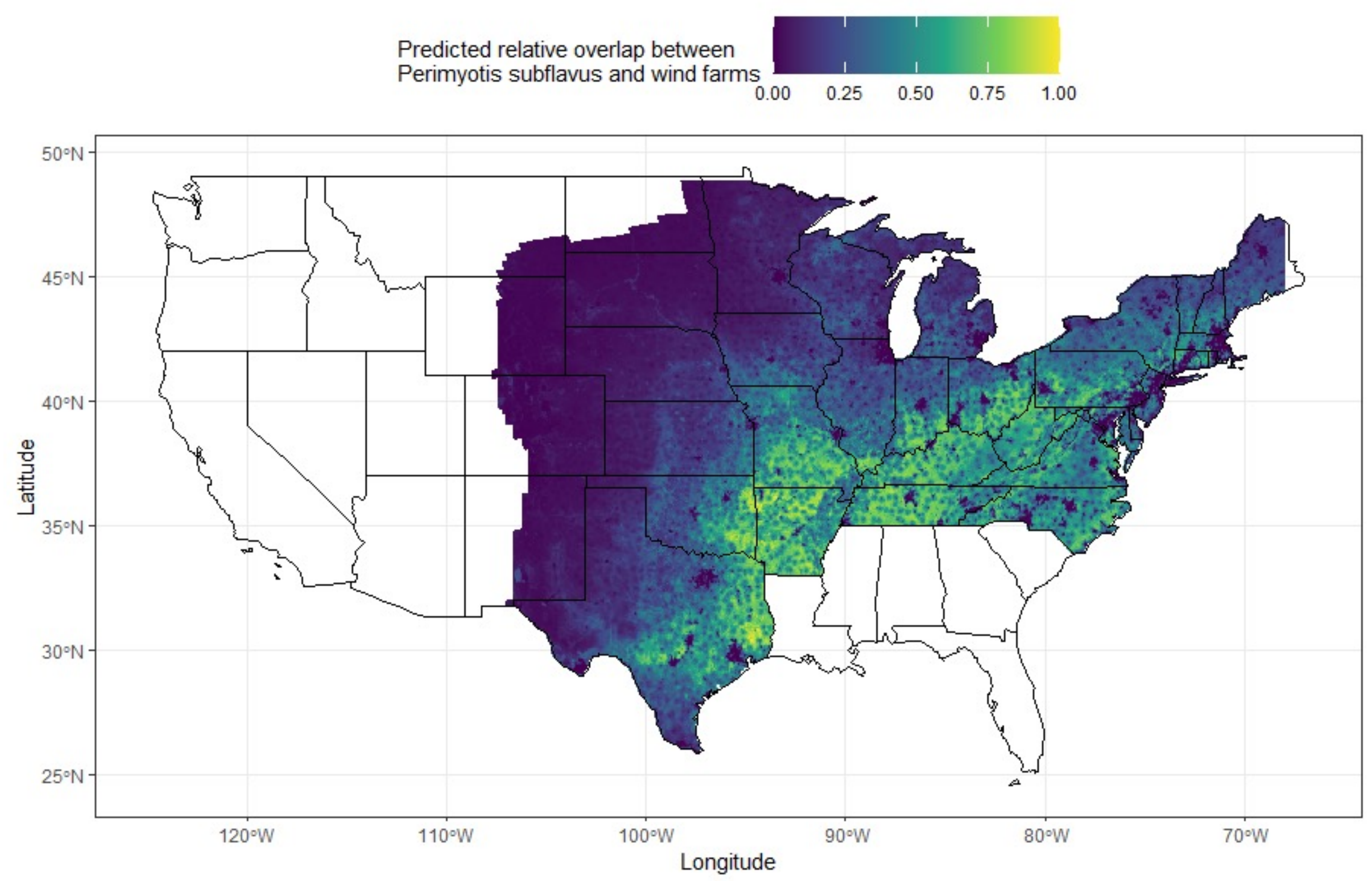

FIGURE 4. Overlap between predicted build out locations and predicted distribution of tricolored bats.

RESULTS AND DISCUSSION

Precipitation and temperature were the most important variables for model prediction (**Figure 2**). The highest predictive power was found for the RF model (AUC = 0.88; TSS = 0.60) and GAM (AUC = 0.82; TSS = 0.53). An ensemble model weighted by TSS depicted high likelihood of occurrence throughout much of the eastern U.S. with sparse areas of high likelihood in the Great Plains and Upper Midwest (**Figure 3**). There was high predicted uncertainty in these same areas, which may be explained by the lack of documented records and associated surveys in these regions. Further review of survey data, especially from NABat, may confirm this or may confirm considerable absence data from numerous surveys.

