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Accounting for weather and time-of-day parameters when analysing count data from monitoring programs

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Abstract Problems induced by heterogeneity in species and individuals detectability are now well recognized when analysing count data. Yet, most recent techniques developed to handle this problem are still hardly applicable to many monitoring schemes, and do not provide abundance estimates at the point count scale. Here, we show how using simple weather variables can be a useful surrogate to detect variability in species detectability. We further look for a potential bias or loss in statistical power based on count data while ignoring weather and time-of-day variables. We first used the French Breeding Bird Survey to test how each of the counts of the 97 most common breeding species was influenced by weather and time-of-day variables. We assessed how the estimation of each species response to fragmentation could be influenced by correcting counts with such variables. Among 97 species, 75 were affected by at least one of the five weather and time-of-day variables considered. Despite these strong influences, the relationship between species abundance and fragmentation was not biased when not controlling counts for weather and time-of-day variables and further found no improvement in statistical power when accounting for these variables. Our results show that simple variables can be very powerful to assess how species detectability is influenced by weather conditions but they are inconsistent with any specific bias due to heterogeneous detectability. We suggest that raw count data can be used without any correction in case the sources of variation in detectability could be considered independent to the factor of interest.

Keywords Breeding bird survey · Detectability · Fragmentation · Point counts · Relative abundance · Time-of-day · Weather conditions

Abbreviations

BBS	Breeding bird survey

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Introduction

Counts of individuals or species are the result of two processes: a biological process (the true presence or absence of a species or individual), and a methodological filter (the ability of the observer to detect an individual). If variation in detectability among species and/or individuals is not accounted for, an unknown part of the variation in presence or abundance of a given species will result from variation in detectability regardless of its true variation. Therefore, using just the detected bird counts (per unit effort) as an index of abundance is sometimes considered to be neither scientifically sound nor reliable (Burnham 1981). To control the potential bias induced by heterogeneity in detectability, two approaches have been adopted. On the one hand, several methods have been developed to account for the whole detection process and to further directly estimate the probabilities of detection. Yet these methods need either both spatial and temporal replications (Dodd and Dorazio 2004; Royle 2004; Kéry et al. 2005), or temporal replication and marking of individuals (Farnsworth et al. 2002; Alldredge et al. 2007). On the other hand, count data may be corrected with covariables known to be sources of heterogeneity in detectability (Caughley et al. 1976; Link and Sauer 1998, 2002). This approach may be simpler to apply but sources of heterogeneity in detectability may remain unchecked and can still bias the analyses.

Collecting abundance data from incomplete counts may respond to different objectives which involve different strategies to deal with heterogeneity in detectability. First, it is important to note that estimating a species total abundance over an area requires an estimation of detectability even if detectability is constant across sites (Thompson et al. 1998). For these objectives, a direct estimation of detectability seems to perform well (Kéry et al. 2005; Royle et al. 2007). However, most ecological studies do not need an absolute measure of abundance, but rather an index, usually named relative abundance, to infer spatial or temporal variations of species abundance. In these cases, imperfect detection must be accounted for if detectability covaries with the dimension to be compared. Here we focused on the use of count data to infer on abundance variations across spatial variations of an ecological factor, which is a common output of large scale monitoring programs (Jiguet et al. 2006; Julliard et al. 2006; Posthuma and De Zwart 2006; Vaughan et al. 2007). As many ecological factors such as habitat characteristics are measured very locally, these studies often need a measure of relative abundance on a very local scale (e.g. for each point count), which unfortunately precludes using any spatial replication of count data. Thus, in many cases, a direct estimation of detectability is still not possible. In such cases, accounting for factors that potentially affect species detectability could be a valuable proxy in counts analysis (Link and Sauer 1998). Moreover, some of these factors are easily recorded by observers. Here, we focused on time-of-day and weather variables which are more likely directly linked to detection processes rather than to variations in true abundance (Robbins 1981; Verner 1985). We thus provided a framework to test how these simple variables can influence the power of classical analyses based on counts. We specifically addressed two objectives: (i) relating variations in counts to weather and time-of-day factors, (ii) assessing how accounting for these variables could correct bias and/or improve statistical power while testing ecological predictions. For this purpose, we chose to use landscape fragmentation as an ecological factor impacting a wide range of common species (Fahrig 2003; Devictor et al. 2008). Monitoring data came from the French Breeding Bird Survey (Jiguet et al. 2007), which is similar to many classical monitoring programs.

We predict that time-of-day influences detectability of species in either a positive or a negative way depending on the type of activity enhancing detectability (e.g. song activity generally decrease and foraging activities might increase with time after sunrise; Robbins 1981; Lindenmayer et al. 2004). We also predict that weather conditions should affect detectability if they restrain sighting or hearing of individuals or if they influence bird activities (Verner 1985).

Material and methods

The French Breeding Bird Survey

A breeding bird survey (BBS) was started in France in 2001 carried out by volunteer skilled ornithologists and following a standardized protocol with the same sites sampled for several years. Each observer provided a locality from which, within a 10 km-radius, a 2 × 2 km plot to be sampled was randomly selected (i.e. among 80 possible plots). Such random selection ensures the survey of representative habitats (including farmlands, woodlands, suburbs and cities). In each site, observers monitored 10 point-counts separated by at least 300 m. Data collected by observer on each permanent point-count stations were the counts and specific identification of all individuals seen and/or heard during a fixed period of 5 min.

