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PREDICTING POTENTIAL CONFLICT AREAS BETWEEN WIND ENERGY DEVELOPMENT AND EASTERN RED BATS (*LASIURUS BOREALIS*) IN INDIANA

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ABSTRACT. Wind turbines pose threats to bats due to the risk of collisions, barotrauma, habitat loss, and environmental changes. To assess potential conflicts between wind energy development and the summer habitat of the eastern red bat (*Lasiurus borealis*) in Indiana, we used a species distribution modeling approach (MaxEnt) to generate two predictive models. We created a model representing areas with the potential for future wind energy development based on six environmental characteristics along with the locations of wind turbines. To create models of habitat suitability for summer resident eastern red bats, we used detections of eastern red bats collected via mobile acoustic surveys. We modeled these with 20 environmental variables that characterize potentially suitable eastern red bat summer habitat. Wind power at a height of 50 m, wind speed at a height of 100 m, and land cover type were the most influential predictors of wind energy development. Proportion of forest within 500 m and 1 km and forest edge within 5 km were the most important variables for predicting suitable summer habitat for red bats. Overlaid maps revealed that approximately three-quarters of the state was unsuitable for both wind development and red bats. Less than 1% of the state showed areas suitable for both wind development and red bats, which made up an area of about 4 km^2. Primarily, these were rural areas where cropland was adjacent to forest patches. Predicting areas with potential conflicts can be an invaluable source for reducing impacts of wind energy development on resident red bats.

Keywords: Bats, EchoClass, *Lasiurus borealis*, MaxEnt, wind energy

INTRODUCTION

Understanding habitat preferences of a species can be important for assessing potential ecological impacts of large-scale developments, such as the establishment of wind energy facilities (Roscioni et al. 2013; Santos et al. 2013). The installation of wind turbines can result in environmental costs, including habitat fragmentation, habitat loss (Larsen & Madsen 2000), and the direct threat to wildlife through collisions with turbine blades (Arnett & Baerwald 2013) and barotrauma (Baerwald et al. 2008). In particular, concerns for birds and bats have increased due to high mortality rates reported at wind energy facilities (Orloff & Flannery 1992; Barrios & Rodríguez 2004; Kunz et al. 2007). Both the placement of wind turbines and the habitat selected by wildlife depend on environmental and geographic variables (Limpert et al. 2007; Brower et al. 2010; Roscioni et al. 2013). As such, understanding the conditions needed for both imperiled species and high quality wind energy may allow us to identify areas where development poses a risk to a species and its habitat. Such understanding can aid in setting conservation priorities and managing wind energy development.

The wind energy sector is an emerging threat to eastern red bats (*Lasiurus borealis*), henceforth referred to as red bats (Johnson et al. 2004; Kunz et al. 2007; Arnett & Baerwald 2013). This is a migratory, relatively common, and widely distributed foliage-roosting bat in North America (Shump & Shump 1982; Cryan 2003). However, the red bat is one of the few species most

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frequently killed by wind turbines (Johnson et al. 2003; Kunz et al. 2007; Arnett et al. 2008) and is a state-listed species of special concern in Indiana (Whitaker & Mumford 2009; IDFW 2015).

Red bats are considered to be declining in many parts of their range (Winhold et al. 2008). Although fatality rates are highest during fall migration, they also occur throughout the entire summer (Arnett & Baerwald 2013; Foo et al. 2017). Currently, Indiana has 1,203 wind turbines in operation with wind energy development expected to increase (AWEA 2018). To reduce the detrimental effects wind turbines have on this species, an accurate understanding of the potential for conflict between red bats and present and future wind energy development is critical.

The red bat is often associated with hardwood, and occasionally, coniferous, forests and use water sources, such as streams, for foraging, drinking, and traveling (Hutchinson & Lacki 1999; Jung et al. 1999; Limpert et al. 2007). Their roosts are found in forests with varying degrees of tree density but most often occur in low to moderately dense forests (Hutchinson & Lacki 2000; Elmore et al. 2005; Limpert et al. 2007). Furthermore, red bats often forage along forest edges (Krusic et al. 1996; Mager & Nelson 2001; Morris et al. 2010). Although developed areas are not a preferred habitat, they will utilize such areas for foraging (Furlonger et al. 1986; Mager & Nelson 2001; Walters et al. 2007). Red bats have been known to forage over 5 km from a roost site in a single night (Hutchinson & Lacki 1999). With the ability to fly long distances, bats likely select habitat in a hierarchical manner (Johnson 1980; Limpert et al. 2007). Thus, it is important to consider habitat preferences of red bats at several scales, such as the scale at which they consider optimal foraging habitat (Limpert et al. 2007).

Species distribution models (SDMs) are useful tools for quantifying suitable habitat for wildlife. MaxEnt is an SDM tool that combines presence-only data with a set of environmental features within a geographic spatial grid and uses machine-learning to predict the potential distribution and/or habitat of a species (Phillips et al. 2006; Merow et al. 2013; Elith et al. 2011). This method has been used for several organisms, including bats (Rebelo & Jones 2010; Razgour et al. 2011). Because of their nocturnal behavior bats can be difficult to survey, so absence data may not be reliable or accurate (Hirzel et al. 2006; Rebelo & Jones 2010). Thus MaxEnt, with its use of presence-only data, offers an efficient and valuable solution for creating SDMs for bats.

The goal for this study was to determine the potential for habitat conflict between summer resident red bats and wind turbines in Indiana. Our objectives were to examine the presence locations of resident red bats and known locations of wind turbines, along with environmental variables that influence red bat habitat and wind energy development selection, to (1) identify those variables that most influence suitability for both red bats and wind energy; (2) identify habitats with a high probability of suitability for this species and for wind energy development; and (3) use bat and wind energy suitability maps to quantify areas of potential conflict by generating a map of low conflict and high conflict areas.

