Bird and bat responses to wind energy development in Iowa

by

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CHAPTER 1. GENERAL INTRODUCTION

BACKGROUND

Wind energy has been used since the early 1970s in North America (Arnett et al. 2007) and there are currently 35,600 mega-watts (MW) of total wind power capacity operating in the United States, enough to power 9.7 million homes (American Wind Energy Association 2010). Wind energy is touted as a "green" source of energy and results in a reduction of greenhouse gas emissions (Arnett et al. 2007, American Wind Energy Association 2010). Yet there are growing concerns regarding the effects of wind energy on wildlife, which can be affected by wind energy facilities both directly (e.g., mortality or decreased reproductive success) and indirectly (e.g., habitat loss or an avoidance/displacement behavioral response) from both the turbines and the related infrastructure (Arnett et al. 2007, Kuvlesky et al. 2007, Pearce-Higgins et al. 2012). These threats seem especially prevalent for airborne wildlife, specifically birds and bats. It has been proposed that avoidance behavior might be the greatest impact wind energy has on wildlife, especially for wide-ranging species (Arnett et al. 2007). This additional habitat loss from avoidance can be significant for some sensitive bird and bat species (Drewitt and Langston 2006).

Iowa is currently third in the nation in installed wind energy capacity, with 4,536 MW in operation as of October 2012 and 10,801 MW of potential projects currently planned (American Wind Energy Association 2012). This current operating wind energy in Iowa avoids 7.7 million metric tons of CO_2 emissions each year (American Wind Energy Association 2012), and development continues to be an important priority for the state's energy independence and economic development (Harr and Vannoy 2009). Previous

studies have found that avian mortality due to wind turbines in Iowa is low, although mortality is greater for bats but still lower than estimates from Eastern deciduous forests (Jain 2005, Jain et al. 2011). Additionally, it has been proposed that placing turbines on already disturbed lands, such as row-crop agriculture in Iowa, will reduce any impacts of future developments on wildlife (Kuvlesky et al. 2007, Kiesecker et al. 2011, Fargione et al. 2012). Thus, much of the future wind energy development in the United States may be focused on agricultural lands such as those encompassing much of Iowa. Yet few studies have investigated the indirect impacts of wind energy development in an agricultural landscape, which, when combined with mortality, may pose a major threat to wildlife.

GOALS AND OBJECTIVES

The overall goal of this study was to investigate the indirect impacts of wind turbines on birds and bats in primarily agricultural portions of Iowa. This goal was achieved by addressing these three objectives:

1. Document bird use at wind farm sites in Iowa by estimating the density of breeding birds in relation to proximity to turbines.

2. Assess relationships between the nest survival of Red-winged Blackbirds (*Agelaius phoeniceus*) and proximity to a wind turbine.

3. Monitor bat activity patterns near wind turbines to determine if proximity to turbine affects activity of bats.

THESIS ORGANIZATION

This thesis follows the journal paper format. Chapter 1 provides a general introduction to the thesis. Chapters 2 through 4 address the research objectives outlined above. Specifically, Chapter 2 is a paper focusing on behavioral responses of birds to wind

turbine proximity, Chapter 3 is a paper investigating the effects of wind turbine proximity on the nest survival of Red-winged Blackbirds, and Chapter 4 is a paper on bat activity patterns at an Iowa wind farm. Chapter 5 summarizes general conclusions from the three journal papers that comprise this thesis. Manuscript authors each contributed to the design, data analyses, or writing of one or more papers.

LITERATURE CITED

American Wind Energy Association. 2010. Market Update: Record 2009 leads to slow start in 2010. American Wind Energy Association. http://www.windturbineins.com/_literature_59898/Market_Update

American Wind Energy Association. 2012. Wind Energy Facts: Iowa. American Wind Energy Association. http://awea.org/learnabout/publications/factsheets/upload/4Q-11-Iowa.pdf

Arnett, E., D. Inkley, D. Johnson, R. Larkin, S. Manes, A. Manville, J. Mason, M. Morrison, M. Strickland, and R. Thresher. 2007. Impacts of wind energy facilities on wildlife and wildlife habitat. Wildlife Society Technical Review 07-2, 49 pp. The Wildlife Society, Bethesda, Maryland, USA.

Drewitt, A. L. and R. H. Langston. 2006. Assessing the impacts of wind farms on birds. Ibis 148:29-42.

Fargione, J., J. Kiesecker, M. J. Slaats, and S. Olimb. 2012. Wind and Wildlife in the Northern Great Plains: Identifying Low-Impact Areas for Wind Development. PLoS One 7:e41468.

Harr, D. and L. Vannoy. 2009. Wind Energy and Wildlife Resource Management in Iowa: Avoiding Potential Conflicts. Iowa Department of Natural Resources. http://www.iowadnr.gov/portals/idnr/uploads/wildlife/wind_wildliferecs.pdf

Jain, A. A. 2005. Bird and bat behavior and mortality at a northern Iowa wind farm. Thesis. Iowa State University, Ames, USA.

Jain, A. A., R. R. Koford, A. W. Hancock, and G. G. Zenner. 2011. Bat mortality and activity at a northern Iowa wind resource area. The American midland naturalist 165:185-200.

Kiesecker, J. M., J. S. Evans, J. Fargione, K. Doherty, K. R. Foresman, T. H. Kunz, D. Naugle, N. P. Nibbelink, and N. D. Niemuth. 2011. Win-win for wind and wildlife: a vision to facilitate sustainable development. PLoS One 6:e17566.

Kuvlesky, W. P., L. A. Brennan, M. L. Morrison, K. K. Boydston, B. M. Ballard, and F. C. Bryant. 2007. Wind Energy Development and Wildlife Conservation: Challenges and Opportunities. Journal of Wildlife Management 71:2487-2498.

Pearce-Higgins, J. W., L. Stephen, A. Douse, and R. H. W. Langston. 2012. Greater impacts of wind farms on bird populations during construction than subsequent operation: results of a multi-site and multi-species analysis. Journal of Applied Ecology 49:386-394.

CHAPTER 2. BREEDING BIRD RESPONSES TO WIND TURBINES IN AN AGRICULTURAL LANDSCAPE

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ABSTRACT

Most previous studies of wind energy's impacts on wildlife in the United States have measured direct mortality. Yet it is known that wind energy can also indirectly impact birds by altering habitat use around the turbines. Our study goal was to identify species-specific responses of birds from three habitat groups (generalist, agriculture, and grassland) to wind turbines in an agricultural landscape. We conducted 1,880 point counts at three wind farms and paired control sites in Iowa during 2011 and 2012. Data were analyzed for detection probability in program MARK, and these detection probabilities were then used to estimate densities in proximity to turbines, which we then compared with patterns of density at our paired control sites. We documented avoidance behavior (particularly with grassland and generalist species, including Dickcissel, Common Yellowthroat, Red-winged Blackbird, and American Robin), attraction behavior (mostly in agricultural species, and especially in Killdeer) and multiple examples of species unaffected by turbine proximity (including Song Sparrow and Common Grackle). Additionally, we found significantly lower species richness at two of our three sites at the turbine base as compared to points ≥250 m from the turbine. As wind energy development continues on agricultural lands, our work will help the wind industry and natural resource managers identify potential

avoidance or attraction behavior and ultimately make more informed decisions about wind turbine placement to benefit breeding birds.

KEY WORDS: Agriculture, breeding bird, density, point count, program MARK, turbine, wind energy

INTRODUCTION

As the costs of nonrenewable energy resources continue to rise, both financially and politically, the development of alternative energy sources has accelerated. The U.S. Department of Energy released a report in May 2008 stating that having 20% of U.S. electricity needs met from wind energy by 2030 was feasible without any additional technological advances, and would reduce emissions of greenhouse gases by 825 million metric tons (U.S. Department of Energy 2008). Wind power is an alternative energy source that generates no emissions (American Wind Energy Association 2009) and provides a cost-competitive energy source (Swisher et al. 2001). Wind power is often considered "green" energy and the installation of wind turbines in the Midwest and elsewhere has steadily increased particularly since the early 2000s (American Wind Energy Association 2012).

The installation of infrastructure to support wind energy, including wind turbines, power lines, and access roads, can impact birds in many ways (Kuvlesky et al. 2007). Most previous studies of wind energy effects on birds have focused on direct mortality caused primarily by collisions with infrastructure. The estimated number of birds killed by turbines has ranged from 0.63 birds per turbine per year to 7.70 birds per turbine per year across the U.S. in a variety of habitats, studies, and years (McCrary et al. 1986, Howell and DiDonato 1991, Howell and Noone 1992, Erickson et al. 2000, Johnson et al. 2000,

Johnson et al. 2003, Young Jr. et al. 2003). Due to the flight patterns of birds near wind turbines and the relatively low documented mortality rates, other energy industries or human-made structures such as communication towers may be more harmful than wind turbines to birds in cropland areas (Osborn et al. 1998, Osborn et al. 2000). Overall, wind farms are responsible for an estimated 33,000 bird deaths each year in the U.S., compared to 4 to 5 million from communication towers and 60 million deaths by car collisions (U.S. Fish and Wildlife Service 2002). This direct mortality is important, but doesn't account for other, less studied, effects on birds.

Wind energy may also result in indirect effects to birds by altering how they use habitat in close proximity to wind turbines. The greatest threat facing birds today is habitat loss or degradation due to human development and disturbance (U.S. Fish and Wildlife Service 2002) and wind turbines are known to cause a direct loss of habitat as well as habitat fragmentation and disturbance (Larsen and Madsen 2000, Drewitt and Langston 2006). Past studies have shown varied influences of wind turbines on bird abundance, ranging from no effect (Koford et al. 2004, Jain 2005, Devereux et al. 2008, Jain et al. 2011) to effects extending from 100 to 500 m from the base of the wind turbine (Leddy et al. 1999, Johnson et al. 2000, Pearce-Higgins et al. 2009), with up to a four-fold increase in density away from the turbine base (Leddy et al. 1999). Additionally, one study found that turbines lower species richness up to 200 m away from the turbine base (Villegas-Patraca et al. 2012). Despite this knowledge, there are far fewer studies of indirect effects when compared to mortality studies, and the extent of disturbance varies by site and species (Drewitt and Langston 2006).

We focused on the indirect effects of wind turbine proximity rather than direct habitat loss, which accounts for less than 2% of the actual wind farm area (Fox et al. 2006). The objective of our study was to quantify the indirect impacts of wind farms on the densities of multiple breeding bird species in an intensive agricultural landscape in Iowa. Findings from this study may help us to better understand the indirect effects of future wind energy development on breeding birds and better inform future siting guidelines.

METHODS

Study sites

We studied breeding birds at three sites in Hancock, Osceola and Story counties in Iowa (Figure 1). These sites were distributed across the central, north-central and northwestern parts of the state in areas with high concentrations of wind farms. These three sites were chosen because of the cooperation of Nextera Energy and to spatially replicate the study in different regions of Iowa. Paired control sites were located within 2-5 km of each wind farm, a distance that is generally accepted to be beyond the influence of the wind farm (U.S. Fish and Wildlife Service 2003) while still being close enough to minimize differences in topography and land use. All sites had roads every, or nearly every, 1 mile, creating 1-mile square sections dominated by row-crop agriculture (primarily corn and soybeans) with small amounts of grasslands (from the Conservation Reserve Program) and woodlots (mainly as windbreaks around homesteads). The counties differed in the ratio of agriculture to grassland on the landscape with Story County having the most agriculture (>90%) and Hancock County the least (<75%).

Point counts

We used point counts during the breeding seasons (late May through mid-July) of 2011 and 2012 to sample the breeding bird community. These dates include the peak breeding times for almost all birds using these areas, except for a few early breeders (e.g., Great Horned Owl). At each wind farm, 14-15 turbines (15-25% of the total turbines per farm) were randomly chosen for starting points, and 6-11 starting points at the control sites were selected based upon landowner cooperation. Random selection of controls was infeasible due to low landowner participation, and we were sometimes unable to find a paired control for each turbine within the preferred 2-5 km radius of each wind farm. From these starting points, we created 1000 m transects with points every 250 m from the starting point (either a wind turbine or one of the selected control points) until the last point was 1000 m from the starting point. We positioned the control starting points in the middle of agricultural fields when possible, mimicking the potential placement of a turbine on the landscape. Each of these points was visited three times each year, except when prohibited due to turbine maintenance or landowner consent issues. The point counts at each turbine and paired control site were done by a single observer each year, but observers differed between counties (except that the same observer did all work in Story County).

We used unlimited radius 6-minute point counts and binned sightings into five distance bins: 0-25 m, 25-50 m, 50-75 m, 75-100 m, and >100 m (Lueders et al. 2006). Sightings were also binned into 2-minute time intervals for the removal method to estimate detection probability (Farnsworth et al. 2002). Combining distance sampling and removal methods is a newer tool to estimate detection probabilities, and does not require the assumption that all birds at the observer are detected (Farnsworth et al. 2005). When birds are primarily

being detected by song, detection probability is the product of two probabilities, (1) the

probability of a bird singing during the point count, and (2) the probability that the

observer detects the bird given that it sang (Farnsworth et al. 2002, Farnsworth et al. 2005).

Distance sampling addresses the second part of that product (the probability of detection

provided that the bird sings), while the removal method addresses the first portion of the

probability (the probability of a bird singing). The assumptions of the removal model

included a closed population (observers were trained to only record birds that were within

the sampling area during the survey, excluding birds that flew in), no double-counting of

individuals (easier to accomplish in an open-habitat like a wind farm where there are

smaller numbers of birds and fewer visual obstructions), and that time and distance bins

were accurately assigned/recorded (Farnsworth et al. 2002, Farnsworth et al. 2005).

Detection probability

It is now well understood that detection probability of birds can vary by species

(Best 1981), often due to differences in the species' singing frequency (Farnsworth et al.

2002). Additionally, observers may have slightly different detection probabilities based

upon their experience (Sauer et al. 1994) or distance from the bird (Buckland et al. 1993).

Detection probability also differs based upon time of day, day of season (Ralph 1981,

Skirvin 1981), and wind speed (Robbins 1981). It has also been hypothesized that turbine

noise might alter detection probability, with birds being less detectable nearer the turbine

(Johnson et al. 2000). At a point, we collected data on these covariates, including the time

of day, day of season, wind speed, distance to turbine, and percent cloud cover and

incorporated these into our models along with the distance bin of each detection (Table 1).

Detection probability was modeled for all bird species with adequate detections, which we

defined as ≥25 detections for 4 or more of the 5 observers. We classified each species into one of three habitat groups (generalist, agricultural, or grassland) based upon their known habitat associations and breeding preferences.

Models of detection probability

We created species-specific models of detection probability in program MARK (White and Burnham 1999) using the Huggins Closed Captures model (Huggins 1989, 1991) with the probability of recapture set to zero (Farnsworth et al. 2002). Models were selected using Akaike's Information Criterion (AIC, Akaike 1973). We used stepwise backward selection, creating main effects models (either a constant detection probability across observers, or detection varying by observer), and then used the best main effects model to create a model with all covariates. We then sequentially eliminated the least important covariate (determined by looking at the minimum absolute value of the beta estimate divided by the standard error of the covariate) and continued until the elimination of a covariate resulted in an increase of the AIC value (Pagano and Arnold 2009, Arnold 2010). Detection probability was then estimated using model-averaging, and densities were estimated by model averaging the density estimates from each model.

Analysis of relative abundance/species richness

Once the detection probabilities were calculated, we adjusted the study counts before estimating density/abundance and their accompanying standard error/precision estimates (Burnham 1981). Detection probability ($\hat{p}$), area surveyed (A), and raw count data ($x.$) were used to estimate the number of individuals ($\hat{N}$) at a point, the density ($\hat{D}$), and the variance of the density estimate ($\widehat{Var}\hat{D}$) according to the following equations (Farnsworth et al. 2002):

$$\widehat{N} = x./\hat{p}$$

$$\widehat{D} = \widehat{N}/A$$

$$\widehat{Var}\widehat{D} = \frac{(x.)^2\widehat{Var}(\hat{p})}{A^2\hat{p}^2} + \frac{(x.)(1-\hat{p})}{A^2\hat{p}^2}$$

Relative densities and their corresponding 95% confidence intervals were calculated for each site by year combination. We tested three behavioral response hypotheses for each species – attraction, avoidance and no effect. If a species was attracted to the turbine base, it would be found in greater densities near the turbine base than at similar points at the control site, as well as points further from the turbine on the treatment site. If a species was avoiding the turbines, it would be found in significantly lower densities at the turbine base than at similar control points, as well as points on the treatment plot that were further from the base. Finally, if a species was not affected by the presence of turbines, it would be found in similar densities at the control and treatment sites, and at all distances from the turbine base. The 95% confidence intervals of the density estimates were compared to determine avoidance, attraction, or no effect by comparing trends between the treatment and control sites for significant differences.

Species richness was defined as the mean number of species detected per survey point (Johnson et al. 2000) using only points that were visited three times each season to have the same per-unit effort. We compared mean richness (with corresponding 95% confidence limits) at the turbine base and at 250 m, 500 m, 750 m, and 1000 m from the turbine base with mean richness at corresponding control sites.

