# No evidence for cumulative effects of small wind turbines on Pipistrelle bat activity

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**Key words**: microturbines, domestic turbines, renewables, renewable energy, conservation, planning, wildlife impact

# Summary

1. While the effects of large wind farms on wildlife (particularly birds and bats) are generally well-studied, 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 Pipistrelle bat actvity at a sample of 34 SWT sites in the UK (**give dimensions**), 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 show that although observed Pipistrelle activity was up to 10% lower within 100m of multiple turbine sites compared to activity at 100-200m, when accounting for confounding effects of habitat and environmental conditions, this effect is non-existent, irrespective of the number of turbines installed.
5. We conclude that within our sample these is no evidence of cumulative effects of SWTs on the activity of Pipistrelle bats on a landscape scale (i.e. over >100m distances). Our previous studies did show that single SWTs may adversely affect bat activity on smaller spatial scales (within 25m), so the combination of these findings suggest that any adverse effects of SWTs may be relatively localised, even if more than one SWT is present. It should be noted that this study focused on small wind turbines only, and that these findings should not be direcly extrapolated to larger wind turbines.

# Introduction

Rapidly changing world, development, crucial to understand effects on wildlife. Particularly when effects may accumulate over space and time; cumulative effects, definition.

Good example wind farm developments. Range of evidence of adverse effects on wildlife; mortality and avoidance. Recent studies show (possibility of?) cumulative effects.

Small wind turbines (SWTs, also referred to as micro-turbines or domestic turbines) are a more recent development. These turbines are not only much smaller in size (in the UK, typical units are between 6 and 25m hub height) than those installed in wind farms, they are also commonly installed in a much wider range of habitats. Thus, their impacts on wildlife is likely to be different to that of large turbines, but up until recently this had not been quantified systematically. Our previous work found evidence for adverse effects of SWTs on bat activity (Minderman *et al.* 2012, Tatchley et al. submitted) as well as direct mortality (Minderman *et al.* 2014). These previous studies focused on a relatively limited spatial scale (e.g. within 25m of installed SWTs) and on single SWTs only. As a result, it is unclear whether any such adverse effects of SWTs on wildlife could be cumulative, i.e. whether they could operate over a larger spatial scale when the number of turbines installed is greater.

Impacts that result from incremental changes caused by other past, present or reasonably foreseeable actions together with the project

This lack of understanding of the potential cumulative effects is particularly important for SWTs for two reasons. First, the number of SWTs installed is growing rapidly, both in the UK **REF** and worldwide **REF**, and this growth is set to continue **REF**. As a result, the density of installed SWTs is likely to increase even if they are not installed in the same scheme or by the same owner. Secondly, the number of SWTs installed in groups is growing rapidly, with installations of 2-4 turbines now relatively common in the UK. Indeed, some installers now specifically promote the installation of multiple SWTs in so-called "wind crofts" **REF**, which may benefit more from government financing schemes or feed-in tariffs **REF**. As a result, where SWTs installation requires planning permission (Park, Turner & Minderman 2013), decision makers are increasingly faced with the question whether mutiple-turbine installations would have greater effects on wildlife, or if limiting the number of SWTs to be installed would be a feasible mitigation option. Currently, the evidence base for such decisions for SWTs specifically is entirely lacking.

Here, we aim to address this knowledge gap by quantifying and analysing 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

## 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 5 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 (approximately 2.5km h-1) 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 turbine (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 (3-4, mean 3.7 per site, length: 300-500m). 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 was taken at the end of each section (i.e. in each distance band) on each survey visit, and minimum daily temperature measures for each survey visit were obtained from the UK MIDAS weather station data at Grangemouth (N 56° 1' 5.15, W 3° 43' 5.88) (‘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 '[Statistical analysis](#statistical-analysis)'. 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 (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 (m2) (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) 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 [Introduction](#introduction)), 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 two selected (see [Habitat data and variable selection](#habitat-data-and-variable-selection)) 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 (C), wind speed (m s-1), julian day number, time to midnight (mins) and time to midnight2 (to account for potential non-linear effects of the latter). Thus, accounting for any confouding 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, but we calculate and present model predictions on the response scale. Summary statistics of unstandardised model inputs are given in 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

The full model set was constrained to (1) only include the time to midnight2 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, yielding a 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 interpret 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 R2 (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 occassions (2-6 surveys), but four sites were only visted 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 (AICc<4) of GLMMs for the probability of a bat pass per hectare contained 10 models. The top model retained 7 out of the 10 predictors in the full model, including distance band but neither the number of turbines nor an interaction between distance band and number of turbines. This model was = 0.244/0.155 = 1.574 (evidence ratio) times more strongly supported than second-best model, and = 0.244/0.033 = 7.394 times better supported than the saturated model (ranked 10th). The null model was ranked 446th and had no support ( < 0.001) (**Table 2**).

Although it was retained in the top model, four out of ten models in the candidate set did not retain an effect of distance band (predictor weight = 0.66). The relative importance of both the number of turbines and its interaction with distance band was even lower ( = 0.42 and = 0.1, retained in 5 and 2 models in the candidate set respectively). With the exception of minimum temperature ( = 0.32) all other predictors were retained in all models in the candidate set (Table 3).

Thus, although at multiple turbine sites the observed probability of a Pipistrelle bat pass appeared to be lower in the closest (0-100m) distance band compared to the 100-200m distance band, this difference was relatively small (0.29 vs. 0.37) (Figure 1, dark bars, and Table 3). Moreover, this effect is no longer apparent when considering model predictions that account for the effects of habitat- and environmental conditions. For example, in multiple turbine sites, predicted bat activity ranged from 0.2 to 0.34 in the nearest distance band (0-100m), and from 0.24 to 0.39 in the 100-200m distance band. Similar overlapping prediction intervals apply for both single turbine sites as well as the further distance bands (Figure 1, points and error bars).

# Discussion

We show that, when accounting for confounding effects of habitat and environmental conditions, Pipistrelle bat activity is not systematically lower within 100m of SWTs compared to at longer distances (100-200m, 200-300m, 300-400m and 400-500m), irrespective of the number of turbines (single or multiple) installed. On this basis, we conclude that there is no evidence for cumulative effects of SWTs on a landscape (i.e. >100m scale).

# Acknowledgements

We are extremely grateful to all site- and turbine owners who kindly allowed us access to their property for the survey work; this study would have been impossible without their help. Kathryn Hamilton made substantial contributions to the data collection in 2013, and Sofia Motta Pralon assisted with GIS data entry - thank you both. Many thanks to Cerian Tatchley, Paul Lintott, Nils Bunnefeld, Chris Pendlebury and Claudia Garratt for useful discussions. This study was funded by a University of Stirling Impact Fellowship to JM.

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# Appendix 1: Preliminary habitat data analysis and variable selection

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