METHODS

Study area.—Our field sites consisted of 17 areas in Indiana, the majority occurring in and around state forests. Thirteen of these publicly managed regions occurred within 8 km of an Indiana state forest, one occurred within the Indiana Dunes National Lakeshore, and three were rural areas in east-central Indiana being sampled for another project. The dominant forest types of these areas include oak-hickory, beech-maple, mixed hardwood, and pine (Shao et al. 2014). Forests of white oak (*Quercus alba*), red oak (*Q. rubra*), chestnut oak (*Q. montana*), and hickories (*Carya* spp.) were predominate (Shao et al. 2014). Study areas were chosen in order to incorporate much of the area that red bats in Indiana were expected to use, which included agricultural, forested, and developed areas (Cryan 2003; Limpert et al. 2007; Walters et al. 2007). These sites were used to obtain red bat presence data, but our modeling study area consisted of the entire state of Indiana.

MaxEnt Species Distribution Modeling Software.—Several SDMs require information on the presence and absence of a species. However, absence data can be difficult to obtain for some species and false absences may bias model results (Hirzel et al. 2006). So, rather than comparing presence data to absence data, MaxEnt contrasts presence data and background data (Phillips et al. 2009). Background data is the set of conditions where the focal species could have been found based upon the survey technique (Phillips et al. 2009). MaxEnt randomly samples the area containing the background data (creating pseudo-absences) and contrasts these against the presence data (Merow et al. 2013).

MaxEnt models utilize Area Under the Curve (AUC) of the receiver operating characteristic to evaluate model performance (Elith et al. 2011). AUC measures the models ability to discriminate between a random presence point and a random absence point (or a random background point) on a scale from 0 to 1; a value of 1 represents perfect discrimination, while a value of 0.5 represents random discrimination (Fielding & Bell 1997; Rebelo & Jones 2010).

MaxEnt has grown in popularity for its use in predicting species distributions since it is accurate in its predictions and user-friendly (Merow et al. 2013). However, the predictive ability of MaxEnt is dependent upon the quality of input data and the satisfaction of model assumptions such as data independence and random sampling.

Red bat presence data.—A total of 28 mobile acoustic surveys was conducted in and in proximity to Indiana state forests from 30 May to 7 August 2012 (Tonos et al. 2014). An additional 19 surveys were carried out in northwestern Indiana between 7 July and 8 August 2013 (D'Acunto et al. 2018). Each route was surveyed once. Although fall is generally when bat mortalities peak (Arnett & Baerwald 2013), we chose to focus on red bats in the summer (Britzke & Herzog 2009) because it may be particularly informative to identify habitat that could potentially put resident summer bats at risk. Additionally, summer bat surveys are easier to conduct since summer is a broader window of time and does not require timing of surveys to perfectly coincide with migration. Surveys traversed all major cover types in the region (agriculture, forests, developed areas, open water) and occurred throughout Indiana, including in some of the same general areas as the wind turbines.

Ultrasonic echolocation calls of bats were recorded with a microphone mounted to the roof of a vehicle connected to an Anabat SD2 (Titley Scientific, Inc., Ballina, NSW, Australia) and an iPAQ Personal Digital Assistant (PDA; Hewlett-Packard Company, Palo Alto, CA; Britzke & Herzog 2009). The length of the routes ranged between 16.1 and 51.2 km (mean = 39.4 km, SD = 10.6 km). Each route was driven at a consistent speed between 24–32 kph. The locations of recordings were registered using a CompactFlash SiRF STAR III Global Positioning System (GlobalSat, New Taipei City, Taiwan). To maximize likelihood of red bat identification, surveys began 20 min after sunset when the temperature was at least 12.8° C, there was little to no chance of rain, and wind speeds were forecasted to be less than 24 kph.

The automated acoustic bat identification software, EchoClass (v2), was used to identify red bats from echolocation call files, and thus obtain presence locations. Echolocation call files were identified using "Species Set 2" in EchoClass, which includes a suite of nine species to which the calls can be identified, i.e., big brown bats (*Eptesicus fuscus*), silver-haired bats (*Lasionycteris noctivagans*), red bats, hoary bats (*Lasiurus cinereus*), eastern small-footed bats (*Myotis leibii*), little brown bats (*M. lucifugus*), northern long-eared bats (*M. septentrionalis*), Indiana bats (*M. sodalis*), and tricolored bats (*Perimyotis subflavus*). These are the most commonly encountered species in our study area throughout the summer. Classification accuracy of these species often exceeds 90% from call libraries, though field recordings are expected to introduce more potential for misidentification (Britzke et al. 2002, 2011). Given a particular call, the species identified by the program is referred to as the "prominent species". If another bat is present, that species is the second prominent species. Files that identified red bats as the prominent species or those that classified the red bat as the second most prominent species when the first prominent species was unknown were included in our presence data.