RESULTS

Point counts

Across the three counties of our study we detected 67 bird species at 956 point counts in 2011 and 47 bird species at 924 point counts in 2012 (Table 2). Of these totals, 8 species from three habitat groups had adequate detections for analysis (Table 3). The generalist species included American Robin (AMRO), Song Sparrow (SOSP), Red-winged Blackbird (RWBL), and Common Grackle (COGR). Agricultural species included Killdeer (KILL) and Vesper Sparrow (VESP), and the grassland species were Common Yellowthroat (COYE) and Dickcissel (DICK).

Detection probability

The best models of detection probability for three of the species (AMRO, VESP, SOSP) included evidence of constant detection across observers, but all other species showed evidence of observer differences (Table 4). The time of day of a point count had had a small effect on the detection probability of one species (RWBL). Increased wind speeds were found to increase detection probabilities for three species (COYE, VESP, RWBL) and decrease detection for one (COGR). Cloud cover also had varied effects on detection probability, with cloudier days increasing detection probability for one species (RWBL) while decreasing detection for five species (COYE, VESP, SOSP, DICK, COGR). The distance from the bird to the observer (Distance Bin) negatively impacted detection probability for four species (KILL, COYE, VESP, COGR). The distance to the turbine had a small effect on detection probability with detection lower at the turbine base for four species (COYE, VESP, RWBL, COGR) and higher for two species (KILL, DICK). Day of season had a negative effect on American Robin ($\beta_{Day} = -0.0291$) and a

positive effect on Common Yellowthroat ($\beta_{Day} = 0.0174$). The interaction between wind speed and distance to turbine was a small negative effect for three species (COYE, VESP, RWBL).

Relative densities

All species showed avoidance behavior at one or more sites during our study, ranging from avoidance only at the turbine base to avoidance across the entire treatment site (Table 5). Avoidance was strongest for the grassland species, and Dickcissel showed avoidance at all six sites and avoided the turbines for at least 250 m from the turbine base. The other grassland species (COYE) showed avoidance at five of the six sites, and again avoided the turbines for at least 250 m when avoidance was evident. Of the four species that were generalists, all showed avoidance behavior at half or more of the sites. This behavior was strongest in Hancock County where they tended to avoid the entire treatment site, versus the more agricultural Story and Osceola counties, which tended to only have avoidance behavior at the turbine base. The agricultural species were the least likely to show avoidance behavior, avoiding the turbine at only one of the six sites for each species.

Attraction behavior was found in five species (Table 5), but four of those species (AMRO, COYE, VESP, COGR) only showed attraction at one site each. Attraction ranged from spanning the entire treatment site (>1000 m) to attraction out to at least 250 m from the turbine base. However, Killdeer showed attraction at four sites across almost the entire treatment site, out to at least 1000 m from the turbine base.

Six of the species (KILL, AMRO, VESP, SOSP, RWBL, COGR) showed at least one example of no evidence of an effect of turbine proximity (Table 5). Of these, three species showed this at multiple sites (VESP, SOSP, COGR). None of the grassland species was

unaffected by the presence of turbines on the landscape. Species preferring agricultural habitat, or those with generalist habitat requirements, did not seem to be affected by proximity to turbines at some sites, although there was no real pattern between sites or years.

Species richness

Species richness was significantly lower at the turbine base than at points 250 m from the turbine in two counties (Table 6). Additionally, richness was greater at the starting point in Hancock County's control site than at the turbine base. No other distances from turbine or control-turbine combinations differed in their species richness.

DISCUSSION

Much like previous studies, our findings showed varied influences of wind turbines on bird abundance. Our study extended the scope of turbine proximity beyond the distances that had previously been documented for density effects (up to 500 m; Leddy et al. 1999, Johnson et al. 2000, Pearce-Higgins et al. 2009). Furthermore, we were able to find avoidance and attraction behavior that extended beyond 1000 m from the turbine base. These findings add to our knowledge of the behavioral responses of birds to wind turbines.

It has been proposed that birds see wind turbines as disturbance due to increased noise levels and human presence. Birds may avoid turbines to minimize potential collisions or to shun the presence of tall structures for species that prefer open landscapes (Leddy et al. 1999, Drewitt and Langston 2006, Devereux et al. 2008). The extent of disturbance will vary by site and species, and can occur during construction and operation phases due to the presence of the turbines themselves (visual, noise or vibration impacts) or due to vehicle/personnel activity related to maintenance (Drewitt and Langston 2006).

Accordingly, we found that grassland species (COYE, DICK) showed the strongest avoidance behaviors, which are probably due to their more specific habitat needs and preference for open habitats. Turbines tended to be placed in heavily agricultural settings in our study, leaving little habitat for specialized grassland species that are also area-sensitive and possibly avoid tall structures such as turbines (Leddy et al. 1999). Grassland birds in general are of particular concern due to their severe population declines, which are among the greatest of North America's Neotropical migrants (Sauer et al. 2003). Between 1980 and 1999, long-distance migrants that breed in grasslands had the greatest population declines of any group of birds (Murphy 2003). Many of these declines are associated with changes in land use, which are correlated with 25-30% of the variation in population trends among states (Murphy 2003).

Species with general habitat requirements showed the strongest avoidance in Hancock County. This site had the most grassland and native habitat left, so perhaps these species could avoid more of the area surrounding the turbine because there was more suitable habitat available nearby. In Osceola and Story counties they tended to show avoidance only at the turbine base. These sites tended to be heavily agricultural, with little grassland or other native habitats. The agricultural species were the least likely to show evidence of avoiding the turbines, showing this behavior at only one site each. These species may be more adapted to increased human activity and the presence of human-made structures on the landscape (U.S. Fish and Wildlife Service 2003).

While attraction behavior was documented in five species, most of these were only documented at one of the six sites, and may have been simply due to differences in habitat availability between control and treatment sites. However, Killdeer showed attraction at

four sites across almost the entire treatment site, out to at least 1000 m from the turbine base. Killdeer are tolerant of human activity and breed on gravel substrates (Jackson and Jackson 2000), which is more prevalent with the construction of wind turbines that require gravel access roads and gravel pads for the turbine placement and maintenance. Thus, for Killdeer, the development associated with wind energy actually increases the available nesting habitat on the landscape.

Some species did not show evidence of being affected by proximity to turbine. Of the six species that showed examples of no behavioral avoidance or attraction, three of the species showed this at multiple sites (VESP, SOSP, COGR). All of these species were classified as either generalist or agricultural habitat species, and no grassland species were unaffected by turbine proximity. Some of these species exhibiting no behavioral response to turbine proximity may have become acclimated to the presence of turbines on the landscape (Madsen and Boertmann 2008), and time since construction may also play a role.

Perhaps due to the combination of avoidance and attraction behaviors, species richness was significantly lower at the turbine base in Hancock and Osceola counties than control sites or points 250 m from the turbine base. This fit with another study that found lower species richness up to 200 m from the turbine base (Villegas-Patraca et al. 2012). Because behavioral responses to turbine proximity can vary by site and species (Drewitt and Langston 2006, U.S. Fish and Wildlife Service 2012), studies need to be conducted across multiple sites and habitats to fully understand the impact of increased wind turbine development on species richness in different habitat types. By focusing development on heavily agricultural lands, and creating grassland habitat >1000 m from the turbine base,

wind energy development may be able to help mitigate some of the effects on species richness.

Our study documented a range of responses by breeding birds to wind energy development in an intensive agricultural landscape in Iowa. Grassland birds were affected the most and generally exhibited avoidance of wind turbines. Generalist and agricultural species showed fewer and more varied responses that spanned a spectrum from attraction to avoidance behavior. Thus, the effects of wind turbines do not appear to be the same for all breeding birds, which is consistent with previous work (Leddy et al. 1999). Iowa's intensive agricultural landscape has low densities and low species richness of birds (Best et al. 1995), suggesting that overall impacts to breeding birds are less in such a heavy agricultural landscape than in other habitats such as native or restored grasslands. By siting turbines farther from grasslands, some of the avoidance of those species may be averted, limiting the impact of turbine development in this landscape. Future plans call for continued development of wind energy resources in Iowa (American Wind Energy Association 2012), primarily on lands currently managed for agriculture, and our work should help the wind industry and natural resource managers make more informed decisions about wind turbine placement to benefit breeding birds.

LITERATURE CITED

Akaike, H. 1973. Information theory and an extension of the maximum likelihood principle. Pages 267-281 *in* International Symposium on Information Theory, 2 nd, Tsahkadsor, Armenian SSR.

American Wind Energy Association (AWEA). 2009. Wind power and climate change. American Wind Energy Association. http://www.awea.org/learnabout/publications/upload/Climate_Change.pdf

American Wind Energy Association. 2012. Wind Energy Facts: Iowa. American Wind Energy Association. http://awea.org/learnabout/publications/factsheets/upload/4Q-11-Iowa.pdf

Arnold, T. W. 2010. Uninformative Parameters and Model Selection Using Akaike's Information Criterion. Journal of Wildlife Management 74:1175-1178.

Best, L. 1981. Seasonal changes in detection of individual bird species. Studies in Avian Biology 6:252-261.

Best, L. B., K. E. Freemark, J. J. Dinsmore, and M. Camp. 1995. A review and synthesis of habitat use by breeding birds in agricultural landscapes of Iowa. American Midland Naturalist 134:1-29.

Buckland, S. T., D. R. Anderson, K. P. Burnham, and J. L. Laake. 1993. Distance sampling: estimating abundance of biological populations. Chapman & Hall, New York, New York, USA.

Burnham, K. P. 1981. Summarizing remarks: Environmental influences. Pages 324-325 in Estimating Numbers of Terrestrial Birds (CJ Ralph and JM Scott, Eds.). Studies in Avian Biology 6:324-325.

Devereux, C. L., M. J. H. Denny, and M. J. Whittingham. 2008. Minimal effects of wind turbines on the distribution of wintering farmland birds. Journal of Applied Ecology 45:1689-1694.

Drewitt, A. L. and R. H. Langston. 2006. Assessing the impacts of wind farms on birds. Ibis 148:29-42.

Erickson, W., G. Johnson, M. D. Strickland, and K. Kronner. 2000. Avian and bat mortality associated with the Vansycle Wind Project, Umatilla County, Oregon: 1999 study year. Technical Report prepared by WEST, Inc. for Umatilla County Department of Resource Services and Development, Pendleton, Oregon. 21pp.

Farnsworth, G. L., J. D. Nichols, J. R. Sauer, S. G. Fancy, K. H. Pollock, S. A. Shriner, and T. R. Simons. 2005. Statistical approaches to the analysis of point count data: a little extra information can go a long way. USDA Forest Service General Technical Report PSW–GTR–191:735-743.

Farnsworth, G. L., K. H. Pollock, J. D. Nichols, T. R. Simons, J. E. Hines, J. R. Sauer, and J. Brawn. 2002. A removal model for estimating detection probabilities from point-count surveys. The Auk 119:414-425.

Fox, A., M. Desholm, J. Kahlert, T. K. Christensen, and I. Krag Petersen. 2006. Information needs to support environmental impact assessment of the effects of European marine offshore wind farms on birds. Ibis 148:129-144.

Howell, J. A. and J. E. DiDonato. 1991. Assessment of avian use and mortality related to wind turbine operations, Altamont Pass, Alameda and Contra Costa Counties, California, September 1998 through August 1989. Final report submitted to US Windpower. Inc., Livermore, California.

Howell, J. A. and J. Noone. 1992. Examination of Avian Use and Mortality at a US Windpower, Wind Energy Development Site, Montezuma Hills, Solano County, California: Final Report. Solano County, Department of Environmental Management.

Huggins, R. 1989. On the statistical analysis of capture experiments. Biometrika 76:133-140.

Huggins, R. 1991. Some practical aspects of a conditional likelihood approach to capture experiments. Biometrics 47:725-732.

Jackson, B. J. and J. A. Jackson. 2000. Killdeer (*Charadrius vociferus*).*in* A. Poole and F. Gill, editors. The Birds of North America [Online]. Cornell Lab of Ornithology, Ithaca, New York.

Jain, A. A. 2005. Bird and bat behavior and mortality at a northern Iowa windfarm. Thesis. Iowa State University, Ames, USA.

Jain, A. A., R. R. Koford, A. W. Hancock, and G. G. Zenner. 2011. Bat mortality and activity at a northern Iowa wind resource area. The American midland naturalist 165:185-200.

Johnson, G., W. Erickson, M. Strickland, M. Shepherd, and D. Shepherd. 2000. Avian monitoring studies at the Buffalo Ridge Wind Resource Area, Minnesota: Results of a 4-year study. Final report prepared for Northern States Power Company, Minneapolis, Minnesota, by Western EcoSystems Technology, Inc.(WEST), Cheyenne, Wyoming.

Johnson, G., W. Erickson, J. White, and R. McKinney. 2003. Avian and Bat Mortality During the First Year of Operation at the Klondike Phase I Wind Project, Sherman County, Oregon.

Koford, R., A. Jain, G. Zenner, and A. Hancock. 2004. Avian mortality associated with the top of Iowa wind farm. Progress report calendar year 2003.

Kuvlesky, W. P., L. A. Brennan, M. L. Morrison, K. K. Boydston, B. M. Ballard, and F. C. Bryant. 2007. Wind Energy Development and Wildlife Conservation: Challenges and Opportunities. Journal of Wildlife Management 71:2487-2498.

Larsen, J. and J. Madsen. 2000. Effects of wind turbines and other physical elements on field utilization by pink-footed geese (Anser brachyrhynchus): A landscape perspective. Landscape Ecology 15:755-764.

Leddy, K. L., K. F. Higgins, and D. E. Naugle. 1999. Effects of wind turbines on upland nesting birds in Conservation Reserve Program grasslands. The Wilson Bulletin 111:100-104.

Lueders, A. S., P. L. Kennedy, and D. H. Johnson. 2006. Influences of management regimes on breeding bird densities and habitat in mixed-grass prairie: an example from North Dakota. Journal of Wildlife Management 70:600-606.

Madsen, J. and D. Boertmann. 2008. Animal behavioral adaptation to changing landscapes: spring-staging geese habituate to wind farms. Landscape Ecology 23:1007-1011.

McCrary, M., R. McKernan, and R. Schreiber. 1986. San Gorgonio wind resource area: Impacts of commercial wind turbine generators on birds, 1985 data report. Prepared for Southern California Edison Company. 33pp.

Murphy, M. T. 2003. Avian population trends within the evolving agricultural landscape of eastern and central United States. The Auk 120:20-34.

Osborn, R. G., C. D. Dieter, K. F. Higgins, and R. E. Usgaard. 1998. Bird flight characteristics near wind turbines in Minnesota. The American midland naturalist 139:29-38.

Osborn, R. G., K. F. Higgins, R. E. Usgaard, C. D. Dieter, and R. D. Neiger. 2000. Bird mortality associated with wind turbines at the Buffalo Ridge Wind Resource Area, Minnesota. The American midland naturalist 143:41-52.

Pagano, A. M. and T. W. Arnold. 2009. Detection Probabilities for Ground-Based Breeding Waterfowl Surveys. The Journal of Wildlife Management 73:392-398.

Pearce-Higgins, J. W., L. Stephen, R. H. W. Langston, I. P. Bainbridge, and R. Bullman. 2009. The distribution of breeding birds around upland wind farms. Journal of Applied Ecology 46:1323-1331.

Ralph, C. J. 1981. An investigation of the effect of seasonal activity levels on avian censusing. Studies in Avian Biology 6:265-270.

Robbins, C. S. 1981. Bird activity levels related to weather. Studies in Avian Biology 6:301-310.

Sauer, J. R., J. E. Fallon, and R. Johnson. 2003. Use of North American Breeding Bird Survey data to estimate population change for bird conservation regions. The Journal of Wildlife Management 67:372-389.

Sauer, J. R., B. G. Peterjohn, and W. A. Link. 1994. Observer differences in the North American breeding bird survey. The Auk 111:50-62.

Skirvin, A. A. 1981. Effect of time of day and time of season on the number of observations and density estimates of breeding birds. Studies in Avian Biology 6:271-274.

Swisher, R., C. R. De Azua, and J. Clendenin. 2001. Strong winds on the horizon: wind power comes of age. Proceedings of the IEEE 89:1757-1764.

U.S. Department of Energy. 2008. 20% wind energy by 2030: Increasing wind energy's contribution to US electricity supply. Department of Energy, Washington, D.C. http://www.nrel.gov/docs/fy08osti/41869.pdf

U.S. Fish and Wildlife Service. 2002. Migratory bird mortality fact sheet. United States Fish and Wildlife Service, Washington, D.C. http://www.fws.gov/birds/mortality-fact-sheet.pdf

U.S. Fish and Wildlife Service. 2003. Interim Guidelines To Avoid and Minimize Wildlife Impacts from Wind Turbines. United States Fish and Wildlife Service, Washington, D.C. http://www.fws.gov/habitatconservation/wind.pdf

U.S. Fish and Wildlife Service. 2012. US Fish and Wildlife Service Land Based Wind Energy Guidelines. U.S. Fish and Wildlife Service, Washington, D.C. http://www.fws.gov/windenergy/docs/WEG_final.pdf

Villegas-Patraca, R., I. MacGregor-Fors, T. Ortiz-Martínez, C. E. Pérez-Sánchez, L. Herrera-Alsina, and C. Muñoz-Robles. 2012. Bird-Community Shifts in Relation to Wind Farms: A Case Study Comparing a Wind Farm, Croplands, and Secondary Forests in Southern Mexico. The Condor 114:711-719.

