1	Short title: Variability in collision rate predictions
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3	Modelled sensitivity of avian collision rate at wind turbines varies with number of hours of
4	flight activity input data
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Collision risk modelling of birds at wind turbines typically requires vantage point (VP) data to 1 2 quantify bird flight activity. The number of VP observation hours required to provide such data, 3 and the associated error in predicted collision rate, have not been formally assessed. Using the 4 Band model and a randomisation procedure, we examine the sensitivity of collision rate predictions for the White tailed Eagle Haliaeetus albicilla to varying hours of input data on flight 5 6 activity. Variability in collision rate decreased with increasing number of observation hours. 7 However, at the asymptote in variability (about 62 observation hours) there was still 8 considerable variability in predicted collision rate. VP watches are likely to be inherently 9 variable, and collision rate predictions should assess the potential error associated with such 10 results.

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Keywords: Avian flight activity, Band model, collision risk modelling, onshore wind, renewable
energy, vantage point watches, wind farms.

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A variety of models has been developed to predict avian collision risk at wind turbines, typically 1 2 requiring input data on bird flight activity and turbine specifications (e.g. Tucker 1996, Podolsky 3 2003, Smales 2006). In the UK and elsewhere (e.g. Norway, May et al. 2010), the model 4 developed by Band et al. (2007, see also SNH 2000) remains the standard method for predicting 5 collision rate for a range of bird species, including raptors and wildfowl, at proposed wind 6 farms. The model requires various stages of input data which are then multiplied to calculate 7 collision rate: (1) bird flight activity within the rotor swept zone (RSZ), determined from 8 surveys; (2) site- and species-specific collision probabilities, determined by the structure and 9 operation of the turbines and relevant bird size and flight (Table S1); and, (3) collision rate can 10 be further refined by the inclusion of avoidance rate (Band et al. 2007). Key parameters in 11 determining collision probability in Stage 2 are bird flight speed, rotor diameter and rotation 12 speed, and predicted collision rate is highly sensitive to avoidance rate (Chamberlain et al. 13 2005, 2006).

14 A key knowledge gap remaining is the unknown sensitivity of the model outputs to 15 varying levels of input data relating to flight activity in the RSZ (i.e. Stage 1). These are the data 16 on which the calculations are based, and are often treated as providing definitive knowledge 17 regarding flight activity at a site, but are only estimates, with associated error that is rarely 18 considered in Environmental Impact Assessments (EIA). At onshore sites, bird flight activity is 19 typically recorded using vantage point (VP) watches, conducted by either a single observer or 20 multiple observers operating simultaneously. Flight activity observed during VP watches can be 21 highly variable, and sufficient hours must be conducted to quantify flight activity at a site. As an

example, Scotland's statutory government agency Scottish Natural Heritage (SNH) recommends
a minimum of 36 observation hours per season (e.g. breeding season) to provide input data for
calculating collision rate (SNH 2005), on the assumption that this level of observation will
provide a reasonable estimate of true flight activity. However, this assumption has not been
formally tested, although such testing is advocated by SNH (SNH 2005), partly because of a lack
of larger datasets from which to draw sample subsets of observation hours to assess the
change in variability with increasing observation hours.

8 Here we utilise an extensive dataset on flight activity of a large raptor species of high 9 conservation concern, the White-tailed Eagle *Haliaeetus albicilla*, at an operational wind farm. 10 We examine the sensitivity of collision rate calculations from the Band model to varying hours 11 of input data on flight activity, predicting that variability in collision rate decreases with 12 increasing observation hours. Using current SNH guidelines for VP watches as an example (SNH 13 2005), we use our results as a test of whether these are adequate in quantifying flight activity 14 and the variability associated with collision rate predictions.