Red bat environmental variables.—For the habitat suitability model of red bats, five major feature types were selected following Weber & Sparks (2013), i.e., proportion of forest, proportion of area with forest edge, proportion of area with streams in forest, length of streams, and proportion of developed area. These variables are relatively consistent throughout the study area and represent habitat over a long time period. All maps were created in ArcMap 10.2.2 (Environmental Systems Research Institute, Inc., Redlands, CA). Focal statistics was used to calculate the proportion of each cover type within circular plots at four spatial scales: 500 m, 1 km, 3 km, and 5 km. Red bats have been observed foraging 5 km away from their roost sites (Hutchinson & Lacki 1999) and was considered the maximum area they could explore when selecting habitat. Variables relating to forest, forest edge, and developed area were calculated using the U.S. Geological Survey's 2006 National Land Cover Database (Xian et al. 2011). Forest edge was identified as forested raster cells adjacent to non-forested areas (e.g., hay/pasture, cultivated crops, water, developed areas with open space). In order to calculate stream lengths, the number of stream raster cells within circular plots at each scale was determined and we assumed that any cell designated as a stream constituted a stream length of 30 m (due to raster cells being 30 $\times$ 30 m). Stream variables were based on maps created from the U.S. Geological Survey National Hydrography Dataset (intermittent code 46003; perennial code 46003 and 55800; nhd.usgs.gov). Because our sampling effort was concentrated along country roads, we only included high–intensity and moderate–intensity areas of development for our proportion of developed area variable so as not to impose bias based upon our sampling along low–intensity developed roads. Cells of all raster maps were 30 $\times$ 30 m.

Wind presence data.—For locations of current and developing wind turbines, we obtained archives generated by the Federal Aviation Administration (FAA). Turbines and meteorological towers that were determined to be "no hazards" to air navigation by the FAA between 2008 and 2013 were selected because these serve as the best representation of where turbines are located in Indiana (GEC 2005). Meteorological towers are used to gather on-site environmental data, including wind parameters, near a potential wind energy facility and assess the wind resource availability for wind energy sites (Brower et al. 2010). These sites were included as presence data in the model. Any turbine categorized as a "work in progress" also was included since the environmental characteristics of these proposed wind turbine locations were considered to be informative of future development. A number of large-scale wind energy projects are situated in northwestern Indiana and compose the majority of the wind turbines in the state (GEC 2005).

Wind environmental variables.—For wind energy development potential, variables that are considered to influence wind resource potential or wind turbine construction were chosen (Bailey et al. 1997; Brower et al. 2010; Copeland et al. 2013; Pocewicz et al. 2013; Petrov & Wessling 2015). Variables included wind power in watts (W/m^2) at a height of 50 m and 100 m, wind speed (m/s) at a height of 50 m and 100 m, percent slope, and land cover. The wind resource maps were produced by the Mesoscale Atmospheric Simulation System and WindMap (TrueWind Solutions). The NLCD served as the basis for our land cover data. Percent slope was calculated using elevation data from the U.S. Geological Survey's National Map Viewer and the slope tool on ArcMap 10.2.2.

Spatial autocorrelation.—MaxEnt assumes that the presence data input into the software is independent and free from spatial autocorrelation (Merow et al. 2013). Therefore, a random distribution of occurrence data should be utilized within MaxEnt. Failure to account for spatial autocorrelation would introduce error into the model that may affect the model performance and result in overfitting and errors in prediction (Elith et al. 2011; Merow et al. 2013). As stated below, to alleviate some of the spatial autocorrelation in the wind turbine data, we randomly selected data for model training, while the rest were used for model evaluation (Pocewicz et al. 2013). However, the wind turbine data in this study represents a census, rather than a sample, of all wind turbines within the state of Indiana. Thus, any bias revealed is intrinsic to the entire wind turbine "population" and should be included in the model without modification to produce accurate predictions.

Sampling bias.—MaxEnt models assume that every point within a landscape has an equal chance of being sampled (Merow et al. 2013). However, sampling along roads violates this assumption, thus, giving rise to sampling bias (Reddy & Dávalos 2003; Merow et al. 2013). If such bias is not accounted for, the model's output may only represent the survey effort and/or intensity rather than the species' actual distribution (Phillips et al. 2009; Merow et al. 2013). To account for this bias, it is necessary that the background data be drawn from the area actually sampled (Phillips et al. 2009). Because our acoustic surveys took place along roads, our sampling area was considered to be all locations located within a 30 m buffer area along all routes surveyed, representing the sampling limits of our acoustic detectors. Similarly, the placement of wind turbines is not random. Therefore, we considered only the counties in Indiana in which turbines were located based on the FAA archived data to be the sampling area for background data, including counties with "work in progress".

Model selection.—MaxEnt utilizes a user-adjustable regularization parameter to constrain model complexity (Phillips et al. 2006; Warren & Siefert 2011; Merow et al. 2013). Comparison of models with various regularization values provides a method to determine the model that best balances model fit and complexity (Warren & Seifert 2011). For this study, ten models were created with varying regularization values (1, 3, 5, 7, 9, 11, 13, 15, 17, and 19) in MaxEnt 3.3.3k (Phillips et al. 2006) using red bat and wind development datasets and their respective environmental variables following the methods outlined by Warren & Siefert (2011). Results from each set of models were compared using ENMTools 1.4.4 (Warren et al. 2008). The model with the lowest AICc value was chosen for both red bats and wind turbines with the corresponding regularization value for each "best" model used for the empirical models.

Empirical models.—Empirical models for both red bats and wind energy development were run in MaxEnt using the appropriate regularization value obtained from the model selection method outlined above. Duplicate presence records in the same grid cell were removed within MaxEnt in order to prevent further autocorrelation (Diniz-Filho et al. 2003). Five red bat presence records were removed within MaxEnt for occupying the same grid cell, thus 450 red bat presence records were used for MaxEnt modeling – 315 for model training, 135 for model evaluation. All 1678 wind turbine records were used for MaxEnt modeling – 1,175 for model training and 503 for model evaluation. For each model, 70% of total presence records were used for model training and the remaining 30% were withheld for model evaluation. Background data for both red bats and wind turbines consisted of 10,000 points randomly distributed throughout the respective sampling areas. From our MaxEnt models we obtained raw output representations depicting relative occurrence probabilities for red bat habitats and wind energy development potential.