White, G. C. and K. P. Burnham. 1999. Program MARK: survival estimation from populations of marked animals. Bird Study 46:120-139.

White, G. C., K. P. Burnham, and D. R. Anderson. 2001. Advanced features of program MARK. Pages 368-377 *in* Wildlife, land, and people: priorities for the 21st century. Proceedings of the second international wildlife management congress. The Wildlife Society, Bethesda, Maryland, USA.

Young Jr., D., W. Erickson, R. Good, M. Strickland, and G. Johnson. 2003. Avian and bat mortality associated with the initial phase of the Foote Creek Rim Windpower Project, Carbon County, Wyoming, final report, November 1998-June 2002. Prepared for Pacificorp, Inc. Portland, Oregon, SeaWest Windpower Inc. San Diego, California, and Bureau of Land Management, Rawlins District Office, Rawlins, Wyoming.

TABLES

Table 1. Covariates measured and recorded at each point count, and later incorporated in models of detection probability in program MARK.

Covariate	Measurement
Observer	Observer
Date	Date of count
Time	Time at start of count
Wind speed	Wind speed (km/h)
Cloud cover	Percent cloud cover (%)
Turbine	Distance to turbine (m)
Distance bin	Distance from observer to bird (m)

Table 2. Number of detections within 100 m of the observer for the ten most detected species by year, from point counts conducted in Hancock, Osceola and Story counties, Iowa, 2011-2012. Detections have been combined for treatment (within 1000 m of a wind turbine) and control (2 to 5 km from a turbine) sites.

| | Year | |
Species	2011	2012
Killdeer *(Charadrius vociferus)*	332	289
Horned Lark *(Eremophila alpestris)*		112
Barn Swallow *(Hirundo rustica)*	176	
American Robin *(Turdus migratorius)*	171	
Common Yellowthroat *(Geothlypis trichas)*	249	245
Vesper Sparrow *(Pooecetes gramineus)*	163	195
Dickcissel *(Spiza americana)*	793	652
Bobolink *(Dolichonyx oryzivorus)*		174
Red-winged Blackbird *(Agelaius phoeniceus)*	1076	1185
Common Grackle *(Quiscalus quiscula)*	343	277
Brown-headed Cowbird *(Molothrus ater)*	357	112
American Goldfinch *(Carduelis tristis)*	127	103

Table 3. Species analyzed for detection probability and relative abundances, along with their common habitat associations, in Iowa, 2011-2012. Four-letter alpha codes for species are in parenthesis.

Habitat	Species
General	American Robin (AMRO)
	Song Sparrow (SOSP)
	Red-winged Blackbird (RWBL)
	Common Grackle (COGR)
Agricultural	Killdeer (KILL)
	Vesper Sparrow (VESP)
Grass	Common Yellowthroat (COYE)
	Dickcissel (DICK)

Table 4. Beta estimates for detection probability from the best models of American Robin (AMRO), Song Sparrow (SOSP), Red-winged Blackbird (RWBL), Common Grackle (COGR), Killdeer (KILL), Vesper Sparrow (VESP), Common Yellowthroat (COYE) and Dickcissel (DICK) from a study in Hancock, Osceola, and Story counties in Iowa, 2011-2012. Estimates are from a program MARK Huggins' Closed Captures model with the probability of recapture set to zero. Blank cells indicate that the best model did not include that covariate for the species.

	KILL	AMRO	COYE	VESP	SOSP	DICK	RWBL	COGR
p constant		0.0623		0.7572	0.1553			
p intercept (Story County)	2.2608		-1.4164			1.3927	-1.1137	-1.7479
Hancock 2011	-1.2527		1.2955			0.0098	-0.1377	2.5520
Osceola 2011	-0.0921		1.9561			-0.1911	-1.1872	1.3084
Hancock 2012	-0.7269		1.9474			0.6432	0.2897	2.9683
Osceola 2012	0.1225		2.3554			0.2380	0.3239	2.8659
Time							0.0021	
Wind			0.3854	0.1124			0.0400	-0.0833
Cloud Cover			-0.0111	-0.0146	-0.0174	-0.0037	0.0036	-0.0075
Distance Bin	-0.0200		-0.0190	-0.0158				-0.0181
Distance to turbine	-0.0006		0.0011	0.0021		-0.0013	0.0014	0.0012
Day		-0.0291	0.0174					
Wind*Distance to Turbine			-0.0005	-0.0003			-0.0002	

Table 5. Site-by-year effects of proximity to turbine on the estimated densities of 8 species of breeding birds in Hancock, Osceola, and Story counties in Iowa, 2011-2012. Effects were based upon 95% confidence limits of relative density estimates. Species included Killdeer (KILL), American Robin (AMRO), Common Yellowthroat (COYE) Vesper Sparrow (VESP), Song Sparrow (SOSP), Dickcissel (DICK), Red-winged Blackbird (RWBL), and Common Grackle (COGR). Distances listed are the proximity to the turbine (in meters) at which attraction or avoidance behavior was no longer evident, and a greater-than-or-equal-to symbol (≥) indicates attraction or avoidance across the entire treatment site. The site in Hancock County went to 500 m, and Osceola and Story County sites went to 1000 m.

Habitat	Species	Hancock		Osceola		Story	
		2011	2012	2011	2012	2011	2012
General	RWBL	Avoidance to ≥500 m	Avoidance to >500 m	Avoidance to 250 m	No effect	Attraction to 250 m	Avoidance to 250 m
	AMRO	Avoidance to ≥500 m	No effect	Avoidance to 250 m	Attraction to 1000 m	Avoidance to 250 m	Avoidance to 250 m
	SOSP	Avoidance to 500 m	No effect	No effect	No effect	Avoidance to 250 m	Avoidance to 500 m
	COGR	Avoidance to ≥500 m	Avoidance to ≥500 m	Avoidance to 250 m	Attraction to 1000 m	No effect	No effect
Agricultural	KILL	Avoidance to 250 m	Attraction to ≥500 m	No effect	Attraction to 1000 m	Attraction to ≥1000 m	Attraction to 1000 m
	VESP	No effect	No effect	No effect	Avoidance to 500 m	No effect	Attraction to 500 m
Grass	DICK	Avoidance to ≥500 m	Avoidance to ≥500 m	Avoidance to ≥1000 m	Avoidance to 500 m	Avoidance to 500 m	Avoidance to 500 m
	COYE	Avoidance to ≥500 m	Avoidance to ≥500 m	Avoidance to 750 m	Attraction to 1000 m	Avoidance to 500 m	Avoidance to 750 m

Table 6. Mean species richness (species per point) at control and treatment sites in Hancock, Osceola, and Story counties in Iowa from point counts conducted from 1 June through 15 July of 2011 and 2012. Points were placed at 0 m from the turbine base out to 1000 m from the turbine base at treatment sites, and at equivalent locations at control sites without turbines. Comparisons were made only within counties; differences were compared between turbine and control points at a fixed distance from the transect start, or within a turbine or control site between adjacent distances. Bold numbers indicate a significant difference ($P < 0.05$). *Hancock County transects only went to 500 m from the turbine base due to the arrangement of turbines at that site.

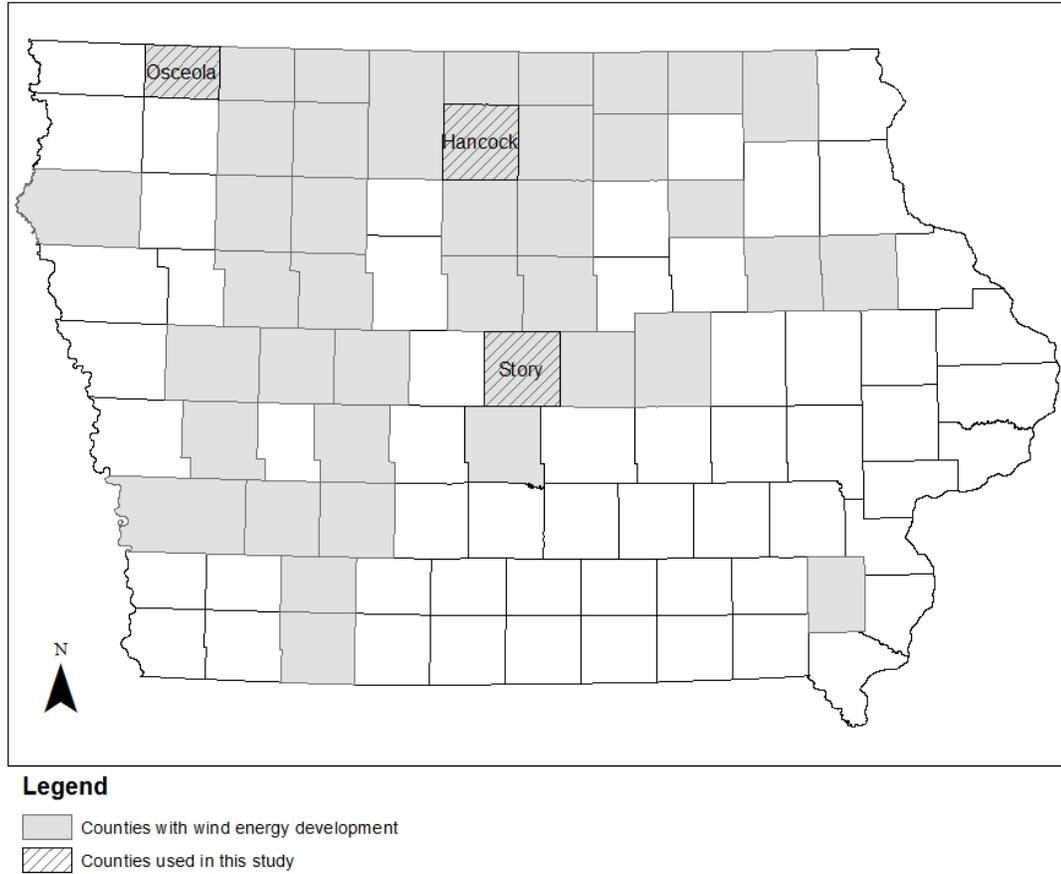|	Hancock		Osceola		Story	
	Control	Turbine	Control	Turbine	Control	Turbine
0 m	**17.0**	**7.6**	**14.2**	**8.7**	6.3	4.6
250 m	16.0	**11.1**	6.6	**15.0**	5.1	6.4
500 m	19.0	11.6	13.5	14.5	4.9	6.7
750 m	*	*	16.8	16.5	5.6	6.2
1000 m	*	*	16.5	18.0	5.7	7.4

FIGURES

Figure 1. Map of Iowa with current counties containing wind energy development (through 2011; American Wind Energy Association 2012) in gray, and the locations of Hancock, Osceola, and Story counties where fieldwork was conducted in 2011 and 2012.

CHAPTER 3. NEST SURVIVAL OF RED-WINGED BLACKBIRDS IN AGRICULTURAL AREAS DEVELOPED FOR WIND ENERGY

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ABSTRACT

Wind energy development is a major priority in the United States, both economically and environmentally. However, there are growing concerns about the impacts to wildlife, including direct mortality and indirect effects such as displacement. Yet little knowledge has been gained regarding effects on reproduction. We monitored 534 Red-winged Blackbird (*Agelaius pheoniceus*) nests at three wind farms and paired control sites in Iowa during 2011 and 2012 to determine what effect, if any, wind turbine proximity had on the survival of nests. We modeled daily nest survival rates during the incubation and nestling stages in program MARK. In addition to proximity to turbine, we included other covariates which are known to effect nest survival including nest height, vegetation above nest, Robel pole vegetation density measures, age of nest, distance to woodlot, and Brown-headed Cowbird (*Molothrus ater*) parasitism. We found no differences in survival between our control and turbine sites at any site or year, and no effect of turbine proximity during the incubation stage. The best model for the nestling stage included a small effect of turbine proximity, with nest survival being slightly higher, though not significantly so, closer to turbines. Our results indicate that, for a generalist

species breeding in an agricultural landscape, wind turbine proximity has negligible effects on reproductive success.

KEY WORDS: *Agelaius phoeniceus*, agriculture, nest survival, program MARK, Red-winged Blackbird, turbine, wind energy

INTRODUCTION

Wind energy is a growing sector, produces no emissions, and is generally considered environmentally friendly (U.S. Fish and Wildlife Service 2003). Worldwide there are commercial wind power installations in approximately 80 countries totaling 240 gigawatts (GW) of installed wind energy capacity (Global Wind Energy Council 2012), and wind energy has been growing globally by about 30% annually during the last 6 years (Grassi et al. 2012). In the United States, wind power contributed to 25% of all new energy sources in 2010 (Tegen et al. 2012), resulting in a total of 35,600 megawatts (MW) of wind power capacity in operation, enough to power 9.7 million homes while reducing both 62 million tons of carbon dioxide emissions and 20 billion gallons of water compared to traditional energy sources (American Wind Energy Association 2010). These wind turbines consist of 31,000 individual utility-scale turbines (Kiesecker et al. 2011), which are defined as turbines capable of producing >1 MW of energy (U.S. Department of Energy 2008). To reach the U.S. Department of Energy's goal of having 20% of U.S. energy coming from wind by 2030 (U.S. Department of Energy 2008), more than 240 GW still need to be installed, which will require an additional 15 million hectares of land (Kiesecker et al. 2011, Grassi et al. 2012).

Much of the future wind energy development may occur in Iowa, which has 10,801 MW of potential projects currently planned, and is ranked as the seventh best state in terms

of wind resources (American Wind Energy Association 2012). The Iowa Department of Natural Resources (IDNR) considers wind energy development a top priority for the state in terms of energy independence, but Iowa has minimal regulations on the siting of turbines (Harr and Vannoy 2009). Direct mortality of birds from wind turbine collisions is low in Iowa (Jain 2005), but indirect effects from wind turbines, such as displacement or changes to reproductive success, are not as well understood (Erickson et al. 2007). In Europe, it is generally accepted that the indirect effects of wind turbines are a more pressing threat than direct mortality (Kuvlesky et al. 2007), but much of the previous research in the U.S. has focused solely on direct mortality. Wind farms may lower habitat quality due to increased human activity and fragmentation of the landscape, both from the turbines themselves and from the additional access roads and transmission lines (Arnett et al. 2007, Kuvlesky et al. 2007).

Bird responses to alterations in habitat quality can be measured in many ways, including shifts in community composition, a change in density or abundance, and impacts to reproductive success (Bock and Jones 2004). We chose to investigate reproductive success because it has been studied less and may be important to understanding population-level changes in response to wind energy development. Population "sinks" can occur when nest success and population density are no longer correlated. A site can have high bird densities, but investigators may miss a population "sink" if they do not also look at nest success (Winter et al. 2003, Anteau et al. 2012). Research has shown that some nest predators, including Hooded Crows (*Corvus cornix*) in Europe, will use human-made structures such as wind turbines or transmission lines as perches when searching for prey (Wallander et al. 2006). Some species avoid human-made structures when selecting nest

sites (Wallander et al. 2006, Dusang 2011), which could result in less available habitat as wind energy infrastructure expands. Additionally, noise can change nesting success by altering predator-prey interactions (Francis et al. 2009). If nest success is altered, either positively or negatively, by the proximity of a nest to a turbine, this could have population-level effects as wind turbine development continues and becomes more widespread.

More than 10 billion birds breed in the U.S. each year (U.S. Fish and Wildlife Service 2002). Because edges and other landscape variables can alter nesting success (Winter et al. 2000, Cox et al. 2012), and wind turbine farms increase edge and change the landscape around nesting habitat, the proximity of a nest to a wind turbine may alter nesting success. The proposed expansion of wind turbines to an additional 15 million hectares of land (Kiesecker et al. 2011, Grassi et al. 2012) could result in population declines for some species if their breeding ranges overlap present and future wind developments and they respond negatively to the presence of wind turbines. Our objective was to assess the influence of wind turbine proximity, landscape context, and nest features on the nest survival of a common breeding bird, the Red-winged Blackbird (*Agelaius phoeniceus*), in Iowa. We hope this information will help us a) understand how a generalist bird species responds to wind energy development, and b) inform future wind turbine siting guidelines.

METHODS

Study sites

We studied nesting Red-winged Blackbird responses to wind energy development at three Iowa wind farms operated by Nextera Energy (Figure 1). Study sites were chosen in part based upon cooperation of wind energy companies and were located in Hancock,

Osceola, and Story counties, Iowa (Figure 1), where there are concentrations of wind farms

due to the high mean wind speeds. Paired control sites were located within 2 to 5 km of

each wind farm, a distance that is generally accepted to be beyond the influence of the

wind farm (U.S. Fish and Wildlife Service 2003) while still being close enough to

minimize differences in topography, land use and other factors. Paired control sites

allowed us to make direct comparisons between nests on and off wind farms. We collected

data across multiple sites and years to enhance the reliability of the findings (Anderson et

al. 1999).

