

# Limited evidence for cumulative effects of small wind turbines on bat activity on a landscape scale

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**Key words:** XXXXX

## Summary

1. While the effects of large wind farms on wildlife (particularly birds and bats) are generally well-studied and widely known, similar effects of small wind turbines (SWTs **give common UK dimensions**) remain relatively unknown. This is problematic, because rapid development and increasing accessibility of SWT technology have led to rapid growth of the number of SWTs installed worldwide.
2. Although recent studies showed that bat activity is negatively affected by the immediate proximity of single operating SWTs, the potential for wider landscape-scale effects of multiple SWTs installed in clusters remains unstudied. By contrast, such cumulative effects are commonly considered in impact studies of large wind farms.
3. We measured variation in bat activity at a sample of 34 SWT sites in the UK, in order to test whether (1) accounting for variation in habitat, bat activity is generally lower in closer proximity of installed SWTs (e.g. 0-100m, compared to 100-200m, 200-300m, etc.), and (2) whether this effect is stronger in sites with multiple SWTs compared to sites with single turbines.
4. After accounting for the effects of confounding variables (e.g. habitat and weather) we here provide evidence that bat activity is lower in close proximity (within 100m compared to 100-500m) from multiple, but not single SWTs. However, the strength of this effect is relatively weak, with the predicted probability of a bat pass **X-X%** within 100m compared to **X%** at 100-200m. **compare strength of effect with e.g. effect of habitat?**
5. We conclude that (1) in accordance with previous findings, although bat activity can be adversely affected by SWT presence or operation this effect is relatively localised, (2) effects can be stronger at sites with multiple SWTs installed. We suggest that although future siting decisions for multiple SWTs should take account of the possibility of cumulative effects, the strength of these effects are likely to be limited relative to the effects of e.g. habitat or environmental variation.

## Introduction

In this paper we aim to quantify and analyse the potential cumulative effect of SWTs on bat activity on a wider landscape scale (up to 500m from installed turbines). Specifically, using data collected at 34 throughout the UK we test the following predictions:

1. Bat activity is systematically lower in closer proximity (e.g. 0-100m from SWTs compared to 100-200m, 200-300m, etc) of operating SWTs, controlling for the effects of habitat and environmental conditions.
2. The effect of SWT proximity on bat activity as tested in Prediction 1 is stronger in sites with multiple (2-4) SWTs installed compared to single SWT sites. Support for this prediction would indicate evidence of cumulative effects of SWTs.

## Methods

General methods text.

### Sites

Data were collected at 34 SWT sites in central and eastern Scotland. Sites were selected from an existing database of owners (Minderman *et al.* 2012; Park, Turner & Minderman 2013) based on how representative they were of common UK SWT installation settings in terms of habitat, turbine models and size. All turbines studied here were free-standing and between 6 and 25m (mean 16m) in hub height, and all were in rural settings but specific habitat in the surrounding area varied (see **XX below**). The number of SWTs installed in each site varied between 1 and 4 (median 1.6). SWTs installed in individual sites were the same size and specification with the exception of one site. More than two SWTs were installed in only **XX** sites in our sample. We therefore limited the analyses presented here to a comparison of single and multiple turbine sites.

### Bat data and transects

Bat activity data were collected between 28 May and 01 September 2013 and 07 July and 04 September 2014. The time of data collection varied but started 30 minutes after sunset at the earliest and finished well before sunrise in all cases.

Bat activity was measured along transects by 1-2 observers walking the length of each transect at a slow **give approx speed** and constant pace, using EchoMeter EM3+ bat detectors (WildLife Acoustics, Mass., USA). A target of four transects was planned for all sites, running out from the turbines (or the central point between turbines in the case of multiple turbine sites) in four cardinal directions. However, because of physical constraints (e.g. walls, impassible fences or ditches, houses or buildings) the actual number of transects per site as well as their length varied (Number: **X-X**, **mean X** per site, length: **X-Xm**, **mean Xm**). All transects were placed so that (1) the combination of all transects within each site covered all major habitats present, and (2) overall distance separating each transect was maximised. Transects were divided into 100m sections running out from the turbine centre point, giving up to five distance bands running away from the turbine.

One measure of ground level wind speed **anemometer make** was taken at the end of each section (i.e. in each distance band) on each survey visit, and minimum daily average temperature measures for each survey visit were obtained from the UK MIDAS weather station data at Grangemouth (**coordinates**) ('UK Meteorological Office' 2006).