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- 16 METHODS
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18 Site details and vantage point data

Flight activity of White-tailed Eagles was recorded over a single breeding season in 2006 at the 68-turbine Smøla wind farm, Norway (Follestad *et al.* 2007). The coincidence of the wind farm with an area of high breeding density of White-tailed Eagles has led to a study of the response

1	of large raptors to wind farm development, including VP watches to record flight activity. VP
2	data from 2006 comprised 175 observation hours between March and August. Sessions ranged
3	from 1 – 6 hours-duration. Although the duration of individual flights within a session was
4	recorded, the precise time of day these occurred was not; As precise flight time was not
5	recorded, wwe therefore required input data from sessions of equal length, and thus
6	standardised observation period, as with 'session' formingforms the minimum unit of analysis
7	possible. For this reason W_W therefore utilised data from the session length with the largest
8	sample size (2 hours, $n = 51$ sessions), retaining only those conducted using comparable
9	methods between sessions (two observers operating simultaneously from the same two VPs).
10	This yielded a sample of 47 2-hr sessions conducted between 13 March and 341 July 2006,
11	between 06:00 – 19:00, representing the diurnal variation in flight activity and flight type
12	(moving flight, soaring, spiralling etc, May et al. 2010) and consistent with recommended VP
13	methodology (SNH 2005). Observations followed the Focal-Animal Sampling method (see May
14	et al. 2010) and flight activity was summarised as the total flight time of all individual eagles at
15	rotor height per session.

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17 Randomisation procedure and calculation of collision rate

18 We selected subsets of observation sessions, increasing incrementally by one session at a time, 19 ranging from 1 to 47 (2 – 94 observation hours). For each number of observation hours, we 20 used a resampling procedure (with replacement) with 10000 permutations, to select a random 21 sample of observation sessions summing to the relevant total number of observation hours, Commented [p1]: Does not make sense. Do you mean "to form"? And what is "flight time" here? Do you mean flight duration? Or time of day? Please re-write and clarify.

with the output value of each permutation being the total flight time within the RSZ across all
sessions. For each permutation, we calculated the predicted number of White-tailed Eagle
collisions using the Band *et al.* (2007) model, assuming no turbine avoidance (see Discussion).
Data on flight activity from the randomisation procedure provided Stage 1 data, and we
incorporated relevant input parameters specific to the wind farm site and White-tailed Eagles
for Stage 2 (Table S1).

7 We examined the effect of varying the number of observation hours upon the accuracy 8 of (variability in) our collision rate predictions. We first calculated the mean and 95% 9 confidence intervals (CI) of the 10000 permutations for each number of observation hours. The 10 values of the upper and lower 95% CI were also calculated as the percentage difference of each 11 relative to the mean. We assessed whether the variability in collision rate predictions reached 12 asymptote with increasing number of observation hours. The calculated range between the 13 upper and lower 95% CI was modelled as a response variable against the number of 14 observation hours. Modelling was conducted using nonlinear regression (3-parameter 15 exponential decay model) in SigmaPlot 12 (Systat Software Inc 2011) which yielded an estimate 16 of the asymptote in the range of 95% CI. We then examined the probability of a single set of 17 observations (i.e. percentage of the 10000 permutations) at each number of observation hours 18 yielding a predicted collision rate outside the asymptotic range of the 95% Cl.

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20 RESULTS

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1 The predicted number of collisions during the study period, calculated using our sample of 94 2 observation hours ($n = 47 \times 2$ hour sessions) and assuming no avoidance, was 22.9 collisions, which was matched by the mean number of collisions calculated from random resamples with 3 4 varying number of observation hours (range 22.6 - 23.1 collisions, Figure. 1a). As expected, 5 there was a marked reduction in the variability of calculated collision rate, as measured by the 6 range of 95% CI around the mean, with increasing number of observation hours (Fig. 1a, b). This 7 variability decreased predictably with increasing effort, reaching an asymptote of $y = 20.3 \pm 0.7$ 8 (the range between the upper and lower 95% CI of number of collisions) at about 62 hours of 9 observation (Fig. 1c), when the predicted number of collisions was 22.9 (95 % CI of 13.4 – 33.8; 10 -41.7 to +47.2 % variation around the mean). The probability of a single set of observations 11 yielding a calculated collision rate outside the asymptotic range of 95% CI also decreased 12 predictably with increasing effort (Fig. 1d). Consistent with the calculated asymptote in 13 variability for this particular dataset, 62 hours was the minimum observation period for which 14 the calculated probability reaches 5% (5.0, Fig. 1d).