Nest Searches

We focused our nest searching efforts on Red-winged Blackbirds (RWBL), North

America's most common marsh-breeding Icterid and one of the best studied species

(Yasukawa and Searcy 1995). Red-winged Blackbirds are a generalist species, breeding in

marsh and upland habitats as well as roadside ditches and agricultural lands (Yasukawa

and Searcy 1995). They lay one egg per day until the clutch is complete (2 to 4 eggs) and

begin incubation with the second to last egg. The incubation period lasts approximately 13

days and is followed by a 12-day nestling period (Yasukawa and Searcy 1995).

We conducted systematic searches for nests in roadside ditches and other suitable

habitat (e.g., fencerows or other habitat patches away from roadsides) starting in mid-May

and continuing until the last young had fledged mid- to late July. The field season began in

mid-May so that observers could improve their nest searching abilities with a few days of

practice and to be timed with territory establishment (Martin and Geupel 1993, Yasukawa

and Searcy 1995). Nest searches were conducted at each of the three wind farms and the

paired control sites, with one observer being responsible for searches and checks at each

pair of sites. The ditches included patchy dense stands of cattail (*Typha* sp.) and horsetail (*Equisetum* sp.) and scattered small shrubs of many species that were preferentially used as nest sites by Red-winged Blackbirds.

We marked each nest with a point taken with a GPS unit and then revisited it every 3-4 days until the nest fate could be determined (Martin and Geupel 1993). The incubation stage of the nest was determined via egg floatation (Lokemoen and Koford 1996, Dinsmore et al. 2002) while nestling age was determined by feather development of the nestlings (Table 1, Holcomb and Twiest 1970). The ability to age a nest allowed us to estimate when the nest transitioned to the next stage (Westerskov 1950). Sites were searched as frequently as possible (typically at 2 to 4 day intervals) to find nests as early in the cycle as possible for the maximum number of exposure days (Johnson 1979, Winter et al. 2003). We modeled survival separately during the incubation and nestling stages due to known differences in parental activity around the nest (Caccamise 1978). A nest was considered successful if one or more young hatched (for the incubation stage) or fledged (for the nestling stage, Mayfield 1961).

Nest survival modeling

Individual nest covariates can be incorporated into models of nest survival and often lead to a greater understanding of the process and more robust estimates of survival (Dinsmore et al. 2002). Nest survival can be affected by factors such as the day of nesting season, nest height, and concealment/vegetation density, as well as larger landscape characteristics (Holm 1973, Johnson 1979, Martin and Roper 1988). We incorporated multiple vegetation and landscape variables (Table 2) into our models of nest survival. We also included the distance to the nearest turbine (in meters), hypothesizing that proximity

to turbine may alter nest survival due to changes in predation or habitat quality (U.S. Fish and Wildlife Service 2012). Vegetation and landscape variables were measured as soon as the nest fate was determined (Martin and Geupel 1993). There is previous evidence of year, nest age, and time of season effects on nest survival of Red-winged Blackbirds in Iowa (Dinsmore and Dinsmore 2007). We modeled year and site combinations as groups because of habitat differences between sites and the drastic weather differences (both temperature and precipitation) between the two years (Dinsmore and Dinsmore 2007), resulting in 12 groups for our analysis (control and treatment sites at each of three counties for two years).

Models were created using the nest survival model (Dinsmore et al. 2002) in program MARK (White and Burnham 1999) and ranked using Akaike's Information Criterion (AIC, Akaike 1973). We used stepwise backward selection to build models, creating an initial model with all covariates and then sequentially eliminating the least important as determined by looking at the minimum absolute value of the beta estimate divided by the standard error of the covariate. We continued this process until the elimination of a covariate resulted in the increase of the AIC value (Pagano and Arnold 2009, Arnold 2010).

RESULTS

We monitored a total of 534 Red-winged Blackbird nests during 2011 and 2012 (Table 3). During incubation we monitored 418 nests for an effective sample size of 3032, and during the nestling stage we monitored 356 nests for an effective sample size of 2445. For the incubation stage, the best model (Table 4) included a quadratic effect of nest age, day of season (negative linear trend), and nest height (positive linear trend; Table 5). Daily

survival was greatest for nests early in the nesting season and for nests that were higher off the ground (Figure 2).

For the nestling stage, the best model included a quadratic effect of nest age, nest height, height of vegetation above the nest, distance to turbine, distance to edge, variance in Robel pole readings, and presence/absence of Brown-headed Cowbird parasitism (Table 6). Daily survival of nests was greatest at the start of the nestling period (hatching), with less vegetation above the nest, higher variance in Robel pole readings, no Brown-headed Cowbird parasitism, and when they were closer to the ground, a habitat edge, or a turbine (Table 7).

There were no significant differences between predicted daily nest survival at control and treatment sites during the incubation or nestling stages, based upon the overlapping 95% confidence intervals of each intercept estimate. The distance to turbine had no effect on the predicted daily survival rate of nests during the incubation stage (Table 5), and only a weak negative effect on survival during the nestling stage (Tables 7). Nests nearer to turbines had slightly greater predicted survival rates than nests further from the turbine base (Figure 3).

DISCUSSION

Our overall finding was that Red-winged Blackbird nest survival was largely unaffected by proximity to wind turbines in Iowa, although this conclusion differed between the two nesting stages we examined. This suggests that a common generalist bird species can adapt to the disturbance caused by wind energy development, at least during the nesting season. Below, we discuss the major implications of our findings on the context of both wind energy and the breeding biology of this species.

We found no evidence that Red-winged Blackbird nest survival was affected by turbine proximity during the incubation stage. The proximity to a turbine did have a small effect on predicted daily survival of Red-winged Blackbird nests in the nestling stage, with nests closer to the turbine having slightly higher predicted survival rates. However, this effect was small and the 95% confidence interval included zero. It has been predicted that wind turbines may alter predator communities (U.S. Fish and Wildlife Service 2012), and nest predation variation between sites is generally responsible for most differences in nest survival (Galligan et al. 2006). While nest survival increased slightly for Red-winged Blackbirds near turbines, each species reacts differently to the presence of wind turbines (U.S. Fish and Wildlife Service 2003) so other species' nest survival may be affected differently. This study focused on a generalist species breeding in an agricultural landscape, and possibly represents a species and habitat least likely to be affected by wind energy development.

Our study included three paired treatment-control sites to provide some spatial replication and allow us to better understand turbine effects on avian nest survival. We found no differences between predicted daily survival between treatment sites (within 2 km of a turbine base) and control sites (2 to 5 km away from any turbine) for either incubation or nestling stages. This provides further evidence that, for a generalist species like the Red-winged Blackbird, nest survival is not greatly impacted by turbine proximity. The possible weak effect of turbine proximity during the nestling stage, although small, could mean that cumulative effects from multiple large wind farms across a species' range may become biologically significant (Harr and Vannoy 2009, Masden et al. 2010, Garvin et al. 2011). Cumulative effects may be especially important to species with small geographic ranges

where large wind projects could overlap a greater portion of their range and have

significant impacts (Anteau et al. 2012).

The primary intent of our study was to assess the possible impacts of wind turbines

on Red-winged Blackbird nest survival, although our models also included other effects.

For these other effects, our results were generally similar to what previous studies have

found concerning patterns of Red-winged Blackbird nest survival. Stage-specific

(Caccamise 1976, 1978, Dinsmore and Dinsmore 2007), year, and age of nest differences

in nest survival have been well documented (Beletsky 1996, Dinsmore and Dinsmore

2007). Below, we discuss the strongest effects (those that did not include zero in the 95%

confidence interval) relative to other studies. During the incubation stage we found a

negative linear effect of day of season; Dinsmore and Dinsmore (2007) found a quadratic

trend, also negative, although their linear trend model was competitive. Both studies show

that early nests survived better than late-season nests. For the nestling stage, the only

strong effect we found was distance to edge, with nests closer to an edge having higher

survival. This is in contrast to the general belief that edges lower nest survival due to

increased depredation (Paton 1994). We believe this difference was because most of our

nests were located within 7 m of an edge due to the layout of ditch habitat, thus

minimizing the scale of distance to edge needed to tease apart possible edge effects.

The results of our study add to a growing body of literature on the consequences of

wind energy development on wildlife. Importantly, this may be the first study to

specifically examine the reproductive responses (nest survival) by a bird to proximity to

wind turbines. Previous work has shown that raptors may avoid areas with wind turbines

(Usgaard et al. 1997), but it did not look at any difference in survival with regards to

proximity. Another study attempted to show that Lesser Prairie-Chickens will abandon nests near wind turbine developments; however, this study used highways and transmission lines to predict nest survival responses to future wind energy development (Pruett et al. 2009). Future studies should look at more sensitive breeding birds in this landscape, such as Dickcissel (*Spiza americana*), which may show a different nest survival response to wind turbine proximity. Additionally, studies should confirm whether there are predator differences near turbines to better understand the mechanisms behind any nest survival differences.

Others have suggested that focusing wind energy development on disturbed lands, which already have lower wildlife value, could help reduce the future impacts of wind energy development on more sensitive bird species (Jain 2005, Kuvlesky et al. 2007, Fargione et al. 2012). Our findings, albeit for just a single species, lend further support to assertions that placing wind turbines in already disturbed lands (e.g., agricultural fields) minimizes impacts to birds in general, and specifically avoids placing many specialist species at greater risk. There is 3500 GW of wind potential on already disturbed lands (e.g., lands currently used for agriculture or oil and gas development; Kiesecker et al. 2011), which is enough to meet energy goals while also avoiding areas with high wildlife value (Fargione et al. 2012). By broadening our understanding of the indirect effects of wind turbines to include avian nest survival we can refine siting guidelines that will limit the effects of wind farms on the surrounding habitat while still offering the benefits of "green" energy.

LITERATURE CITED

Akaike, H. 1973. Information theory and an extension of the maximum likelihood principle. Pages 267-281 *in* International Symposium on Information Theory, 2 nd, Tsahkadsor, Armenian SSR.

American Wind Energy Association. 2010. Market Update: Record 2009 leads to slow start in 2010. American Wind Energy Association. http://www.windturbineins.com/_literature_59898/Market_Update

American Wind Energy Association. 2012. Wind Energy Facts: Iowa. American Wind Energy Association. http://awea.org/learnabout/publications/factsheets/upload/4Q-11-Iowa.pdf

Anderson, R., M. L. Morrison, K. Sinclair, and D. Strickland. 1999. Studying Wind Energy/Bird Interactions: A guidance document. Avian Subcommittee and National Wind Coordinating Committee, Washington, D.C. Studying Wind Energy/Bird Interactions: A guidance document

Anteau, M. J., T. L. Shaffer, M. H. Sherfy, M. A. Sovada, J. H. Stucker, and M. T. Wiltermuth. 2012. Nest survival of piping plovers at a dynamic reservoir indicates an ecological trap for a threatened population. Oecologia 170:1167-1179.

Arnett, E., D. Inkley, D. Johnson, R. Larkin, S. Manes, A. Manville, J. Mason, M. Morrison, M. Strickland, and R. Thresher. 2007. Impacts of wind energy facilities on wildlife and wildlife habitat. Wildlife Society Technical Review 07-2, 49 pp. The Wildlife Society, Bethesda, Maryland, USA.

Arnold, T. W. 2010. Uninformative Parameters and Model Selection Using Akaike's Information Criterion. Journal of Wildlife Management 74:1175-1178.

Beletsky, L. 1996. The Red-winged Blackbird: the biology of a strongly polygynous songbird. Academic Press. London.

Bock, C. E. and Z. F. Jones. 2004. Avian habitat evaluation: should counting birds count? Frontiers in Ecology and the Environment 2:403-410.

Caccamise, D. F. 1976. Nesting mortality in the Red-winged Blackbird. The Auk 93:517-534.

Caccamise, D. F. 1978. Seasonal patterns of nesting mortality in the Red-winged Blackbird. The Condor 80:290-294.

Cox, W. A., F. R. Thompson, and J. Faaborg. 2012. Landscape forest cover and edge effects on songbird nest predation vary by nest predator. Landscape Ecology 27:659-669.

Dinsmore, S. J. and J. J. Dinsmore. 2007. Modeling avian nest survival in program MARK. Studies in Avian Biology 34:73-83.

Dinsmore, S. J., G. C. White, and F. L. Knopf. 2002. Advanced techniques for modeling avian nest survival. Ecology 83:3476-3488.

Dusang, D. 2011. Impacts of Energy Development on the Lesser Prairie-Chicken Ecology and Management. Thesis. University of Oklahoma.

Erickson, W., D. Strickland, J. A. Shaffer, and D. H. Johnson. 2007. Protocol for Investigating Displacement Effects of Wind Facilities on Grassland Songbirds. National Wind Coordinating Committee. http://www.nationalwind.org/assets/publications/SongbirdProtocolFinalJune07.pdf

Fargione, J., J. Kiesecker, M. J. Slaats, and S. Olimb. 2012. Wind and Wildlife in the Northern Great Plains: Identifying Low-Impact Areas for Wind Development. PLoS One 7:e41468.

Francis, C. D., C. P. Ortega, and A. Cruz. 2009. Noise pollution changes avian communities and species interactions. Curr Biol 19:1415-1419.

Galligan, E. W., T. L. DeVault, and S. L. Lima. 2006. Nesting Success of Grassland and Savanna Birds on Reclaimed Surface Coal Mines of the Midwestern United States. The Wilson Journal of Ornithology 118:537-546.

Garvin, J. C., C. S. Jennelle, D. Drake, and S. M. Grodsky. 2011. Response of raptors to a windfarm. Journal of Applied Ecology 48:199-209.

Global Wind Energy Council. 2012. Global Wind Energy Outlook 2012. Global Wind Energy Council/GreenPeace. http://www.gwec.net/wp-content/uploads/2012/11/GWEO_2012_lowRes.pdf

Grassi, S., N. Chokani, and R. S. Abhari. 2012. Large scale technical and economical assessment of wind energy potential with a GIS tool: Case study Iowa. Energy Policy 45:73-85.

Harr, D. and L. Vannoy. 2009. Wind Energy and Wildlife Resource Management in Iowa: Avoiding Potential Conflicts. Iowa Department of Natural Resources. http://www.iowadnr.gov/portals/idnr/uploads/wildlife/wind_wildliferecs.pdf

Holcomb, L. C. and G. Twiest. 1970. Growth rates and sex ratios of red-winged blackbird nestlings. The Wilson Bulletin 82:294-303.

Holm, C. H. 1973. Breeding sex ratios, territoriality, and reproductive success in the Red-winged Blackbird (Agelaius phoeniceus). Ecology 54:356-365.

Jain, A. A. 2005. Bird and bat behavior and mortality at a northern Iowa windfarm. Thesis. Iowa State University.

Johnson, D. H. 1979. Estimating nest success: the Mayfield method and an alternative. The Auk 96:651-661.

Kiesecker, J. M., J. S. Evans, J. Fargione, K. Doherty, K. R. Foresman, T. H. Kunz, D. Naugle, N. P. Nibbelink, and N. D. Niemuth. 2011. Win-win for wind and wildlife: a vision to facilitate sustainable development. PLoS One 6:e17566.

Kuvlesky, W. P., L. A. Brennan, M. L. Morrison, K. K. Boydston, B. M. Ballard, and F. C. Bryant. 2007. Wind Energy Development and Wildlife Conservation: Challenges and Opportunities. Journal of Wildlife Management 71:2487-2498.

Lokemoen, J. T. and R. R. Koford. 1996. Using Candlers to Determine the Incubation Stage of Passerine Eggs Journal of Field Ornithology 67:660-668.

Martin, T. E. and G. R. Geupel. 1993. Nest-Monitoring Plots: Methods for Locating Nests and Monitoring Success Journal of Field Ornithology 64:507-519.

Martin, T. E. and J. J. Roper. 1988. Nest predation and nest-site selection of a western population of the Hermit Thrush. Condor 90:51-57.

Masden, E. A., A. D. Fox, R. W. Furness, R. Bullman, and D. T. Haydon. 2010. Cumulative impact assessments and bird/wind farm interactions: Developing a conceptual framework. Environmental Impact Assessment Review 30:1-7.

Mayfield, H. 1961. Nesting success calculated from exposure. The Wilson Bulletin 73:255-261.

Pagano, A. M. and T. W. Arnold. 2009. Detection Probabilities for Ground-Based Breeding Waterfowl Surveys. The Journal of Wildlife Management 73:392-398.

Paton, P. W. C. 1994. The effect of edge on avian nest success: how strong is the evidence? Conservation Biology 8:17-26.

Pruett, C. L., M. A. Patten, and D. H. Wolfe. 2009. Avoidance behavior by prairie grouse: implications for development of wind energy. Conservation Biology 23:1253-1259.

Tegen, S., M. Hand, B. Maples, E. Lantz, P. Schwabe, and A. Smith. 2012. 2010 Cost of Wind Energy Review. Report No. NREL/TP-5000-52920, National Renewable Energy Laboratory, Golden, CO.