A comparison of the ensemble model with currently installed wind turbines resulted in 110 facilities with at least one turbine with a predictive occurrence of ≥ 0.50 (**Figure 3**). A comparison of the ensemble model with suitable areas for wind energy buildout resulted in 770,563 km² with a predictive occurrence of ≥ 0.50 and 108,583 km² with a predictive occurrence of ≥ 0.75 (**Figure 4**).

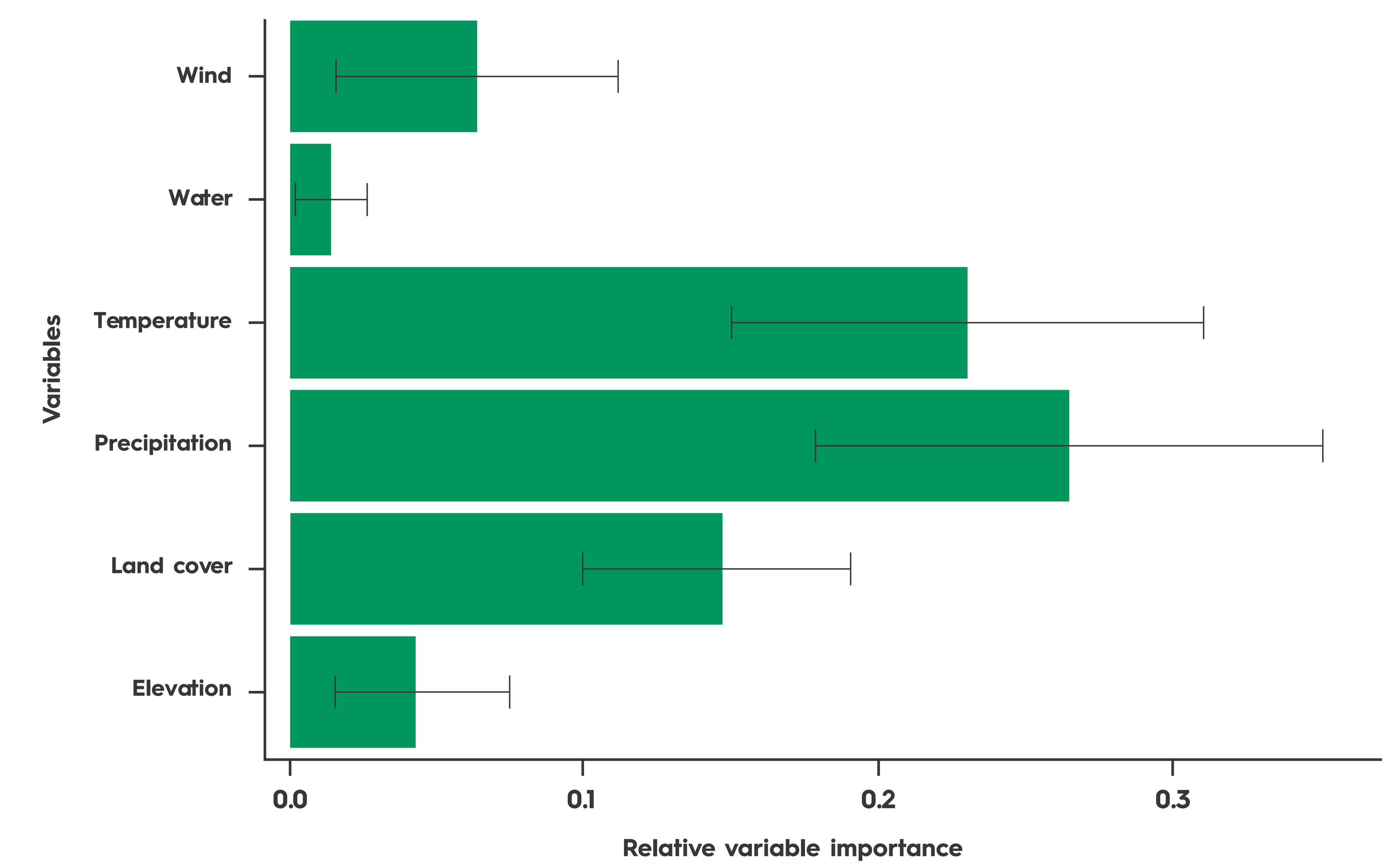

FIGURE 2. Variable importance from four model types and ten replicates.

CONCLUSION

Modeling of tricolored bat distribution predicted high occurrence throughout much of the eastern U.S. with a high degree of uncertainty in the western part of its range. Comparison with current buildout and areas suitable for development suggest a considerable degree of possible interactions between tricolored bats and wind turbines, although more detailed site information is necessary to ascertain this as a generality. Further modeling efforts with additional occurrence data, especially in the western part of the range, and possibly with additional predictor variables will help to elucidate the degree which tricolored bats occur in this region and the potential for interaction with wind turbines.

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