Both models had greater than 455 presence records, and this sample size allows MaxEnt to create complex response curves, or features, for the environmental variables (i.e., linear, quadratic, product, hinge, and threshold). In our case, MaxEnt utilized all features (linear, quadratic, hinge, product, and threshold) because of our large number of presence records (Elith et al. 2011; Merow et al. 2013).

MaxEnt null models.—AUC is the most popular predictor used in the literature to assess model accuracy of presence-only data in MaxEnt (Merow et al. 2013; Raes & ter Steege 2007). However, the use of background data (acting as pseudo-absences) decreases the maximum achievable AUC value to less than 1.0 and it is not always possible to determine based upon this value alone if a model contributes significantly to predicting suitable habitat (Raes & ter Steege 2007; Phillips et al. 2006). Therefore, it is necessary to assess whether the AUC value of a model significantly differs from that expected by chance through comparison to null models with AUC values from models created using randomly distributed presence locations (Raes & ter Steege 2007). Null models for both red bats and wind turbines were created by generating 500 sets of random locations (each set representing the same number of presence locations from original models) within each sampling area (Raes & ter Steege 2007). Each set of presence data for the null models was processed in MaxEnt utilizing the exact same parameters used for each empirical model. The AUC value for each empirical model was then compared to the distribution of AUC values of the corresponding null-model to determine whether the discrimination power of the empirical model was significantly greater than random.

Conflict potential.—Based on the best model, MaxEnt provides a map for both the red bat and wind energy models. Each cell within the maps is given a value that represents the relative probability of suitability for either red bats or wind energy. Each map was classified into distinct suitability categories using the maximum sum of sensitivity and specificity (max SSS) for each model as a threshold (Liu et al. 2005). Values above this threshold in each model were considered 'suitable' while values below this threshold were deemed 'unsuitable.' To quantify the potential for conflict between suitable red bat habitat and wind energy development potential, these maps were overlaid and the amount of area for each possible combination of suitability levels from both maps was determined. For each of these groups, the area and the percentage of each

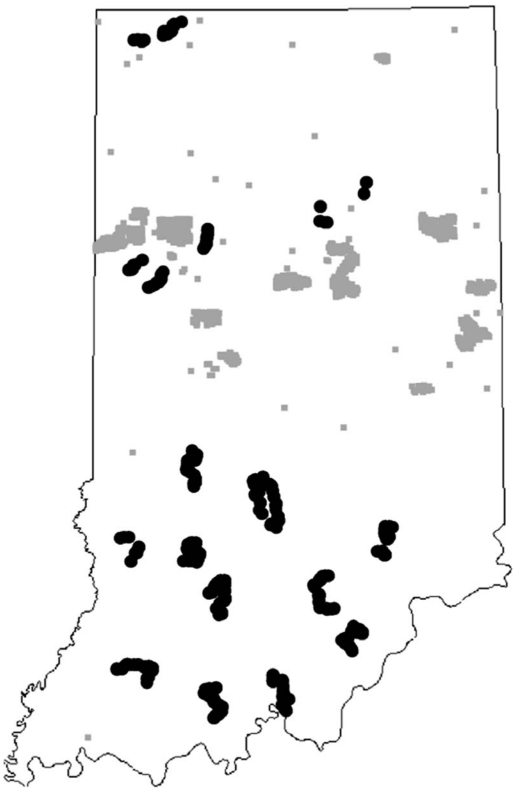

Figure 1.—Presence records of the eastern red bat (black circles) and wind turbines (gray squares) in Indiana, USA.

group present was calculated. All map manipulations were conducted in ArcMap 10.2.2.

RESULTS

Presence data.—A total of 4,649 echolocation calls was obtained from 47 surveys conducted across the state of Indiana. Figure 1 shows the 455 echolocation calls identified by EchoClass (v2) as red bats. Because red bats were relatively common, this map closely resembles the entire area surveyed. Spatial autocorrelation analysis resulted in a calculated ANN value of 639.58 m. When compared to the 500 null models created, the ANN of red bat occurrences showed no difference from random ($p = 0.058$), thus occurrences were considered independent and free from spatial autocorrelation. In addition 1678 wind turbine records were obtained (Fig. 1).

Empirical models.—The optimum model for red bats had the lowest AICc and a regularization parameter multiplier value of 3. The southern portion of the state had the highest predicted suitability for red bats (Fig. 2a). The training AUC for the red bat model was 0.705, while the AUC for the evaluation data set was 0.615 (SD = 0.025) with a max AUC of 0.671 (maximum AUC is calculated based on using total MaxEnt distribution and, in practice, training and evaluation AUC values may exceed this maximum; Philips et al. 2006). AUC values were significantly greater than those of null models ($p < 0.002$). The variables that contributed the most to the predicted suitability of this model were proportion of forest within 500 m, proportion of area with forest edge within 5 km, and proportion of forest within 1 km. The first two variables showed a strong positive effect on suitability while the final variable showed a strong negative effect on suitability (Fig. 3). It should be noted that the response curves of covariates assume all other environmental variables are held at mean values (Table 1). Thus, the seemingly contradictory results of optimal habitat suitability with complete forest cover within 500 m but no forest within 1 km is neither possible nor the actual conclusion of the model.

