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

*Jeroen Minderman1$, Mairi H. Gillis2, Helen F. Daly3 & Kirsty J. Park1*

1. Biological & Environmental Sciences, University of Stirling, Stirling, FK9 4LA, United Kingdom.
2. 228 Galashiels Road, Stow, Galashiels, Selkirkshire, TD1 2RA, [mgillis4a7i@gmail.com](mailto:mgillis4a7i@gmail.com)
3. 20/11 Duff Street, Dalry, Edinburgh, Midlothian, EH11 2HG, [hfdaly@outlook.com](mailto:hfdaly@outlook.com)

$***Corresponding author***. Current address: School of Biology, University of St Andrews, St Andrews, Fife, KY16 9ST, UK. Email: [jm340@st-andrews.ac.uk](mailto:jm340@st-andrews.ac.uk).

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# 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, in the UK usually up to 25m in hub height) 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 actvity at a sample of 34 SWT sites in the UK (free-standing SWTs between 6 and 25m in hub height), 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. We focused our analysis on Pipistrelle bats because more than 98% of our recorded activity was from this genus. 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 there 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

Understanding and predicting how wildlife is affected by disturbance or habitat loss is becoming increasingly important as anthropogenic pressures on the natural world continue to grow (Tuomainen & Candolin 2011). This is particularly pertinent were incremental changes or disturbances could combine to produce cumulative effects. For example, the rapid growth of the wind energy sector worldwide provides a vital contribution to sustainable energy production, a growing range of studies show that wind farms can have adverse effects on wildlife. Although the recognition of the potential importance of cumulative effects (defined as "*the additional changes caused by a proposed development in conjunction with other similar developments or as the combined effect of a set of developments, taken together*", SNH (2012)) is relatively recent and its quantification is in its infancy (Masden *et al.* 2010), both direct (collision mortality of birds and bats, e.g. Drewitt & Langston (2006), Rydell *et al*. (2010)) and indirect effects (disturbance or displacement, e.g. Larsen & Guillemette (2007), Pearce-Higgins *et al*. (2009)) of individual turbines or wind farms have been widely studied.

By contrast, similar effects of small wind turbines (SWTs, also referred to as micro-turbines or domestic turbines) on wildlife remain relatively unknown. 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 the combined effects of multiple SWT installations could have greater adverse effects on wildife.

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 and worldwide and this growth is set to continue (WWEA 2013; RenewableUK 2014). 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?**. As a result, where SWT 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 [Habitat data and variable selection](#habitat-data-and-variable-selection)). 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 v. 1.8 (‘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 [Bat data and transects](#bat-data-and-transects)), 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.

#### 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 (*Pipistrellus pipistrellus* or *P. pygmaeus*) bats. Thus, here we only present analyses of Pipistrelle bat activity. Overall, Pipistrelle 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.

By contrast, we previously showed that bat activity can be systematically lower in the immediate vicinity (<25m) of operating SWTs (Minderman *et al.* 2012), and indeed subsequent experimental studies of bat activity before- and after installation of SWTs near hedgerows confirmed such adverse effects on activity (Tatchley *et al*. submitted). Combined with the present finding of a lack of similar effects on a larger scale (i.e. within 100m), this suggests that such adverse effects are relatively localised. Although the mechanism causing such avoidance behaviour is unclear, experimental studies in a laboratory setting have shown that the return of echolocation pulses off spinning turbine blades may be erratic, potentially causing navigational problems for bats **REF Long etal**. Other experimental studies have shown that some species of bat may avoid foraging in noisy environments **REF Schaub** but whether noise generated by turbines (including SWTs) has the same effect has not been tested. In either case, it would be reasonable to assume that the strength of such interference would dissipate relatively rapidly with distance, especially if it involves relatively high-frequency noise (which should attenuate more strongly over shorter distances, **REF Jon Russ?**), limiting the spatial scale of any adverse effect of the turbine.

This apparently relatively localised effect of SWTs may in turn also explain the lack of evidence for any cumulative effect (i.e. effects were not different between single- or multiple turbine sites). If avoidance behaviour only operates over relatively short (as per our previous findings, <25m) distances, it may be possible for bats to avoid individual turbines rather than whole "clusters" of turbines. Indeed, in our multiple turbine sitesturbines were sited 13 - 122 m apart with this distance being less than 23 m in only one case (mean 49.4m). This suggests that in most cases bats would be able to avoid individual turbines without coming in very close proximity of another, limiting the possibility of any cumulative effects. Further detailed study of individual flight paths would be required to confirm whether this is the case, however. Moreover, it should be noted that although the possibility of cumulative effects is often raised for larger turbines and wind farms **REF Masden, SNH**, empirical studies that unequivocally demonstrate such effects are rather rare and have tended to focus on birds rather than bats (**REF Schaub, others?**). Although this may be due to the logistical difficulty of study such large-scale effects, it is possible that cumulative effects themselves are rare, except in specific circumstances.

There are a number of important caveats with our findings that should be considered. First of all, these findings and conclusions should not be generalised to species other than *Pipistrellus* sp. Although Pipistrelle bats are by far the commonest species in both our wider study area as well as in the specific habitats we studied **REF**, it is likely that the collection of sufficient data to draw species-specific conclusions would rely on targeted surveys. The need to collect data at a wide range of sites rather than in specific habitats (where less widespread species may be more abundant) prevented us from doing this here. However, species-specific behavioural responses have been recorded for larger turbines **REF** and we therefore consider this to be a research priority for SWTs**REF Cerian's prelim findings?**. Secondly, the limited number of sites with more than two turbines in our sample means that we cannot exclude the possibility that a larger number of turbines *would* cause cumulative effects; indeed modelling studies in birds **REF Schaub** show that this may well be the case. Similarly, we here chose to record bat activity over a relatively large scale (up to 500m from SWTs), and dividing bat activity into 100m sections along the transects may mean that we have missed more subtle effects on a smaller scale.

Final concluding/summarising point. Perhaps recommendation?

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