Usgaard, R. E., D. E. Naugle, R. G. Osborn, and K. F. Higgins. 1997. Effects of wind turbines on nesting raptors at Buffalo Ridge in southwestern Minnesota. Pages 113-117 *in* Proceedings of the South Dakota Academy of Science.

U.S. Department of Energy. 2008. 20% wind energy by 2030: Increasing wind energy's contribution to US electricity supply. Department of Energy, Washington, D.C. http://www.nrel.gov/docs/fy08osti/41869.pdf

U.S. Fish and Wildlife Service. 2002. Migratory bird mortality fact sheet. United States Fish and Wildlife Services, Washington, D.C. http://www.fws.gov/birds/mortality-fact-sheet.pdf

U.S. Fish and Wildlife Service. 2003. Interim Guidelines To Avoid and Minimize Wildlife Impacts from Wind Turbines. U.S. Fish and Wildlife Service, Washington, D.C. http://www.fws.gov/habitatconservation/wind.pdf

U.S. Fish and Wildlife Service. 2012. US Fish and Wildlife Service Land Based Wind Energy Guidelines. U.S. Fish and Wildlife Services, Washington, D.C. http://www.fws.gov/windenergy/docs/WEG_final.pdf

Wallander, J., D. Isaksson, and T. Lenberg. 2006. Wader nest distribution and predation in relation to man-made structures on coastal pastures. Biological Conservation 132:343-350.

Westerskov, K. 1950. Methods for determining the age of game bird eggs. The Journal of Wildlife Management 14:56-67.

White, G. C. and K. P. Burnham. 1999. Program MARK: survival estimation from populations of marked animals. Bird Study 46:120-139.

Winter, M., S. E. Hawks, J. A. Shaffer, and D. H. Johnson. 2003. Guidelines for finding nests of passerine birds in tallgrass prairie. Prairie Naturalist 35:197-211.

Winter, M., D. H. Johnson, and J. Faaborg. 2000. Evidence for edge effects on multiple levels in tallgrass prairie. The Condor 102:256-266.

Yasukawa, K. and W. A. Searcy. 1995. Red-winged Blackbird (*Agelaius phoeniceus*).*in* A. Poole, editor. The Birds of North America [Online]. Cornell Lab of Ornithology, Ithaca, New York.

TABLES

Table 1. Aging of Red-winged Blackbird eggs and nestlings (in days since start of stage) based upon egg floatation in a column of water (for incubation) and based upon feather development (for nestling). Guidelines for incubation were developed from the nests found during the egg-laying stage at sites in Hancock, Osceola, and Story counties in Iowa, 2011 and 2012. Guidelines for the nestling stage were developed by Holcomb and Tweist (1970), with projection defined as the feather sheath breaking through the epidermis, and fringe defined as when the feather barbs became visible (Holcomb and Twiest 1970). Feather development patterns were used to age nestlings found after hatching at sites in Hancock, Osceola and Story counties in Iowa, 2011 and 2012.

Stage	Age (d)	Description
Incubation	0	egg lying flat on bottom
	1	
	2	large end of egg starting to float
	3	egg standing upright on bottom
	4	
	5	egg floating, about to break surface
	6	
	7	egg floating with large end slightly out of water
	8	
	9	egg floating at a tilt with large end out of water
	10	
	11	eggs pipping or hatching
Nestling	0	orange-colored skin
	1	pink skin, down, no feather development
	2	projection of feathers on alar tract
	3	some development of humeral, ventral, spinal and/or femoral feather tracts
	4	eyes begin to open, projection of humeral, spinal, crural, femoral and ventral feathers
	5	eyes 1/2 open - capital tract
	6	feathers start to fringe on alar, humeral and ventral tracts
	7	eyes fully open, fringing continues on spinal, crural, and femoral tracts
	8	egg tooth usually disappears, caudal and capital tracts fringe
	9	continued fringing of caudal and capital tracts
	10	
	11	young perched on edge of nest, may fledge

Table 2. Individual nest covariates measured at nests and used in modeling predicted daily survival in MARK from nests in Hancock, Osceola, and Story counties in Iowa, 2011 and 2012, with the mean, standard deviation (SD) and range of each covariate.

Covariate	Measurement	Mean	SD	Range
Height	height of nest from ground (cm)	71.00	27.70	25 to 500
Veg	height of vegetation above nest (cm)	37.00	17.00	6 to 120
Edge	distance from nest to nearest road or fencerow (m)	5.82	18.40	0 to 383
Woodlot	distance from nest to nearest woodlot (m)	349.00	248.00	0 to 1459
Turbine	distance from nest to nearest turbine (m)	877.50	341.60	135 to 2940
RobelVar	variance of Robel pole readings at nest and 1 m in each of the four cardinal directions	1.26	0.79	0 to 5
RobelMean	mean of Robel pole readings at nest and 1 m in each of the four cardinal directions	6.85	1.78	0 to 10
Cowbird	presence of cowbird parasitism at nest (0=unparasitized, 1=parasitized)	0.38	0.48	0 to 1

Table 3. Number of Red-winged Blackbird nests monitored during the incubation and nestling stages at treatment (within 2 km of a wind turbine) and control sites (2 to 5 km from a wind turbine) in Hancock, Osceola, and Story counties in Iowa, 2011 and 2012.

| | | 2011 | | 2012 | |
		Treatment	Control	Treatment	Control
Incubation	Story	44	32	62	47
	Hancock	21	38	20	20
	Osceola	43	23	26	42
Nestling	Story	24	30	46	35
	Hancock	11	42	15	23
	Osceola	28	30	29	43

Table 4. Models of daily survival rate for the incubation stage of Red-winged Blackbird nests monitored from 14 May through 28 July of 2011 and 2012 at wind farm and control sites in Hancock, Osceola, and Story counties in Iowa. Models are listed in descending order by AICc weight. Models were created in Program MARK using the following covariates; site by year effects (yr*site), linear and quadratic effects of age of nest from start of incubation (Age and Age^2), height of nest from ground (in cm; Height), distance from nearest turbine (in m; Turbine), distance from nearest road or fencerow (in m; Edge), distance from nearest woodlot (in m; Woodlot), variance and mean of Robel pole readings at nest and 1 m in each of the 4 cardinal directions (RobelVar and RobelMean), presence/absence of Brown-headed Cowbird parasitism (Cowbird), and linear and quadratic effects of day within nesting season (Day and Day^2).

Model	Δ AIC*	Weight	K	Deviance
S(yr_site+Age+Age^2+Day+Heightt)	0	0.38	16	838.67
S(yr_site+Age+Age^2+Day+Height+RobelMean)	0.51	0.30	17	837.16
S(yr_site+Age+Age^2+Day+Height+RobelMean+RobelVar)	1.67	0.17	18	836.30
S(yr_site+Age+Age^2+Day+Height+RobelMean+RobelVar+Cowbird)	3.01	0.09	19	835.61
S(yr_site+Age+Age^2+Day+Height+RobelMean+RobelVar+Cowbird+Veg)	4.38	0.04	20	834.95
S(yr_site+Age+Age^2+Day+Day^2+Height+RobelMean+RobelVar+Cowbird+Veg)	6.30	0.02	21	834.84
S(yr_site+Age+Age^2+Day+Height+RobelMean+RobelVar+Cowbird+Veg+Edge)	8.23	0.01	22	834.75
S(yr_site+Age+Age^2+Day+Height+RobelMean+RobelVar+Cowbird+Veg+Edge+Turbine)	10.21	0.00	23	834.70
S(yr_site+Age+Age^2+Day+Height+RobelMean+RobelVar+Cowbird+Veg+Edge+Turbine+Woodlot)	12.22	0.00	24	834.68

*Best model had an AIC value of 870.85.

Table 5. Intercept and slope estimates from the best incubation model in program MARK for the predicted daily survival rate of Red-winged Blackbird nests during the incubation stage from Hancock, Osceola, and Story counties in Iowa, 2011-2012. Treatment is considered nests found within 1000 m of a turbine, and control sites were located 2 to 5 km away. The standard error (SE), lower 95% confidence limit (LCL) and upper 95% confidence limit (UCL) are also reported. The best model included a quadratic effect of nestling age (in days; Age+Age^2), a linear effect of day of season (Day) and a linear effect of nest height from ground (in cm; Height).

	Site*Yr Group	Estimate	SE	LCL	UCL
Site*Year intercept estimates	Hancock Treatment 2011	3.106	0.446	2.231	3.981
	Hancock Control 2011	3.079	0.458	2.183	3.976
	Hancock Treatment 2012	2.914	0.473	1.987	3.841
	Hancock Control 2012	3.165	0.492	2.201	4.130
	Osceola Treatment 2011	3.445	0.422	2.618	4.272
	Osceola Control 2011	4.769	0.795	3.211	6.327
	Osceola Treatment 2012	3.093	0.499	2.116	4.071
	Osceola Control 2012	3.159	0.462	2.253	4.065
	Story Treatment 2011	2.262	0.393	1.492	3.031
	Story Control 2011	2.611	0.441	1.746	3.477
	Story Treatment 2012	3.358	0.433	2.510	4.207
	Story Control 2012	3.116	0.447	2.240	3.991
Covariate slope estimates	Age	0.096	0.072	-0.046	0.237
	Age^2	-0.015	0.005	-0.025	-0.006
	Day	-0.156	0.063	-0.279	-0.033
	Height	0.006	0.004	-0.001	0.013

Table 6. Models of daily survival rate for the nestling stage of Red-winged Blackbird nests monitored from 14 May through 28 July 2011 and 2012 at wind farm and control sites in Hancock, Osceola, and Story counties in Iowa. Models are listed in descending order by AICc weight. Models were created in Program MARK using the following covariates; site by year effects (yr*site), linear and quadratic effects of age of nest from hatching (Age and Age^2), height of nest from ground in (in cm; Height), distance from nearest turbine (in m; Turbine), distance from nearest road or fencerow (in m; Edge), distance from nearest woodlot (in m; Woodlot), variance and mean of Robel pole readings at nest and 1 m in each of the 4 cardinal directions (RobelVar and RobelMean), Brown-headed Cowbird parasitism (0 = unparasitized, 1 = parasitized; Cowbird), and linear and quadratic effects of day within nesting season (Day and Day^2).

Model	Δ AIC*	Weight	K	Deviance
S(yr_site+Age+Age^2+Height+Veg+Turbine+Edge+RobelVar+Cowbird)	0.00	0.58	20	768.92
S(yr_site+Age+Age^2+Height+Veg+Turbine+Edge+RobelVar+Cowbird+Woodlot)	1.65	0.26	21	768.53
S(yr_site+Age+Age^2+Height+Veg+Turbine+Edge+RobelVar+Cowbird+Woodlot+Day)	3.48	0.10	22	768.32
S(yr_site+Age+Age^2+Height+Veg+Turbine+Edge+RobelVar+Cowbird+Woodlot+Day+Day^2)	5.26	0.04	23	768.07
S(yr_site+Age+Age^2+Height+Veg+Turbine+Edge+RobelVar+Cowbird+Woodlot+Day+Day^2+RobelMean)	7.17	0.02	24	767.94

*Best model had an AIC value of 809.27.

Table 7. Intercept and slope estimates from the best nestling model in program MARK for the predicted daily survival rate of Red-winged Blackbird nests during the nestling stage from Hancock, Osceola, and Story counties in Iowa, 2011-2012. Treatment is considered nests found within 1000 m of a turbine, and control sites were located 2 to 5 km away. The standard error (SE), lower 95% confidence limit (LCL) and upper 95% confidence limit (UCL) are also reported. The best model included a quadratic effect of nest age (in days since hatch; Age+Age^2), a linear effect of nest height from ground(in cm; Height), a linear effect of vegetation above the nest (in cm; Veg), distance to turbine (in m; Turbine) distance to nearest road or fencerow (in m; Edge), variance of Robel pole readings at the nest and 1 m in each of the cardinal direction (RobelVar), and Brown-headed Cowbird parasitism (0 = unparasitized, 1 = parasitized; Cowbird).

|		Estimate	SE	LCL	UCL
Site*Year intercept estimates	Hancock Treatment 2011	5.180	0.970	3.278	7.082
	Hancock Control 2011	5.216	0.599	4.042	6.390
	Hancock Treatment 2012	3.923	0.624	2.700	5.147
	Hancock Control 2012	2.865	0.525	1.836	3.894
	Osceola Treatment 2011	4.384	0.546	3.315	5.454
	Osceola Control 2011	4.275	0.601	3.098	5.452
	Osceola Treatment 2012	5.385	0.741	3.932	6.838
	Osceola Control 2012	4.930	0.594	3.766	6.095
	Story Treatment 2011	4.146	0.509	3.148	5.143
	Story Control 2011	4.156	0.568	3.042	5.270
	Story Treatment 2012	4.190	0.443	3.322	5.059
	Story Control 2012	3.861	0.538	2.806	4.916
Covariate slope estimates	Age	-0.120	0.034	-0.186	-0.053
	Age^2	0.002	0.001	-0.001	0.004
	Height	-0.003	0.002	-0.008	0.001
	Veg	-0.011	0.005	-0.022	0.000
	Turbine	-0.001	<0.001	-0.001	0.000
	Edge	-0.006	0.003	-0.012	-0.001
	RobelVar	0.095	0.089	-0.080	0.270
	Cowbird	-0.266	0.195	-0.648	0.116