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16 DISCUSSION

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18 Increasing numbers of observation hours of flight activity markedly reduced the variability in 19 the predicted number of eagle collisions, with an asymptote in variability at about 62 hours for 20 this particular dataset. Whilst drawn from a much larger sample of VP data than are normally 21 collected to quantify flight activity at a site, these results are however based on only one season

in one year, and should not be treated as definitive. Furthermore, the extent to which this 1 2 asymptote in observer effort is site- and species-specific is not assessed. Eagle activity at Smøla may be relatively high, and lower flight activity at other sites may lead to greater variability in 3 4 collision rate predictions, which would likely raise the asymptote in observation hours above 5 that calculated for this dataset. Even at 62 hours' observation of flight activity, there is still 6 considerable variability in the predicted number of collisions, which varied from 13.4 - 33.8, a 7 2.5 fold range. Vantage point watches are likely to be inherently variable, and the results of a 8 single set of observation hours from the field should not be treated as definitive in impact 9 assessments, with no consideration of the potential error. Instead, EIAs should include an 10 assessment of the likely variability in their predictions from a resampling procedure. Our 11 predicted collision rate (22.9 eagles, using the sample dataset of 94 observation hours) assumes 12 no turbine avoidance by flying eagles. The high sensitivity of predicted collision rate to 13 avoidance rate (Chamberlain et al. 2006) could potentially outweigh the sensitivity of collision 14 rate predictions to observer effort. However, a simultaneous assessment of sensitivity to both 15 observer effort and avoidance rate was outside the scope of this study. Although not 16 considered here, additional factors may affect estimates of flight activity within the RSZ, 17 including the level of missed observations and the accuracy of estimating flight height of birds, 18 particularly at distance (Madders & Whitfield 2006).

As a comparison with our results, Scotland's statutory government agency SNH recommends a minimum of 36 hours of vantage point observations per season to quantify flight activity at a proposed wind farm site and predict collision rate using the Band model (SNH

1 2005). Our calculations suggest that with 36 observation hours, the 95% CI of predicted collision rate range from 10.8 to 37.0 collisions (equivalent to -53.0 - 61.8% below and above the mean 2 3 value of 22.9 collisions respectively), compared to 95% Cl of 13.4 – 33.8 at the asymptote of 62 4 hours. Thus the range between the upper and lower 95% CI at the asymptote of 62 hours (20.4) 5 is c. 22% lower than at 36 hrs (26.3). The probability of a single set of 36 hours of observations 6 yielding a predicted collision rate outside the range of 95% CI at the asymptote is 14.4%, 7 compared to 5.0% at 62 hours. Statistical power analyses typically aim for an 80% probability of 8 detecting a significant result for a particular test. Here, this could be defined as an 80% 9 probability of a single set of observations yielding a collision rate prediction within the 95% CI at 10 the asymptotic range in variability. For our results this occurs at a minimum of 28 hours of 11 observations (80.6%). Therefore deciding whether current guidelines for predicting collision 12 rate need refinement requires consideration as to the acceptable level of uncertainty 13 associated with such calculations. The results presented here provide a first attempt at 14 quantifying such variability, and we would encourage the randomisation methods employed 15 here to be repeated on additional VP datasets of avian flight activity, for a range of species 16 vulnerable to collision with wind turbines. These methods could be further extended to 17 examine the sensitivity of collision rate predictions within spatial subunits or individual turbines 18 at a site and the influence of weather during VP watches (May et al. 2010, Ferrer et al. 2011).

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1	Figure.1. Effect of varying observation hours of vantage point watches on predictions of
2	collision rate of White-tailed Eagles at Smøla wind farm from March – July 2006, calculated
3	using the Band model: (a) Predicted number of collisions with varying observation hours
4	(solid line = mean, dotted lines = 95% confidence intervals (CI)) from randomisation
5	procedure; (b) Percentage variation in upper and lower 95% CI around the predicted number
6	of collisions from randomisation procedure; (c) variation in the range between upper and
7	lower 95% CI (circles = raw data from randomisation procedure with fitted line from
8	modelling calculated range as the response variable against number of observation hours
9	using non-linear regression); (d) probability of a single set of observations at each number of
10	total observation hours yielding a collision rate prediction outside the asymptotic range in
11	95% Cl at <i>c</i> . 62 hours.