The optimum model for wind turbines had the lowest AICc and a regularization parameter multiplier value of 3. The predicted suitability for wind energy occurred mostly in the central portion of the state (Fig. 2b). The training AUC for the wind energy development model was 0.896 and the evaluation AUC was 0.890 (SD = 0.006) with a maximum AUC of 0.883. AUC values were significantly greater than those of null models ($p < 0.002$). The highest contributing variables were wind power at 50 m, land cover type, and wind speed at 100 m/s. Suitability peaked around 300 W/m^2 for wind power at 50 m and showed a strong positive effect between approximately 250 W/m^2 and this peak (Fig. 4a). Above 300 W/m^2, suitability dropped dramatically. Wind speed at 100 m showed a strong positive effect approximately between 8.0 m/s and 8.6 m/s with suitability plateauing at greater wind speed (Fig. 4b). Land cover types were treated categorically. The most positively associated land cover types were "cultivated crops" and "hay/pasture" (Fig. 4c).

Conflict potential.—For red bat and wind turbine suitability maps, max SSS threshold values of 37.26 and 14.15, respectively, were used to categorize each map into suitable and

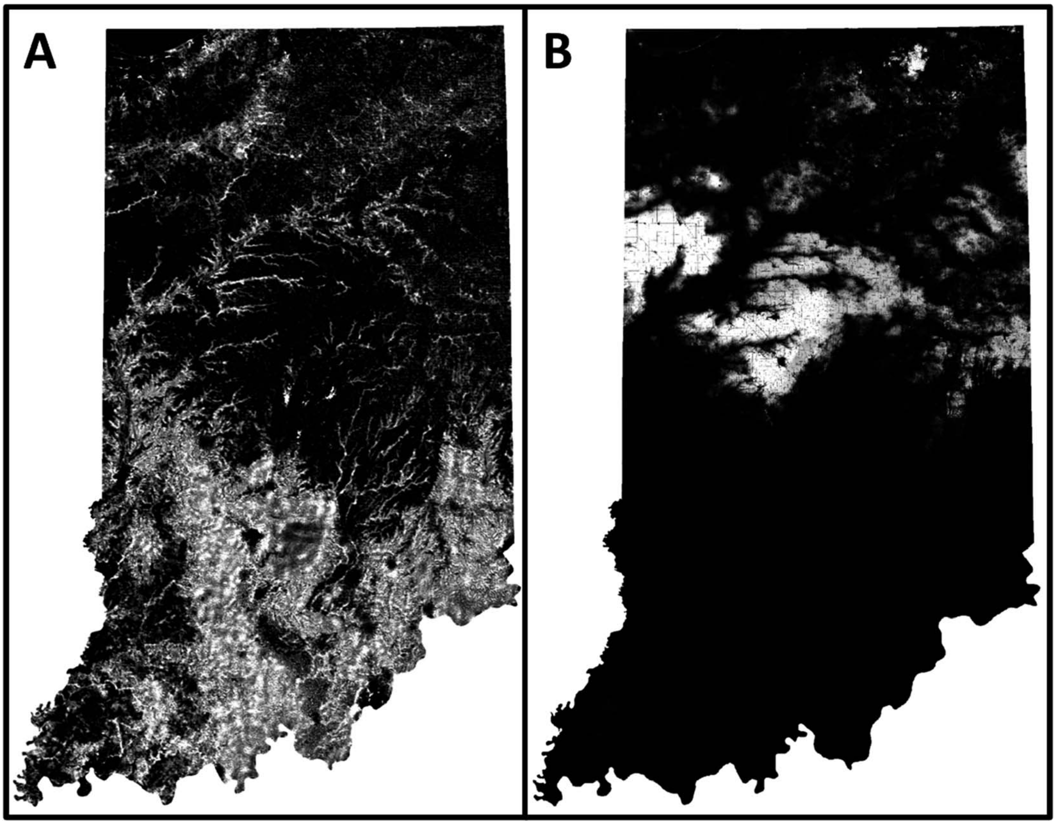

Figure 2.—Raw output maps showing (A) red bat habitat suitability and (B) wind development habitat suitability. For both maps, lighter colored areas, or areas with a greater value, represent greater suitability.

unsuitable regions. When maps were overlain, the majority of the state exhibited a low conflict potential between wind energy development potential and suitable red bat habitat (Fig. 5). Approximately 73.8% of the state was unsuitable for both wind energy development and red bats (Table 2), constituting an area of about 69,554 km^2. The majority of the remaining areas were regions with suitable habitat for either wind energy development or red bats, but not both. Less than 1% of the entire state represented areas suitable for both wind turbine development and red bats. The areas of high conflict were located in the northwestern and west-central portions of the state and comprised approximately 4 km^2. Areas where cropland is adjacent to deciduous forest patches dominate much of the conflict. This is particularly evident in rural areas (i.e., areas not highly or moderately developed). A portion of the area along Lake Michigan, where there is a high density of forest, also revealed a high conflict potential. This area has a relatively high wind power (> 250 W/m^2) at 50 m, as well.

DISCUSSION

With a rapidly changing landscape, identifying areas that may support potentially threatened species but that may put such species at risk from human development is of upmost importance (Manel et al. 2001; Roscioni et al. 2013; Santos et al. 2013). Wind energy has the potential to provide a sizable portion of Indiana's energy needs (AWEA 2018), but establishing a coexistence of this clean energy source and maintaining habitat for wildlife populations is a growing management concern (Baerwald & Barclay 2009; Arnett & Baerwald 2013). Due to their ecological importance as consumers of insects (Boyles et al. 2011), temperate bats are of particular concern (Mickleburgh et al. 2002). Additionally, bats are long-lived and have relatively low reproductive rates (Barclay & Harder 2003), so the effect of fatalities