FIGURES
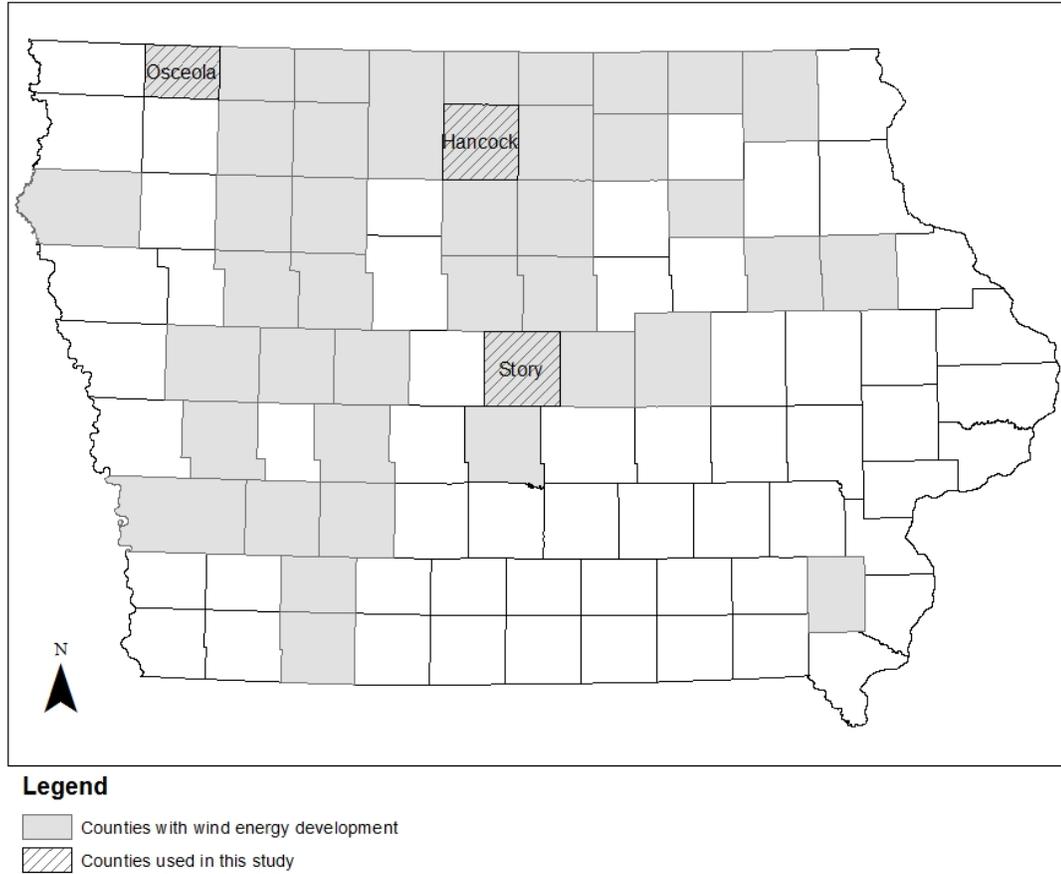
Figure 1. Map of Iowa with current counties containing wind energy development (through 2011; American Wind Energy Association 2012) in gray, and the location of Hancock, Osceola, and Story counties where fieldwork was conducted in 2011 and 2012.
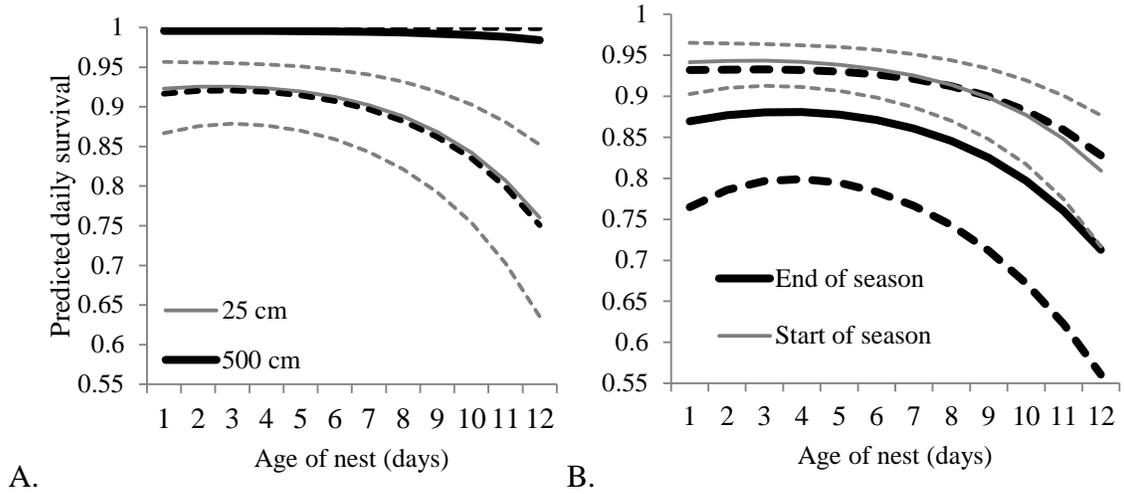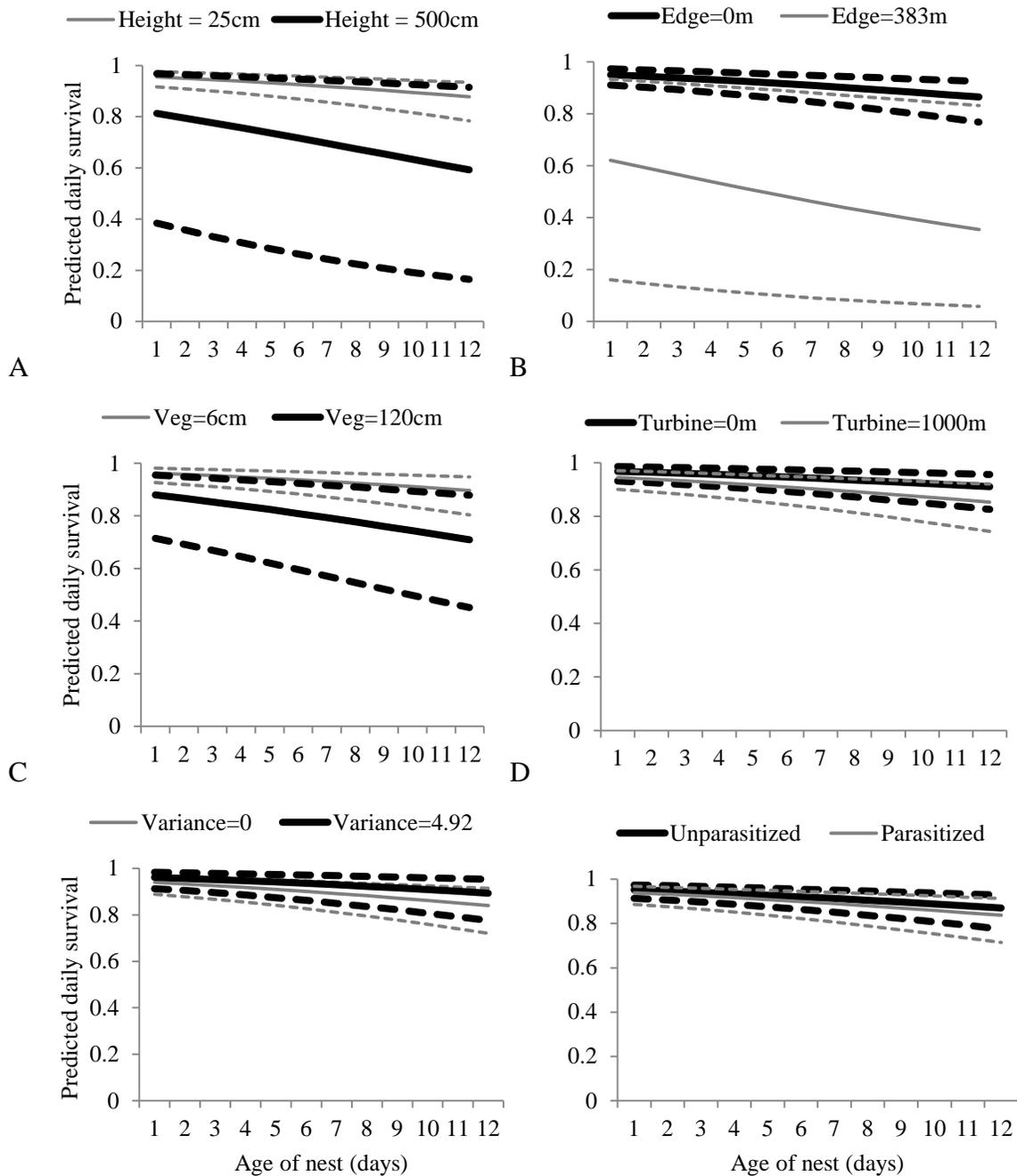
Figure 2. Graph of predicted daily survival for Red-winged Blackbird nests in Story County's treatment site in 2011 from the best model for (A) nests at the beginning of the season (initiation of incubation on 14 May) at 25 cm off the ground and at 500 cm off the ground, and (B) for nests at the beginning of the season (initiation of incubation on 14 May and the end of the season (initiation of incubation on 14 July), with 95% confidence intervals (dashed lines).

Figure 3. Graphs of predicted daily survival for Red-winged Blackbird nests in Story County's treatment site in 2011 at minimum and maximum values of covariates from the best model with 95% confidence intervals (dashed lines) for (A) nests at 25 and 500 cm from the ground, (B) nests at 0 and 383 m from an edge, (C) nests with 6 and 120 cm of vegetation above the nest, (D) nests at 0 and 1000 m from the turbine base, (E) nests with 0 and 4.92 variance in Robel pole readings, and (F) nests that were parasitized (Cowbird = 1) and unparasitized (Cowbird = 0) by Brown-headed Cowbirds.

CHAPTER 4: BAT ACTIVITY PATTERNS NEAR WIND FARMS IN IOWA

A paper to be submitted to the Journal of Wildlife Management

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ABSTRACT

Wind energy is thought to provide a "green" source of energy, but also causes direct mortality of bats and has led to conservation concerns for many bat species in the United States. The amount of bat activity at a site has been used, with varying degrees of success, to predict bat mortality rates. However, few such studies have been conducted in agricultural areas, which until recently have been considered of little importance to bats. Our study goal was to monitor bat activity at varying distances from wind turbines, and at a paired control site, to determine if bats were responding behaviorally to wind turbines either through attraction or avoidance. In addition, we wanted to determine which landscape (e.g., distances to woodlots or wetlands) and night variables (e.g., wind speed or moon phase) influenced the relative activity of bats. We monitored bat activity at 71 sampling points in Story County, Iowa for a total of 698 detector nights during the period June to October in 2011 and 2012. Due to a combination of nights with (24%) and without activity (76%), we constructed two separate models, one to predict the probability of activity at a point on a given night and one to predict the level of activity given that there was activity. The predicted probability of activity was greatest on nights with lower wind

speeds, higher temperatures, and a full moon, and at points further from turbines and closer to woodlots. The amount of activity depended on the day, with a non-parametric response peaking mid-July, and was greatest on nights with lower wind speeds, higher temperatures, less precipitation, and lower barometric pressure, and at points closer to woodlots and rivers. Our findings document the presence and activity patterns of bats at Iowa wind farms, relate these patterns to important environmental variables and habitat features, and may ultimately aid the development of future siting guidelines and investigations into mitigation methods.

KEY WORDS: agriculture, Anabat, bat activity, mixed model, Iowa, turbine, wind energy

INTRODUCTION

Bat mortality has been documented at wind turbine facilities in many different habitats, and although the estimated mortality varies there are several underlying patterns across the United States. Mortality peaks during migration in late summer and fall (Arnett et al. 2008, Grodsky et al. 2012), and on nights with low wind speeds (Arnett et al. 2008). Bat mortality can also vary between turbines within a wind resource area (Jameson and Willis 2012), so if the detection rates of bats at a point can be correlated with mortality rates, pre-construction surveys can help determine siting of individual turbines in low-impact areas. Understanding and minimizing bat mortality and wind facilities is important because bats are long-lived (Wilkinson and South 2002) and many species are presently in decline (Boyles et al. 2011). Losses of bats to wind turbines may be an important and preventable source of mortality for many species that has implications for bat conservation (Boyles et al. 2011).

The wind energy sector continues to grow throughout the United States, and by

2020 there will be an estimated 48,000 large utility-scale (≥1.5 mega-watt) wind turbines

on the landscape (Kunz et al. 2007). However, this continued expansion has raised

concerns about effects on wildlife, especially bats due to the large numbers killed each

year (Erickson et al. 2000, Johnson et al. 2000, Johnson et al. 2003, Young Jr. et al. 2003).

The effects of turbine proximity on bats can be both direct (from mortality) and indirect

(attraction or avoidance behavior). Because bats are sensitive to environmental change

(Stahlschmidt and Brühl 2012), they are an ideal study species for looking at the

environmental quality of the landscapes around wind turbine farms.

Ultrasonic detectors have been widely used to assess activity patterns and habitat

use of bats (Britzke et al. 2011). Bat activity is highly variable, primarily due to a

combination of weather conditions, migration phenologies of different species, proximity

to roost sites, and the temporal and spatial variability in prey abundance (Broders 2003,

Kunz et al. 2007). A study in Australia looked at the factors influencing this variability in

bat activity and found 40% of variation between sites, 10% within a site, 20% between

nights, and 30% was not attributable to any known variables (Fischer et al. 2009). These

ultrasonic detectors offer a practical and cost efficient means to passively monitor bat

activity over long periods of time for comparatively low cost (Kunz and Brock 1975,

Walters et al. 2012, Wimmer et al. 2013). Additionally, they may be less biased than mist-

netting, and allow population monitoring without direct contact which can cause stress

(Murray et al. 1999).

There is evidence that pre-construction activity rates and mortality are correlated

(Johnson et al. 2011a), yet many studies have proposed that bats may be attracted to

turbines from curiosity, misperception, or due to feeding, roosting, flocking or mating opportunities (Horn et al. 2008, Cryan and Barclay 2009). If bat mortality is not a random event, then surveying for the number of bats present at a site prior to construction will not be directly correlated with the number of future fatalities (Cryan and Barclay 2009). Bats actively forage near operating wind turbines, sometimes resulting in higher-than-expected mortality (Horn et al. 2008). A previous study in Iowa found no bat activity differences between turbine and control sites, but did document high mortality of bats at wind turbines (Jain et al. 2011). Despite the higher-than-expected mortality levels, there is some correlation between activity and mortality, and monitoring activity can give a relative indication of mortality to compare two points for potential mortality consequences. Our objective was to use an array of passive ultrasonic detectors to monitor bat activity at a central Iowa wind farm that was located in an area with intensive row-crop agriculture. Specifically, we wanted to determine the landscape and environmental variables responsible for variation in bat activity levels within and between nights and to determine the effect, if any, of turbine proximity on bat activity levels.

METHODS

We studied bat activity at a wind farm in Story County, Iowa with the cooperation of Nextera Energy. This area is representative of the intensive agricultural landscape where most of Iowa's wind energy development is focused and is characterized by row-crop agriculture (>90% corn and soybeans) with small amounts of grassland (from the Conservation Reserve Program) and woodlots (mainly windbreaks around homesteads). A control site was located 2 to 5 km west of the wind farm, a distance that is generally

accepted to be beyond the influence of the wind farm (U.S. Fish and Wildlife Service 2003) but still representative of the general habitat in this region.

In 2011 we monitored bat activity with five Anabat SD2 units (Titley Electronics Pty. Ltd., NSW, Australia, www.titley.com.au), and we obtained a sixth unit for our 2012 field season. Each unit was attached to Anabat Compact Flash Storage Zero-Crossings Analysis Interface Modules (ZCAIM) to record bat calls (Jain 2005). In 2011 we rotated our five units together between the control and treatment sites, and in 2012 we recorded simultaneously at our treatment and control sites (Fischer et al. 2009) with three Anabat units at each site. In 2011, the units were placed at a height of 2 m to be above the height of vegetation, and in 2012 we placed the monitors at a height of 1 m, again to be above the height of the vegetation but low enough to avoid human disturbance. Anabat units were set to record activity from 30 min before sunset to 30 min after sunrise, and calls were then downloaded to program AnaLook to organize, visualize and filter the calls (Titley Electronics Pty. Ltd., NSW, Australia, www.titley.com.au).

In 2011 we selected six turbines at the wind farm based upon landowner cooperation to be the focus of our activity study. From the turbine base, a 1000 m transect was created, with points placed every 250 m from the turbine base out to 1000 m from the turbine. At the control site, we chose four points based upon landowner cooperation to be the start of our transects, placing them in the middle of agricultural fields to mimic the potential placement of a wind turbine. Anabat units were placed on each of these transects for one week at a time, with an Anabat unit at each point along a transect. We rotated between a transect at the turbine farm and a transect at the control site on alternating weeks.

In 2012, we randomly selected eight turbines for our Anabat study. Due to difficulties with obtaining permission to place units in the middle of fields (e.g., interference with agricultural practices), we randomly placed points in roadside ditches approximately 500 m and 1000 m from the selected turbine. Anabat units were placed at a selected turbine and the corresponding 500 m and 1000 m points in roadside ditches for 3-4 nights at a time. Eight roadside point transects were established throughout the control site, with points again placed at approximately 500 m intervals to create transects of 1000 m, each consisting of three points.

Whenever the Anabat units were moved to a new point, the previous calls were downloaded to program AnaLook to organize, visualize, and filter the calls (Titley Electronics Pty. Ltd., NSW, Australia, www.titley.com.au). All files were filtered by hand, deleting files with <3 distinct bat pulses or weather/insect noise (Britzke et al. 1999, Jain 2005). We then created an activity index using the "Count Labels" function within AnaLook (Titley Electronics Pty. Ltd., NSW, Australia, www.titley.com.au), which is based upon the presence or absence of bat activity in a given 1-minute interval (Miller 2001). This was standardized by dividing by the unit effort (total number of minutes the units were recording) on each night (Miller 2001). For our analysis, this value was log-transformed due to the skewed raw data, even after adding a small constant value to all nights (we added 0.000633, which was half of the smallest non-zero activity index) to avoid taking the log of zero. Because of the difficulty with identifying bat species based on their calls (Barclay 1999), we modeled general bat activity without attempting to identify calls to the species level. Known species in our study area include Little Brown Bat (*Myotis lucifugus*), Silver-haired Bat (*Lasionycteris noctivagans*), Tri-colored Bat

(*Perimyotis subflavus)*, Big Brown Bat (*Eptesicus fuscus*), Eastern Red Bat (*Lasiurus borealis*), Hoary Bat (*Lasiurus cinereus*), and the Evening Bat (*Nycticeius humeralis*) either as residents or migrants (Kunz and Schlitter 1968). This bat community has low diversity compared to other regions of the country, but is typical of central Iowa disturbed habitats and includes a mix of resident and migratory species.

We monitored data on two site levels (treatment and control site), and then collected environmental data on night and point variables (Figure 1). We collected weather information from the nearest weather station, including air temperature, wind speed, moon phase, barometric pressure, and precipitation, which have all been proposed as important influences on bat activity levels (Kunz et al. 2007). Additionally, bats are generally associated with trees, wooded areas, and wetlands where their food sources are more abundant (Harr and Vannoy 2009), so we also included the distances to nearest woodlot (stand of trees > 50 m^2), river, and National Wetland Inventory (NWI; Wilen and Bates 1995) water source, which we obtained using GIS tools in ArcMap (ESRI 2011).

Data analyses

We constructed two separate models in program R (R Core Team 2012) using the lme4 package (Bates et al. 2012). We developed one model to explain the probability of bat activity on a given night at a given point (probability of activity model) and a second model for the amount of activity given that there was activity at that point and night (activity model). We used this approach because of the large number of nights with no recorded bat activity, resulting in a bimodal distribution of activity (Figure 2).

For the probability of activity model, we ran generalized linear mixed models (GLMM) with varying intercepts that included random effects for point and day, as well as

a model without any random effects, and ranked models using Akaike's Information Criterion (AIC, Akaike 1973). We used stepwise backward selection, creating main effects models (random effect on point or day or a model with no random effects), and then used the best main effects model to create a model with all covariates (wind speed, mean humidity, precipitation, mean temperature, barometric pressure, percent moon illuminated, distance to turbine, distance to woodlot, distance to river and distance to NWI). We then sequentially eliminated the least important covariate (determined by looking at the minimum absolute value of the beta estimate divided by the standard error of the covariate) and continued until the elimination of a covariate resulted in an increase of the AIC value (Pagano and Arnold 2009, Arnold 2010). We then employed model-averaging to estimate the effects of each covariate. We present the beta estimates from the best model from AIC selection.

Our methods for the activity model were the same as above, except that we modeled activity after accounting for the correlation between day and each of the weather variables. We first fit a non-parametric line to the relationship between the activity index and day of season (Figure 3), and then extracted the residuals from this fit for our model building. Thus, all subsequent models were built using these residuals, rather than the original log of the activity index.