### Habitat data and variable selection

To account for expected confounding effects of habitat variation on bat activity along the transects, we used two key measures of habitat variability in each transect section: (1) edge density and (2) proportion of woodland. These two variables were selected on the basis of a preliminary analysis of the effect of a full set of **XXX** habitat variables on bat activity. This was done to avoid both overparameterisation of the main statistical models presented here, as well as the inclusion of highly collinear habitat metrics. Full details of

this preliminary analysis are given in Appendix **X**. To obtain habitat data per transect section, 50m buffers were placed around digital maps of each transect route, resulting in approximately 100m x 100m transect sections. The exact area of each section varied because of non-linear transect sections, but this was accounted for in the analysis, see **below**. All habitat variables were quantified in each transect section using 1:1250 UK Ordnance Survey MasterMap Topography digital maps, using QGIS **version** ('Quantum GIS Development Team' 2014). Mean distance (m) to both buildings and water was calculated by constructing a raster map of distances between each raster cell and the nearest cell with buildings or water map data, and averaging these raster values across each transect section. Edge density ( $\text{m m}^{-2}$ ) represented the density of "edge" habitat in each transect cell, and was calculated as the total length of all linear habitat features ("line" data in the OS Topography Layer) divided by the area of the transect section. Thus, this is a description of the density of e.g. building-, woodland and water edges, hedgerows, roads and tracks, roadsides, field boundaries. Finally, the proportion of tree coverage in each transect section was the sum of all tree coverage ( $\text{m}^2$ ) (coniferous, non-coniferous and unclassified trees) in the OS Topography polygon data divided by the transect section area. All Pearson correlation coefficients between these four habitat measures were  $<0.2$  with the exception of the correlation between edge density and distance to buildings which was 0.37.

## Data analysis and statistics

### Bat activity: probability of a pass per hectare surveyed

Bat activity was initially quantified as the number of bat 'passes' (defined as a sequence of at least two echolocation calls separated by less than a second **REF?**) per transect section. However, we chose to analyse our data as bat activity presence or absence per transect section, per survey visit, for two reasons. First, the distribution of observed counts was highly skewed (many zeros and excessive variation) so that count-based statistical models did not provide any reasonable fit. Second, using bat 'passes' as a measure of activity provides a relative measure of activity and analyses of absolute pass count would therefore add little information. In addition, because the area covered by each transect section varied slightly (see **Section X** above), we here model the probability of detecting bat activity per section and hectares covered.

### Statistical analysis

We used generalised linear mixed effects models (GLMMs) (Gelman & Hill 2007) and an Information-Theoretic model selection (IT) approach (Burnham & Anderson 1998) to analyse our data.

**Model structure** We modelled the probability of a bat pass per unit area on a given survey visit as the response variable with a GLMM with binomial errors and a complementary log-log link function. This link function allowed us to include transect section area as an offset in the model (thus accounting for slight variation in the size of each transect section). To account for the non-independence of repeated measurements from the same site and transect sections, all models included transect nested within site as a random effect. To test our two predictions (see **XX**), we included two focal fixed factors; (1) transect section (distance bands; 0-100m, 100-200m, 200-300m, 300-400m and 400-500m from the SWTs) and (2) turbine number (single or multiple SWTs), as well as the statistical interaction between the two. In addition to these focal factors we included the four selected (see **above**) habitat variables (distance to buildings, distance to water, edge density and proportion of tree cover) as continuous covariates. Moreover, because bat activity is known to vary with weather conditions (particularly temperature and wind speed) across the season and through the night, we also included covariates for the minimum temperature over 24h ( $^{\circ}\text{C}$ ), wind speed ( $\text{m s}^{-1}$ ), julian day number, time to midnight (mins) and time to midnight<sup>2</sup> (to account for potential non-linear effects of the latter). Thus, accounting for any confounding effects of habitat and environmental conditions, a transect section effect would indicate a systematic difference in bat activity as a function of distance from SWTs (Prediction 1), and an interaction between this and turbine number would indicate that the strength of this effect depends on the number of SWTs installed (Prediction 2). To avoid overparameterisation of the model, interactions between confounding effects were not considered. All inputs were standardised (centered to 0 and scaled to 2 SD)

following Gelman (2008) to improve performance of parameter estimation and allow for direct interpretation of relative effect strength. Summary statistics of unstandardised model inputs are given in Table 1.

Table 1: Table 1 . Summary statistics of GLMM model inputs.