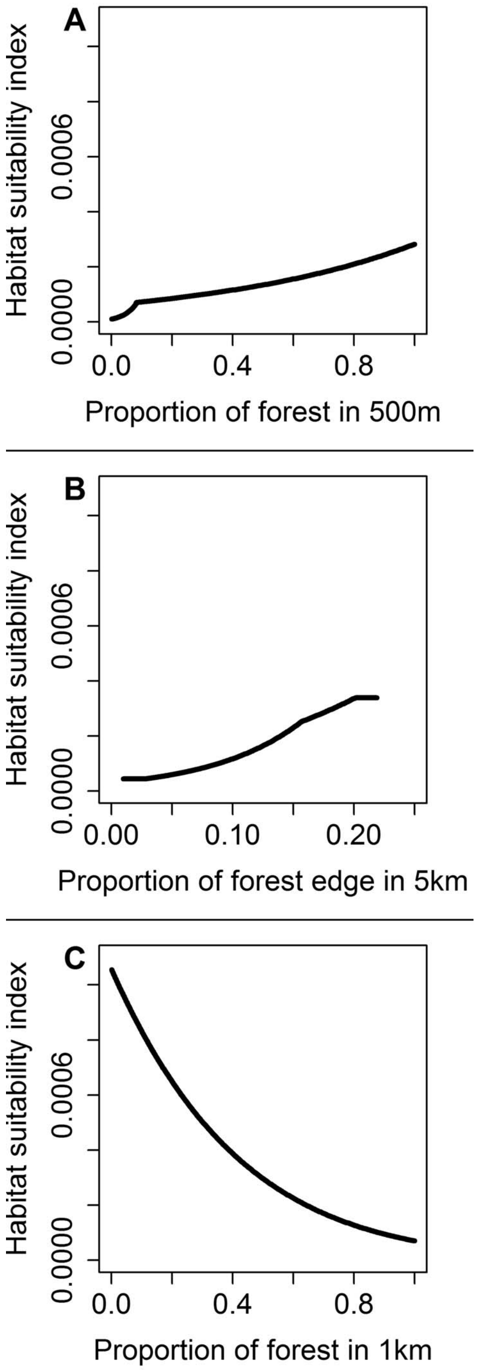

Figure 3.—The response curves of the top three most influential variables on the red bat model. The trend line represents how habitat suitability varies as the following variables change while all other variables are kept constant: (A) proportion of forest within 500 m, (B) proportion of forest edge within 5 km, and (C) proportion of forest within 1 km.

due to wind energy development may have a disproportionate impact on bat populations. Quantifying the potential for conflict between wind energy development and wildlife may be an efficient way to reduce bat mortality from wind energy development (Roscioni et al. 2013; Santos et al. 2013). Models produced by SDMs have the potential to be useful tools aiding in the siting of wind energy facilities in areas to reduce the risk of bat fatalities (Roscioni et al. 2013; Santos et al. 2013.)

While MaxEnt has been shown to produce reliable and informative models, several criticisms of presence-only modeling exist (Royle et al. 2012; Yackulic et al. 2013). Particularly, it is important to emphasize that the results from this study provide only an index of relative habitat suitability and not quantitative estimates of occupancy. Additionally, while the detection probability of red bats was not directly measured, we acknowledge that detection probability may have varied throughout the sampled areas (Yackulic et al. 2013). For example, differences in structural complexity near or above the roads used to survey bats may have affected the ability of the acoustic detectors to identify bats at various intervals along the road (Patriquin et al. 2003; Broders et al. 2004; Yates & Muzika 2006). In addition, while the sampling area of this study was considered to be within a 30 m buffer area along roads, our models predicted suitability across the entire state of Indiana. Although the sampling area represents much of the state of Indiana, this should be taken into consideration when interpreting results.

Red bat suitability models.—While previous studies have investigated habitat selection of red bats, our red bat model estimates the potential for suitable habitat by quantifying features of the habitat and projecting those predictions across a broad area. Furthermore, this model represents nocturnal activity of resident red bats. The habitat needs of foraging red bats may be very different from roosting red bats (Pauli et al. 2015), and these needs likely differ between resident and migrant red bats. The three most important variables for the red bat model were the proportion of forest within 500 m, forest edge within 5 km, and the proportion of forest within 1 km. The proportion of forest within 500 m showed a positive relationship with suitability across Indiana. Forest edges within 5 km also had a positive relationship with suitability, but forest within 1

Table 1.—Mean values of predictor variables at sample locations used for the red bat habitat suitability model and wind energy development model. Generating the response curves from the MaxEnt models involved setting all variables, except for the variable of interest, to this constant mean value. The most common landcover type, which was used in the wind energy development model, was cultivated crops.

	Predictor variable		Mean
Red bat model	Forest edge (%)	500 m	19.15
		1 km	13.27
		3 km	12.77
		5 km	13.03
	Forest (%)	500 m	68.51
		1 km	68.64
		3 km	66.32
		5 km	61.36
	Developed area (%)	500 m	0.10
		1 km	0.11
		3 km	0.19
		5 km	0.27
	Streams in forest (%)	500 m	5.17
		1 km	5.08
		3 km	4.75
		5 km	4.48
	Stream length (m)	500 m	47.28
		1 km	196.61
		3 km	1727.12
		5 km	4649.54
Wind energy model	Wind power (watts per m^2)	50 m	300.75
		100 m	470.94
	Wind speed (m/s)	50 m	6.68
		100 m	7.75
	Slope (%)	-	1.10

km was a negative relationship. Forest edges can be particularly important to foraging red bats and other insectivorous bats (Mager & Nelson 2001; Law & Chidel 2002; Morris et al. 2010), but too much "clutter" (i.e., obstacles) within the foraging area may impede flight and echolocation (Fenton 1990; Elmore et al. 2005). This suggests that although forests, particularly forest edges or openings within forest, may be important for roosting, traveling, and some foraging opportunities within a small spatial scale, contiguous forests at a scale of 1 km may not provide optimal foraging habitat. Southern Indiana is composed of relatively intact forests (Jenkins 2012), and forest edges likely provide highly used foraging and traveling habitats.