RESULTS

In 2011 we monitored bat activity using five Anabat units from 11 July through 5 October at 25 points, resulting in 188 detector nights. In 2012, we used six Anabat units from 2 June through 5 October at 49 points, resulting in 510 detector nights. From all 698 detector nights, 165 nights (24%) had no bat activity while 533 nights (76%) had ≥ 1 bat

call during the night. Overall, we recorded 18,157 individual bat calls ($\bar{x}$=26.01 calls/night) with our activity index ranging from 0.00 to 0.69 ($\bar{x}$=0.03). Bat activity peaked in mid-July (Figure 3) with July 12 having the peak average activity index of -2.20 on the log-scale (0.11 after back-transformation).

For our models of the probability of activity (1=activity, 0=no activity), our best main effects model included a random effect of point, and we created models using this main effect (Table 1). For the point-level variables, there was a negative effect of distance to woodlot, and positive effects for distance to turbine and NWI (Table 2). For the night level variables, there were positive effects of mean temperature and the percent of the moon which was illuminated, and a negative effect of wind speed (Table 2).

The activity model's best main effects model also included a random effect of point and we again created models using this main effects model (Table 3). At the point-level variables, there was a positive effect of distance to NWI, and negative effects of distance to river and woodlot (Table 4). For the night-level variables, we found negative effects of wind speed, precipitation, and barometric pressure, and a positive effect of temperature (Table 4).

When we looked at the effects of individual covariates, with all other covariates held at their mean value, we found that distance to turbine was the strongest predictor (change in probability of activity of 25.16%), followed by distance to NWI (17.38%) and woodlot (17.23%; Table 5). Night variables ranged from 14.22% for mean temperature to 0.01% for the amount of precipitation (Table 5). Because our model of activity was based upon the residuals after looking at the effect of date, the output is not as easily interpretable. However, we found that the landscape variables, when the night variables

were held constant, changed the predicted residuals less (-1.54 to 0.43) than when the landscape variables were held constant and the night variables were changed (-1.88 to 0.77).

DISCUSSION

Contrary to other studies, we found no evidence that bats are attracted to wind turbines, with the probability of activity actually decreasing near the turbine base. However, there was no turbine effect on the level of activity, indicating that perhaps turbines placed in an agricultural landscape have a negligible effect on bat behavior. Unlike the previous study of bat activity in Iowa (Jain et al. 2011), we found differences in activity between our control and turbine sites, with activity more likely at our control site. This could have been due to the closer proximity of the control site to roosting areas, or another unmeasured landscape variable. However, if this is a behavioral response to wind turbines, it has been suggested that avoidance of wind turbines can have the benefit of thus reducing collision mortality by decreasing the number of individuals using the area around the turbine base (Drewitt and Langston 2006).

For both the probability and activity models we found a negative effect of wind speed, which, if mortality and activity are correlated, supports the evidence that more bat mortality occurs on nights with low wind speeds (Arnett et al. 2008). Similar to other studies, we found negative effects of precipitation and barometric pressure, and a positive effect of temperature on bat activity levels (Johnson et al. 2011b). The percent of the moon illuminated had positive effects on the probability of activity, with a greater probability of activity nearer a full moon. It is important to note that many of our night variables are correlated with one another (such as temperature and humidity), and that our models were

unable to tease apart which of the correlated variables, if any, is the actual mechanism for changing bat behavior. Instead, whichever correlated variable has the greater beta signifies which is the best predictor of bat activity.

For landscape variables at a point, the distance to woodlot and river were both negative effects on the amount of activity, and woodlot was also a negative effect on the probability. This supports the general evidence that bat activity is greatest around landscape elements such as trees and water when compared to the middle of open fields (Frey-Ehrenbold et al. 2013). The positive effect of distance to NWI, with greater activity further from NWI wetlands, is probably due to surveying in a drought year, when many of the temporary wetlands were dry. Siting turbines further from woodlots or other habitats preferred by bats could help decrease activity near the turbines, especially because there is evidence that agricultural landscapes with surrounding woodlots can provide stopover sites for migratory bats (Grodsky et al. 2012). We found that most of the variation in the probability of activity was attributable to the point-level variables. Thus, at a certain point, the probability of recording bat activity is more attributable to the landscape variables at or surrounding that point, although the weather variables still played a major role. The level of activity was attributable to both night and landscape variables, and point variables did play a large role in the level of activity, which indicates that preconstruction surveys may be helpful in comparing levels of bat activity between points when choosing where to site turbines.

Management implications

Our study documented several night and point variables that affected bat activity levels in an agricultural landscape in Iowa. The point variables may be of greatest interest

to land managers because they can help when choosing where to site future turbines to decrease bat mortality, assuming that activity and mortality can be correlated (Johnson et al. 2011a). By placing turbines in the middle of open fields, activity around the turbines as well as any possible avoidance effect can be minimized. For the night variables, little can be done from a management standpoint. However, increasing the cut-in speed for turbines (the minimum wind speed needed for the turbines to generate electricity) can greatly decrease mortality with little impact on overall energy production because the blades are not allowed to spin during low wind speeds when bats are most active (Arnett et al. 2011). Our findings suggest that implementing this management practice during fall migration (late July through early October), or at specific turbines, could decrease bat mortality in Iowa.

Future studies should examine the link between bat mortality and bat activity across more than a single wind farm, and investigate the variation in effects of these night and landscape variables at different sites. Additionally, conducting before-after-control-impact studies, with activity monitoring at turbine sites and control sites both before and after construction, would help us better understand attraction or avoidance of turbines. Our study compared activity levels at a single turbine and control site, and we acknowledge that there may have been site differences (e.g., proximity to roosting sites) regardless of the presence of turbines. Future studies of the effects of turbine proximity on bat activity should include pre-construction monitoring to determine if the control and treatment sites have the same baseline activity levels prior to construction. Additional wind energy developments have been proposed throughout much of Iowa (American Wind Energy Association 2012), primarily on agricultural lands, and our work will help state natural

resource managers and wind industry officials make more informed decisions regarding

wind turbine placement to minimize impacts on bats.

LITERATURE CITED

Akaike, H. 1973. Information theory and an extension of the maximum likelihood principle. Pages 267-281 *in* International Symposium on Information Theory, 2 nd, Tsahkadsor, Armenian SSR.

American Wind Energy Association. 2012. Wind Energy Facts: Iowa. American Wind Energy Association. http://awea.org/learnabout/publications/factsheets/upload/4Q-11-Iowa.pdf

Arnett, E. B., W. K. Brown, W. P. Erickson, J. K. Fiedler, B. L. Hamilton, T. H. Henry, A. Jain, G. D. Johnson, J. Kerns, R. R. Koford, C. P. Nicholson, T. J. O'Connell, M. D. Piorkowski, and R. D. Tankersley. 2008. Patterns of Bat Fatalities at Wind Energy Facilities in North America. Journal of Wildlife Management 72:61-78.

Arnett, E. B., M. M. P. Huso, M. R. Schirmacher, and J. P. Hayes. 2011. Altering turbine speed reduces bat mortality at wind-energy facilities. Frontiers in Ecology and the Environment 9:209-214.

Arnold, T. W. 2010. Uninformative Parameters and Model Selection Using Akaike's Information Criterion. Journal of Wildlife Management 74:1175-1178.

Barclay, R. M. 1999. Bats are not birds: a cautionary note on using echolocation calls to identify bats: a comment. Journal of Mammalogy 80:290-296.

Bates, D., M. Maechler, and B. Bolker. 2012. lme4: Linear mixed-effects models using s4 classes. R package version 0.999999-0. http://CRAN.R-project.org/package=lme4.

Boyles, J. G., P. M. Cryan, G. F. McCracken, and T. H. Kunz. 2011. Economic importance of bats in agriculture. Science 332:41-42.

Britzke, E., K. Murray, B. Hadley, and L. Robbins. 1999. Measuring bat activity with the Anabat II system. Bat Research News 40:1-3.

Britzke, E. R., J. E. Duchamp, K. L. Murray, R. K. Swihart, and L. W. Robbins. 2011. Acoustic identification of bats in the eastern United States: A comparison of parametric and nonparametric methods. The Journal of Wildlife Management 75:660-667.

Broders, H. G. 2003. Another quantitative measure of bat species activity and sampling intensity considerations for the design of ultrasonic monitoring studies. Acta Chiropterologica 5:235-241.

Cryan, P. M. and R. M. Barclay. 2009. Causes of bat fatalities at wind turbines: hypotheses and predictions. Journal of Mammalogy 90:1330-1340.

Drewitt, A. L. and R. H. Langston. 2006. Assessing the impacts of wind farms on birds. Ibis 148:29-42.

Erickson, W., G. Johnson, M. D. Strickland, and K. Kronner. 2000. Avian and bat mortality associated with the Vansycle Wind Project, Umatilla County, Oregon: 1999 study year. Technical Report prepared by WEST, Inc. for Umatilla County Department of Resource Services and Development, Pendleton, Oregon. 21pp.

ESRI 2011. Arc GIS Desktop: Release 10. Redlands, CA: Environmental Systems Research Institute.

Fischer, J., J. Stott, B. S. Law, M. D. Adams, and R. I. Forrester. 2009. Designing Effective Habitat Studies: Quantifying Multiple Sources of Variability in Bat Activity. Acta Chiropterologica 11:127-137.

Frey-Ehrenbold, A., F. Bontadina, R. Arlettaz, M. K. Obrist, and M. Pocock. 2013. Landscape connectivity, habitat structure and activity of bat guilds in farmland-dominated matrices. Journal of Applied Ecology 50:252-261.

Grodsky, S. M., C. S. Jennelle, D. Drake, and T. Virzi. 2012. Bat mortality at a wind-energy facility in southeastern Wisconsin. Wildlife Society Bulletin 36:773-783.

Harr, D. and L. Vannoy. 2009. Wind Energy and Wildlife Resource Management in Iowa: Avoiding Potential Conflicts. Iowa Department of Natural Resources. http://www.iowadnr.gov/portals/idnr/uploads/wildlife/wind_wildliferecs.pdf

Horn, J. W., E. B. Arnett, and T. H. Kunz. 2008. Behavioral Responses of Bats to Operating Wind Turbines. Journal of Wildlife Management 72:123-132.

Jain, A. A. 2005. Bird and bat behavior and mortality at a northern Iowa windfarm. Thesis. Iowa State University.

Jain, A. A., R. R. Koford, A. W. Hancock, and G. G. Zenner. 2011. Bat mortality and activity at a northern Iowa wind resource area. The American midland naturalist 165:185-200.

Jameson, J. W. and C. K. R. Willis. 2012. Bat Mortality at a Wind Power Facility in Central Canada. Northwestern Naturalist 93:194-202.

Johnson, G., W. Erickson, M. Strickland, M. Shepherd, and D. Shepherd. 2000. Avian monitoring studies at the Buffalo Ridge Wind Resource Area, Minnesota: Results of a 4-year study. Final report prepared for Northern States Power Company, Minneapolis, Minnesota, by Western EcoSystems Technology, Inc.(WEST), Cheyenne, Wyoming.

Johnson, G., W. Erickson, J. White, and R. McKinney. 2003. Avian and Bat Mortality During the First Year of Operation at the Klondike Phase I Wind Project, Sherman County, Oregon. Northwestern Wind Power, Goldendale, Washington, USA.

Johnson, J. S., K. S. Watrous, G. J. Giumarro, T. S. Peterson, S. A. Boyden, and M. J. Lacki. 2011a. Seasonal and Geographic Trends in Acoustic Detection of Tree-Roosting Bats. Acta Chiropterologica 13:157-168.

Johnson, J. B., J. W. Edwards, and W. M. Ford. 2011b. Nocturnal Activity Patterns of Northern Myotis (Myotis septentrionalis) during the Maternity Season in West Virginia (USA). Acta Chiropterologica 13:391-397.

Kunz, T. H., E. B. Arnett, W. P. Erickson, A. R. Hoar, G. D. Johnson, R. P. Larkin, M. D. Strickland, R. W. Thresher, and M. D. Tuttle. 2007. Ecological impacts of wind energy development on bats: questions, research needs, and hypotheses. Frontiers in Ecology and the Environment 5:315-324.

Kunz, T. H. and C. E. Brock. 1975. A comparison of mist nets and ultrasonic detectors for monitoring flight activity of bats. Journal of Mammalogy 56:907-911.

Kunz, T. H. and D. A. Schlitter. 1968. An annotated checklist of bats from Iowa. Transactions of the Kansas Academy of Science 71:166-175.

Murray, K. L., E. R. Britzke, B. M. Hadley, and L. W. Robbins. 1999. Surveying bat communities: a comparison between mist nets and the Anabat II bat detector system. Acta Chiropterologica 1:105-112.

Miller, B. W. 2001. A method for determining relative activity of free flying bats using a new activity index for acoustic monitoring. Acta Chiropterologica 3:93-105.

Pagano, A. M. and T. W. Arnold. 2009. Detection Probabilities for Ground-Based Breeding Waterfowl Surveys. The Journal of Wildlife Management 73:392-398.

R Core Team. 2012. R: A landguage and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, http://www.R-project.org/.

Stahlschmidt, P. and C. A. Brühl. 2012. Bats as bioindicators - the need of a standardized method for acoustic bat activity surveys. Methods in Ecology and Evolution 3:503-508.

U.S. Fish and Wildlife Service. 2003. Interim Guidelines To Avoid and Minimize Wildlife Impacts from Wind Turbines. United States Fish and Wildlife Service, Washington, D.C. http://www.fws.gov/habitatconservation/wind.pdf

Walters, C. L., R. Freeman, A. Collen, C. Dietz, M. Brock Fenton, G. Jones, M. K. Obrist, S. J. Puechmaille, T. Sattler, B. M. Siemers, S. Parsons, K. E. Jones, and J.

Minderman. 2012. A continental-scale tool for acoustic identification of European bats. Journal of Applied Ecology 49:1064-1074.

Wilen, B. O. and M. K. Bates. 1995. The US Fish and Wildlife Service's national wetlands inventory project. Vegetation 118:153-169.

Wilkinson, G. S. and J. M. South. 2002. Life history, ecology and longevity in bats. Aging cell 1:124-131.

Wimmer, J., M. Towsey, B. Planitz, I. Williamson, and P. Roe. 2013. Analysing environmental acoustic data through collaboration and automation. Future Generation Computer Systems 29:560-568.

Young Jr., D., W. Erickson, R. Good, M. Strickland, and G. Johnson. 2003. Avian and bat mortality associated with the initial phase of the Foote Creek Rim Windpower Project, Carbon County, Wyoming, final report, November 1998-June 2002. Prepared for Pacificorp, Inc. Portland, Oregon, SeaWest Windpower Inc. San Diego, California, and Bureau of Land Management, Rawlins District Office, Rawlins, Wyoming.

TABLES

Table 1. Models for the probability of bat activity, with a random effect of point (indicated by 1|Point), in Story County, Iowa, 2011-2012. We included night variables such as wind speed (WS), mean temperature (TempMean), percent of the moon illuminated (Moon), mean humidity (HumMean), barometric pressure (BP), and amount of precipitation (Precip). Point variables included the distance to the nearest turbine (Turbine), distance to the nearest woodlot (Woodlot), distance to the nearest river (River) and distance to the nearest National Wetland Inventory classified wetland (NWI). The AIC value of the best model was 590.02, and we reported the difference between each model's AIC value and the best model (ΔAIC), the number of covariates (K), and the model weight (Weight).

Model	ΔAIC	K	Weight
P(WS+TempMean+Moon+Woodlot+NWI+Turbine+(1|Point))	0.00	8	0.56
P(WS+TempMean+Moon+HumMean+Woodlot+NWI+Turbine+(1|Point))	1.52	9	0.26
P(WS+TempMean+Moon+HumMean+BP+Woodlot+NWI+Turbine+(1|Point))	3.22	10	0.11
P(WS+TempMean+Moon+HumMean+BP+Woodlot+NWI+River+Turbine+(1|Point))	5.18	11	0.04
P(WS+TempMean+Moon+HumMean+BP+Woodlot+NWI+River+Precip+Turbine+(1|Point))	7.17	12	0.02

Table 2. Beta estimates from the best model for the probability of activity model, from bat activity data collected in Story County, Iowa, 2011-2012. Covariates included wind speed (WS), mean temperature (TempMean), percent of the moon illuminated (Moon), distance to the nearest turbine (Turbine), distance to the nearest woodlot (Woodlot), and distance to the nearest National Wetland Inventory classified wetland (NWI).

Covariate	Beta
Intercept	-1.9160
WS	-0.0880
TempMean	0.0395
Moon	0.0070
Turbine	0.0020
Woodlot	-0.0020
NWI	0.0024

Table 3. Models for the amount of activity, with random effects of point (indicated by 1|Point), in Story County, Iowa, 2011-2012. We included night variables such as wind speed (WS), mean temperature (TempMean), percent of the moon illuminated (Moon), mean humidity (HumMean), barometric pressure (BP) and amount of precipitation (Precip). Point variables included the distance to the nearest turbine (Turbine), distance to the nearest woodlot (Woodlot), distance to the nearest river (River) and distance to the nearest National Wetland Inventory classified wetland (NWI). The AIC value of the best model was 1247.40, and we reported the difference between each model's AIC value and the best model (ΔAIC), the number of covariates (K), and the model weight (Weight).