	Mean	Median	Std. dev	Min.	Max.
MINTEMP	11.76	12.00	2.75	5.0	17.60
DAYNO	196.59	195.00	28.85	147.0	246.00
TTMIDN	-26.07	-41.00	82.54	-202.3	197.77
I(TTMIDN^2)	7487.47	4669.44	8375.13	0.0	40925.29
WINDS	1.07	0.40	1.46	0.0	9.80
EDGED	0.04	0.03	0.02	0.0	0.13
pTREE	0.05	0.00	0.13	0.0	0.92

**Model selection, averaging and predictions** A full model set was built starting with the ‘full model’ including all fixed- and random effects listed above. The model set was constrained to (1) only include the time to midnight<sup>2</sup> term when its linear term was also included, (2) include all random effects in all models, and (3) use the same link function and distribution for all models. This yielded a full model set of  $N = 480$  models. Model fit was assessed using the adjusted Akaike Information Criterion (AICc) and we took the top models within 4 AICc points of the ‘top’ model as our candidate set. To account for model selection uncertainty within the candidate set, we present the averaged parameter estimates and their standard errors calculated using the ‘zero method’ (Burnham & Anderson 1998). Prediction intervals were calculated as the 95% quantiles (weighted by model weight) of predictions from  $N = 1000$  simulated draws from the estimated parameter distributions for each of the models in the candidate set (Gelman & Hill 2007). For each model in the candidate set we also present the marginal and conditional  $R^2$  (Nakagawa & Schielzeth 2013).

We used R version 3.1.3 (2015-03-09) (‘R Development Core Team’ 2015) for all statistical analyses. GLMMs were fit using package *lme4* v. 1.1-7 (Bates *et al.* 2014). Model selection and averaging was performed using package *MuMIn* v. 1.13.4 (Barton 2015), and standardisation of model inputs and parameter simulation used package *arm* v. 1.7-07 (Gelman & Su 2014).

## Results

Over the two years of the study, we collected bat activity data in  $N = 1395$  transect sections, during 78 survey visits. Most sites ( $N = 30$ ) were surveyed on at least two occasions (2-6 surveys), but four sites were only visited once. Within this sample,  $N = 20$  were single-turbine sites, and  $N = 14$  were multiple-turbine sites (2-4 turbines). In total, we recorded  $N = 1867$  bat passes, of which 98.4% ( $N = 1838$ ) were Pipistrelle bats. Thus, here we only present analyses of Pipistrelle bat activity. Overall, Pipistrellus bat activity was detected on 466 section surveys (observed average probability of a Pipistrelle pass = 0.33).

The candidate set ( $\Delta AICc < 4$ ) of GLMMs for the probability of a bat pass per hectare contained 10 models (Table 2).

Table 2: Table 2 . Candidate set of GLMMs for the probability of a Pipistrelle bat pass per hectare surveyed, as a function of **XX** predictors. (continued below)

X.Intercept.	c.TURB	fSECTION	z.DAYNO	z.EDGED
-1.319	NA	+	0.491	0.49
-1.048	NA	NA	0.504	0.507
-1.32	0.182	+	0.503	0.493

X.Intercept.	c.TURB	fSECTION	z.DAYNO	z.EDGED
-1.335	NA	+	0.506	0.493
-1.037	0.174	NA	0.512	0.505
-1.305	-0.075	+	0.506	0.544
-1.053	NA	NA	0.517	0.505
-1.325	0.189	+	0.516	0.491
-1.042	0.18	NA	0.526	0.503
-1.31	-0.069	+	0.52	0.542
-1.121	NA	NA	NA	NA

Table 3: Table continues below

z.MINTEMP	z.pTREE	z.TTMIDN	I.z.TTMIDN.2.	z.WINDS
NA	0.35	-0.2	-0.561	-0.694
NA	0.416	-0.193	-0.581	-0.706
NA	0.355	-0.19	-0.549	-0.689
-0.08	0.349	-0.201	-0.559	-0.702
NA	0.421	-0.183	-0.568	-0.697
NA	0.333	-0.19	-0.565	-0.683
-0.078	0.415	-0.193	-0.577	-0.709
-0.086	0.354	-0.189	-0.545	-0.692
-0.084	0.42	-0.182	-0.564	-0.7
-0.084	0.332	-0.188	-0.561	-0.686
NA	NA	NA	NA	NA

Table 4: Table continues below

c.TURB.fSECTION	df	logLik	AICc	delta	weight
NA	13	-797.3	1621	0	0.244
NA	9	-801.9	1622	0.905	0.155
NA	14	-796.9	1622	1.217	0.133
NA	14	-797.1	1623	1.573	0.111
NA	10	-801.5	1623	2.203	0.081
+	18	-793.4	1623	2.456	0.072
NA	10	-801.6	1623	2.495	0.07
NA	15	-796.7	1624	2.722	0.063
NA	11	-801.2	1625	3.727	0.038
+	19	-793.2	1625	3.996	0.033
NA	3	-853.1	1712	91.18	0

mR2	cR2
0.204	0.391
0.201	0.389
0.213	0.394
0.209	0.391
0.207	0.391
0.222	0.402
0.204	0.387
0.216	0.392

mR2	cR2
0.21	0.388
0.225	0.4
0	0.274

## Discussion

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## Acknowledgements

Turbine owners. Kathryn Hamilton. Sofia Motta Pralon. JM funded by University of Stirling Impact Fellowship.

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### Appendix 1: Preliminary habitat data analysis and variable selection

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