While our model had somewhat low AUC values (Swets 1988; Araujo & Guisan 2006), comparisons with null models show that the potential to provide valuable information on the habitat preferences of red bats is significant (Raes & ter Steege 2007). However, the ability of our model to correctly discriminate between a presence location and a random site, based on AUC values, is still rather low. This could be explained by the fact that species with a broad geographic range and generalized habitat preferences provide models of relatively low predictive power (Kadmon et al. 2003; Hernandez et al. 2006). Red bats appear to be habitat generalists with an ability to use a variety of habitat types (Furlonger et al. 1986; Elmore et al. 2005; Ford et al. 2005). Furthermore, modeling nocturnal activity combines both foraging and commuting detections. This aggregation of locations that bats might select for different activities may dilute some of the precision of habitat selection models. Additionally, the lower AUC of the evaluation data compared to the training data may indicate that overfitting occurred, even though we attempted to account for overfitting (Merckx et al. 2011; Warren & Seifert 2011). Nonetheless, this model is valuable as a method for delineating areas likely to be favored by red bats in Indiana.

Wind development models.—In contrast to the habitat preferred by foraging red bats, sites suitable for wind energy development in Indiana are generally in very open habitats with flat terrain. The main consideration when assessing areas for wind energy development is wind resource availability (Brower et al. 2010). Two factors that greatly influencing wind resource availability are wind power and wind speed. Our model indicated that wind power at 50 m and wind speed at 100 m were the most influential variables predicting suitable areas for wind development. Generally, wind power greater than 400 W/m^2 and wind speed greater than 7.0 m/s at 50 m is suitable for most wind development applications (Bailey et al. 1997). Our results indicated that wind power at 50 m peaked around 300 W/m^2 (Fig. 4a) corresponding to the minimum requirement. Although our results represent wind speed at 100 m, the wind speed minimum requirement at 50 m can be extrapolated to this height using a form of the power function (Bailey et al. 1997) that accounts for wind shear at varying heights. The resulting extrapolated minimum value for wind speed at a height of 100 m is 7.1 m/s. Our

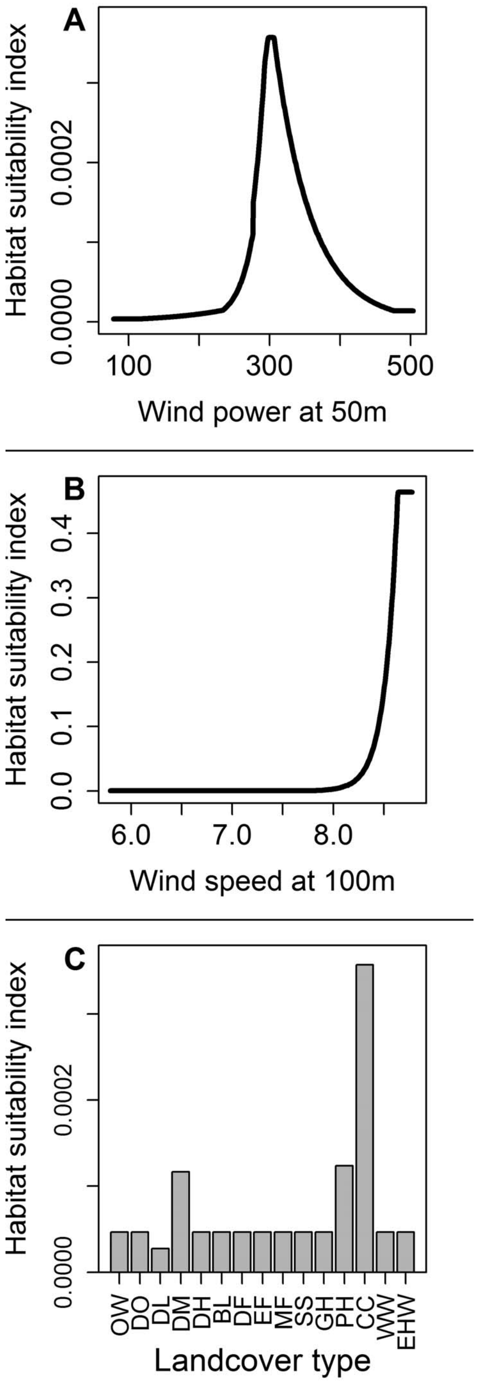

Figure 4.—The response curves of the top three most influential variables on the wind energy development model. The trend line represents how habitat suitability varies as the following variables change while all other variables are kept constant: (A) wind power (W/m^2) at 50 m, (B) wind speed (m/s)

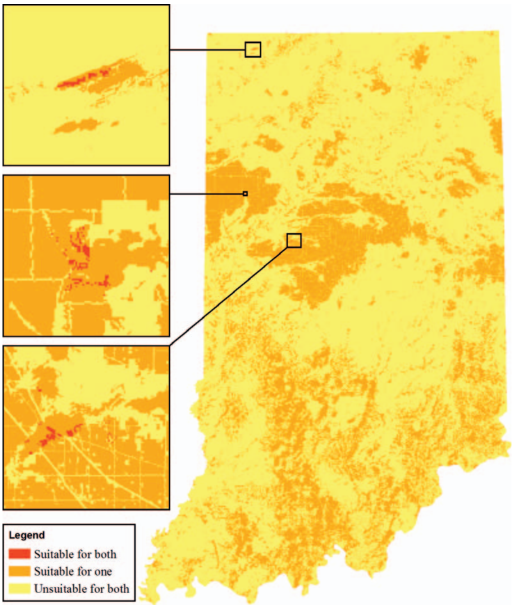

Figure 5.—A representation of the conflict potential between habitat suitability for the red bat and wind energy development describing areas that are unsuitable for both, suitable for one, or suitable for both. The three insets are included to make areas of conflict visible. They contain 57% of the identified areas of conflict on the map.

results indicated that wind speed at 100 m plateaus at 8.6 m/s and greater (Fig. 4b) exceeding this minimum requirement.