Model	ΔAIC	K	Weight
WS+TempMean+BP+Woodlot+NWI+River+Precip+(1|Point)	0.00	10	0.49
WS+TempMean+BP+Woodlot+NWI+River+Precip+HumMean+(1|Point)	0.70	11	0.34
WS+TempMean+BP+Woodlot+NWI+River+Precip+HumMean+Moon+(1|Point)	2.70	12	0.13
WS+TempMean+BP+Woodlot+NWI+River+Precip+HumMean+Moon+Turbine+(1|Point)	4.70	13	0.05

Table 4. Beta estimates from the best model of bat activity in Story County, Iowa, 2011-2012. Covariates included wind speed (WS), precipitation (Precip), mean temperature (TempMean), barometric pressure (BP), distance to the nearest woodlot (Woodlot), distance to the nearest river (River) and distance to the nearest National Wetland Inventory classified wetland (NWI).

Covariate	Beta
Intercept	34.9051
WS	-0.0395
Precip	-0.2676
TempMean	0.0164
BP	-1.1794
Woodlot	-0.0011
River	-0.0004
NWI	0.0006

Table 5. Covariate effects on predicted probability of activity, from the probability model in Story County, Iowa 2011-2012. Covariates are listed in order of importance, with minimum and maximum covariate values, and the corresponding predicted minimum and maximum probability of activity from the model-averaged estimates of probability, when all other covariates are held constant at their means, and the change in probability (Δ probability) between the minimum and maximum predicted values for that covariate. Covariates include the amount of precipitation (inches; Precip), distance to nearest river (meters; River), barometric pressure (inHg; BP), mean humidity (percent; HumMean), the percent of the moon illuminated (percent; Moon), the wind speed (miles per hour; WS), mean temperature (degrees Fahrenheit; TempMean), distance to nearest woodlot (meters; Woodlot), distance to nearest national wetland inventory wetland (meters; NWI), and distance to nearest wind turbine (meters; Turbine).

|	Covariate Values		Probability		
Covariate	Min	Max	Min	Max	Δ probability
Precip	0	1.56	0.9068	0.9069	0.0001
River	31	2559	0.9064	0.9077	0.0013
BP	29.55	30.39	0.9021	0.9111	0.0090
HumMean	44	90	0.8966	0.9144	0.0178
Moon	0	100	0.8716	0.9327	0.0611
WS	1	17	0.8000	0.9393	0.1396
TempMean	47	86	0.8024	0.9446	0.1422
Woodlot	5	881	0.7736	0.9459	0.1723
NWI	31	1332	0.8125	0.9863	0.1738
Turbine	0	1250	0.7142	0.9658	0.2516

FIGURES
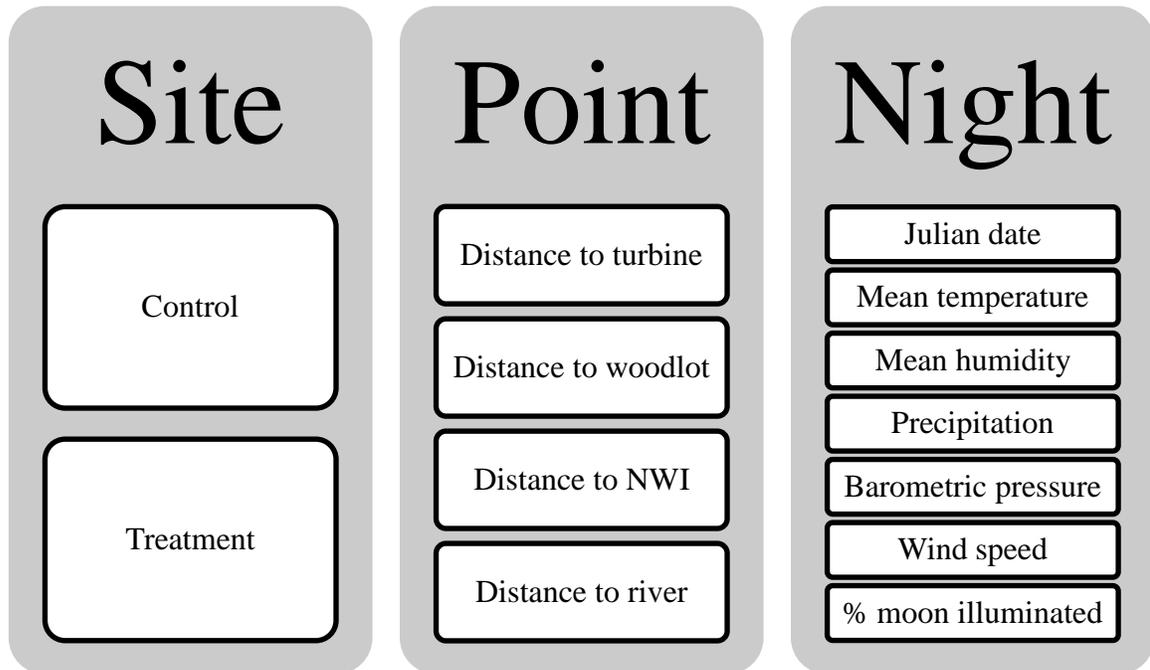
Figure 1. Levels of fixed and random effects in models of bat activity, with corresponding covariates which included the distances to different point variables (nearest turbine, woodlot, national wetland inventory or NWI, annd river) and to night/weather variables (Julian date or day since June 1, mean temperature, mean humidity, amount of precipitation, barometric pressure, mean wind speed, and the percent of the moon which was illuminated).
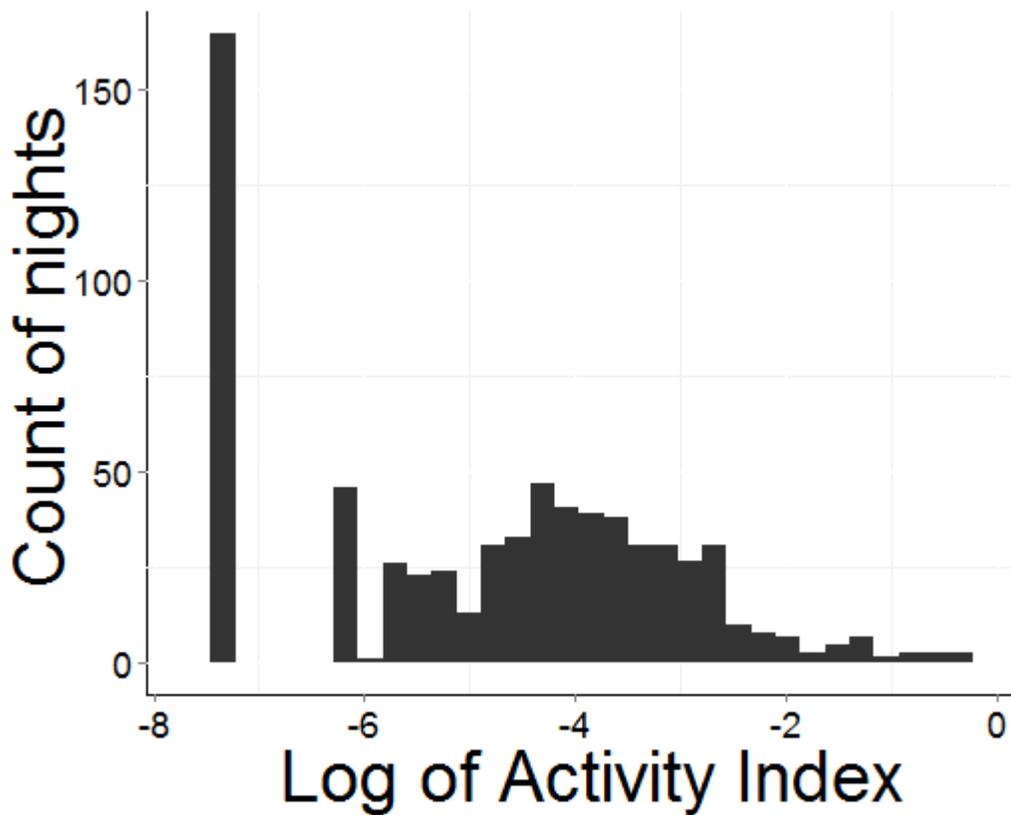
Figure 2. Frequency histogram of the log of the bat activity index, illustrating the bimodal distribution of nights with activity and no activity in Story County, Iowa, 2011-2012. The probability of activity model looks at the probability of a night at a point falling into one of these two groups, while the activity model predicted where a point on a given night would fall in the activity distribution.
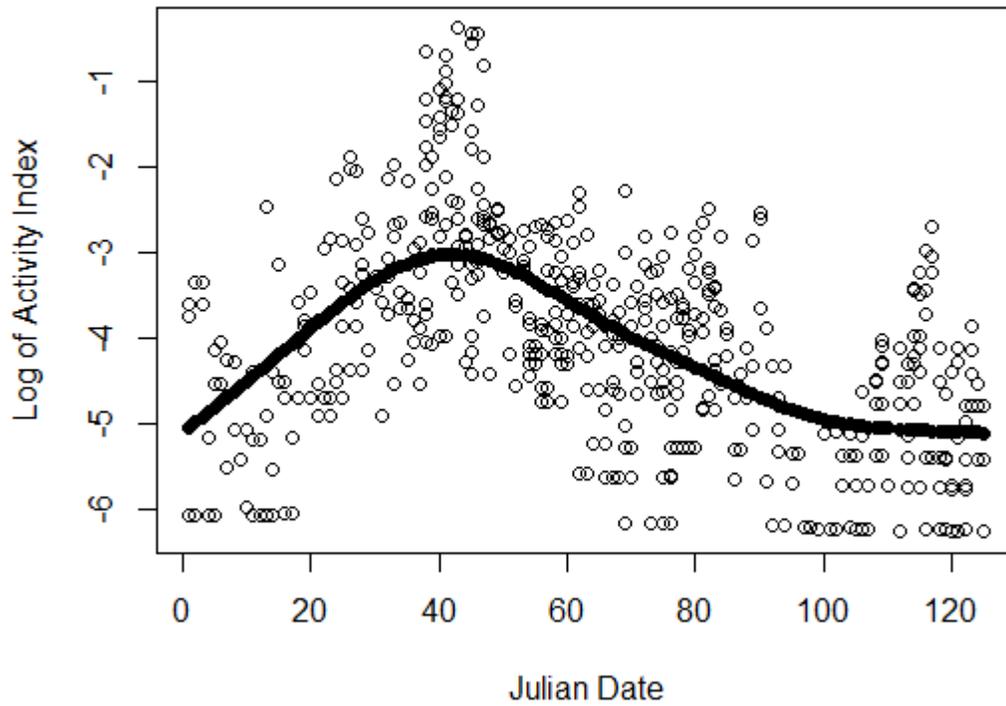
Figure 3. The log-transformed bat activity index values by Julian Date, illustrating the non-parametric effect of date, from data collected in Story County, Iowa, 2011-2012. For Julian Date, day 1 corresponds to 2 June and day 120 corresponds to 5 October.

CHAPTER 5. GENERAL CONCLUSIONS

SUMMARY

As wind energy development continues, having prior knowledge of potential impacts to birds and bats can help with siting decisions and mitigation methods. We focused on the indirect effects of wind turbine proximity rather than the direct habitat loss, which accounts for less than 2% of the actual wind farm area (Fox et al. 2006). The actual habitat loss may be greater than the direct habitat loss, due to avoidance or displacement from both the turbines and the related infrastructure (Arnett et al. 2007, Kuvlesky et al. 2007, Pearce-Higgins et al. 2012). The indirect effects we focused on were 1) behavioral responses of breeding birds, 2) nest survival rates of birds in relation to proximity to turbine, and 3) the probability of bat activity and the level of bat activity in relation to proximity to turbine.

Our study documented avoidance behavior (particularly with grassland and generalist species, including Dickcissel, Common Yellowthroat, Red-winged Blackbird, and American Robin), attraction behavior (mostly by agricultural species, especially the Killdeer), and multiple examples of species unaffected by turbine proximity (including Song Sparrow and Common Grackle). Additionally, we found significantly lower species richness at two of our three sites at the turbine base as compared to points ≥250 m from the turbine. Our work also demonstrated that the breeding bird community in Iowa's intensive agricultural landscape has low densities and species richness (Best et al. 1995), suggesting that overall impacts to breeding birds may effect fewer species and individuals here than in native habitats with greater species richness. Future plans call for continued development of wind energy resources in Iowa (American Wind Energy Association 2012), primarily on

lands currently managed for agriculture, which may help to limit impacts to avian communities.

We found negligible effects of wind turbine proximity on the survival of Red-winged Blackbird (*Agelaius pheoniceus*) nests. However, previous studies have shown that raptors will avoid nest sites near wind turbines (Usgaard et al. 1997), and our study did not attempt to look at nest site selection due to the lack of nesting habitat near turbines. Because each species and site may have different responses to wind turbine proximity, we suggest that this be studied in other, perhaps more sensitive, species such as Dickcissel. This study focused on a generalist species breeding in an agricultural landscape, and possibly represents a species and habitat least likely to be affected by wind energy development.

Contrary to other studies, we found no evidence that bats are attracted to wind turbines, with the probability of activity actually being lowest near the turbine base. However, there was no turbine effect on the level of activity, indicating that perhaps turbines placed in an agricultural landscape have a negligible effect on bat behavior. Unlike the previous study of bat activity in Iowa (Jain et al. 2011), we found differences in activity between our control and turbine sites, with activity more likely at our control site. This could have been due to the closer proximity of the control site to roosting areas, or another unmeasured landscape variable. We recommend that future studies attempt to incorporate before-after-control-impact study design (U.S. Fish and Wildlife Service 2012) to determine if differences in activity are due to turbines or other factors.

Others have suggested that directing wind energy development on disturbed lands, which already have lower wildlife value, could help reduce the future impacts of wind

energy development on more sensitive bird species (Kuvlesky et al. 2007, Fargione et al. 2012). Our findings lend further support to assertions that placing wind turbines in already disturbed lands (e.g., agricultural fields) minimizes impacts to birds and bats, and specifically avoids placing many specialist species at greater risk. By broadening our understanding of the indirect effects of wind turbines to include behavioral responses, avian nest survival, and bat activity we can refine siting guidelines that will limit the effects of wind farms on the surrounding habitat while still offering the benefits of "green" energy.

LITERATURE CITED

American Wind Energy Association. 2012. Wind Energy Facts: Iowa. American Wind Energy Association Fact Sheet, Washington, D.C. 2 p.

Arnett, E., D. Inkley, D. Johnson, R. Larkin, S. Manes, A. Manville, J. Mason, M. Morrison, M. Strickland, and R. Thresher. 2007. Impacts of wind energy facilities on wildlife and wildlife habitat. Wildlife Society Technical Review 07:1-50.

Best, L. B., K. E. Freemark, J. J. Dinsmore, and M. Camp. 1995. A review and synthesis of habitat use by breeding birds in agricultural landscapes of Iowa. American Midland Naturalist 134:1-29.

Fargione, J., J. Kiesecker, M. J. Slaats, and S. Olimb. 2012. Wind and Wildlife in the Northern Great Plains: Identifying Low-Impact Areas for Wind Development. PLoS One 7:e41468.

Fox, A., M. Desholm, J. Kahlert, T. K. Christensen, and I. Krag Petersen. 2006. Information needs to support environmental impact assessment of the effects of European marine offshore wind farms on birds. Ibis 148:129-144.

Jain, A. A., R. R. Koford, A. W. Hancock, and G. G. Zenner. 2011. Bat mortality and activity at a northern Iowa wind resource area. The American midland naturalist 165:185-200.

Kiesecker, J. M., J. S. Evans, J. Fargione, K. Doherty, K. R. Foresman, T. H. Kunz, D. Naugle, N. P. Nibbelink, and N. D. Niemuth. 2011. Win-win for wind and wildlife: a vision to facilitate sustainable development. PLoS One 6:e17566.

Kuvlesky, W. P., L. A. Brennan, M. L. Morrison, K. K. Boydston, B. M. Ballard, and F. C. Bryant. 2007. Wind Energy Development and Wildlife Conservation: Challenges and Opportunities. Journal of Wildlife Management 71:2487-2498.

Pearce-Higgins, J. W., L. Stephen, A. Douse, and R. H. W. Langston. 2012. Greater impacts of wind farms on bird populations during construction than subsequent operation: results of a multi-site and multi-species analysis. Journal of Applied Ecology 49:386-394.

Usgaard, R. E., D. E. Naugle, R. G. Osborn, and K. F. Higgins. 1997. Effects of wind turbines on nesting raptors at Buffalo Ridge in southwestern Minnesota. Pages 113-117 *in* Proceedings of the South Dakota Academy of Science.

U.S. Fish and Wildlife Service. 2012. US Fish and Wildlife Service Land Based Wind Energy Guidelines. U.S. Fish and Wildlife Service, Washington, D.C.