Land cover type was also an important variable in predicting suitable wind energy development areas. In particular, cultivated crops and hay/pasture had the most influence on suitability than any other cover type. Indeed, most of the utility-scale wind farms currently in operation are located in agricultural, grassland, and desert habitats (Kunz et al. 2007; Arnett et al. 2008; Denholm et al. 2009).

For these two factors our results coincide with the industry standards used to assess areas for

←

at 100 m (note the different scale used for y-axis), and (C) land cover type [OW = open water, DO = developed open space, DL = developed low intensity, DM = developed medium intensity, DH = developed high intensity, BL = barren land, DF = deciduous forest, EF = evergreen forest, MF = mixed forest, SS = shrub/scrub, GH = grassland/herbaceous, PH = pasture/hay, CC = cultivated crops, WW = woody wetlands, EHW = emergent herbaceous wetlands].

Table 2.—The area (km^2) and percentage of each combination of suitable and unsuitable cells for the habitat suitability for red bats and the habitat suitability for wind energy development.

Red bat suitability	Wind energy development	
	Unsuitable	Suitable
Unsuitable	69554 (73.8%)	9676 (10.3%)
Suitable	14961 (15.9%)	4 (0.004%)

wind development in Indiana and other Midwestern states. Moreover, much of the best wind resource availability in Indiana is located in the northern part of the state (GEC 2005), and supported by our results

Compared to the predictive power of our red bat model, our wind model showed better predictive power overall (Swets 1988; Raes & ter Steeg 2007), indicating that it is likely sufficient for identifying suitable wind energy development locations within this region based on the given environmental variables and parameters (Pearce & Ferrier 2000). While using SDMs to predict potential development by humans is in its infancy, it has great potential for the prediction of future wind energy developments (Pocewicz et al. 2013; Petrov & Wessling 2015).

Potential conflict.—Our conflict potential map represents an alternative to assessing wind energy impacts on bats during siting analyses conducted before construction of facilities begins (Roscioni et al. 2013; Santos et al. 2013). Modeling future anthropogenic development to determine possible impacts on wildlife can be a useful and relatively quick approach to identifying conflicts (Copeland et al. 2013; Pocewicz et al. 2013). With such contrasting habitat requirements, it was not unexpected that there would be little conflict for suitable locations between bats and wind turbines in the state. Our conflict analysis did show a low potential for conflict between suitable summer habitat for red bats and suitable habitat for wind energy development in Indiana. Presumably, this indicates that summer resident red bats are not likely to occur where wind turbines might be present. However, a small proportion of the state showed a high potential for conflict, particularly in areas where large-scale wind energy projects already exist, and of potential concern is the influence these and future wind projects may have on bats.

For this study, several variables seemed to be of particular influence on high conflict potential. The presence of high conflict areas showed a pattern along areas where rural habitat (i.e., cultivated crops and hay/pasture fields) was adjacent to forest. Red bats readily utilize forest edge and open areas for foraging (Mager & Nelson 2001; Walters et al. 2007; Morris et al. 2010), yet as the distance from edge or forests increases foraging activity decrease (Johnson et al. 2004). Red bats have been observed foraging over agricultural lands (Walters et al. 2007), but generally, when foraging over terrestrial habitat, they prefer foraging over or near areas with some degree of woody vegetation (Furlonger et al. 1986; Hart et al. 1993). At a wind energy facility in Minnesota, Johnson et al. (2003) observed that the majority of bat activity recorded at wind turbines was located at turbines near woodlands. In our case, the wind turbines surveyed are located within rural areas with flat and relatively non-forested terrain. Nevertheless, this pattern of high suitability for wind development in these areas where agricultural fields meet forest edges suggests that wind development could potentially be problematic to foraging bats.

In summary, there is little risk for resident red bats at current wind energy facilities in Indiana except where high quality foraging habitat is situated near wind energy facilities. Because there appears to be little foraging opportunity for bats at wind energy facilities within farmland, conflict may not be great. Nonetheless, our model showed that there is a potential of conflict in areas where forest edge, which can provide quality foraging opportunities, exists near agricultural land. Thus, perhaps the risk for resident bats would be when they are commuting between roosts and foraging areas (Arnett et al. 2005). Furthermore, there is concern for migrating bats, as the peak of bat fatalities is generally during the fall migration period and migratory tree bats comprise a majority of the fatalities in most regions (Arnett & Baerwald 2013), but this warrants additional study in Indiana. Additionally, future studies should consider utilizing more than mobile acoustic surveys, such as stationary acoustic surveys, to detect bats.

Our examination of suitability models and conflict potential using MaxEnt are tools that may be useful for identifying areas that are preferred by red bats but that may be susceptible to development, particularly in states that utilize similar habitats for wind energy development as Indiana. With the rapid increase of wind energy development, a means of securing optimal habitat for bats before the construction of future facilities could be both economically efficient and biologically beneficial.

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