We considered all points surveyed in 2005 for this analysis ($n = 7350$, i.e. from 735 plots). Birds were counted twice (before and after the 8th of May within April to mid-June) in each plot, with 4–6 weeks between the two counts and within 1–4 h after sunrise. Only individuals detected within 100 m of the observer were considered, to avoid bias due to visual detections strongly depending on landscape structure. Habitats were recorded by observers on their point counts, using a standardized code (Julliard et al. 2006). Finally, we retained species for which at least 30 individuals were counted ($n = 97$ species, see Appendix) to conduct the analyses.

Observers were also asked for each point count to note the time of the count start (to the nearest minute) and to describe weather conditions for four variables: cloudiness, rain, wind and visibility. Each of these variables was scored as 1, 2 or 3 (see Table 1). The monitoring recommendations stated that counting during rain, strong wind or deep fog should be avoided, so these extreme meteorological conditions are rarely found in the dataset (mostly when conditions changed during the sampling).

Landscape fragmentation

An estimate of landscape fragmentation within each surveyed plot was obtained using the geographical information system package ArcView 3.2 (ESRI 2000) and the Corine land

Table 1 Criteria used by observers to assess weather conditions for each point counts

Values	Cloudiness (%)	Rain	Wind	Visibility
1	0–33	Absent	Absent	Good
2	33–66	Drizzle	Light	Moderate
3	66–100	Showers	Medium/strong	Poor

Cloudiness is measured in sky covering percentage cover database. CORINE is a national geo-referenced land-cover, based on satellite digital images for the whole country. This land cover layer was created in 2000 to classify, by means of remote sensing, landscape units larger than 25 ha as belonging to one of 44 habitat classes (Bossard et al. 2000). The resolution concerning polygon limits is 20 meters. In other words, the difference between two polygons of different habitat types as well as each polygon complex form was precisely represented by CORINE. The edge density (sum of all contact length between polygons) was thus considered as a good measure of habitat fragmentation (Lausch and Herzog 2002; Devictor et al. 2008). The edge density was highly correlated to the number of polygons and to the average polygon size of the different habitat types enclosed in the landscape (Devictor and Jiguet 2007).

Statistical analyses

We modelled each species counts with two successive statistical models. First, we considered an "uncontrolled model", i.e. for each species, counts was only a function of period (first or second), habitat type (among 18 classes) and habitat fragmentation using a Generalized Linear Model: Counts vary with Period + Habitat + Fragmentation. Second, we considered a "controlled model" by adding in the previous model the five supplementary predictors supposedly linked to detectability: Counts varies with Period + Habitat + Time + Cloudiness + Rain + Wind + Visibility + Fragmentation.

Time recorded by the observer was converted to time after local sunrise (in min, source: USNO 2007). Time and weather variables were considered as continuous predictors, as we expected the response of each species to each variable to be monotone. These five variables were also standardized by a z-transformation to allow comparisons of their magnitudes. Spearman's rank correlations between habitat fragmentation, time-of-day and each weather variable were calculated. We found that habitat fragmentation and time-of-day were extremely weakly correlated to other variables (Table 2). As expected, rain, wind and visibility were weakly correlated to each other (Table 2).

We used generalized linear models accounting for "quasipoisson" distribution of errors, differing from Poisson distribution by allowing overdispersion in the count data for a species (McCullagh and Nelder 1989), with log as a link function.

Note that we didn't account for spatial dependence between point counts (spatial autocorrelation) as statistical models usually run to handle spatial autocorrelation hardly support Poisson regression with large datasets. Despite violating the spatial independence assumption, we assumed that it should impact both models equally (with or without weather variables). Therefore, this problem should not impact the comparison between both models, which is the main focus of our analysis.

Table 2 Spearman's rank correlations between variables used in this study

	Fragmentation	Time-of-day	Cloudiness	Rain	Wind
Time-of-day	−0.067				
Cloudiness	0.008	−0.005			
Rain	0.049	0.006	0.310		
Wind	0.023	0.094	0.172	0.119	
Visibility	0.041	−0.031	0.319	0.282	0.028

We analysed the effects of the five variables supposedly linked to detectability in two steps. First, we performed for each species and for each variable, a *t*-test of the corresponding slope fitted in the controlled model, compared to zero, to assess which species respond significantly to each variable. Second, we gathered for each variable, the 97 species response slopes and performed *t*-tests compared to zero in order to test more general patterns of response to weather and time-of-day variables. Time-of-day effects were also tested for the "vocal" activities species subset ($n = 73$; species most often detected because of their territorial vocalizations) as time-of-day effects were mostly expected for vocal activities (Lindenmayer et al. 2004; Woltmann 2005).

We further looked for a possible bias in the fragmentation effect estimation for the uncontrolled model by correlating fragmentation parameters of the two models in a paired *t*-test. Finally, we compared the fragmentation effect estimation's accuracy in both models. For this purpose, we calculated, for each species, the statistical power gain as follows:

$$\text{Gain} = (\text{SE}_1 - \text{SE}_2)/\text{SE}_1 \times 100$$

where SE_1 and SE_2 are the standard errors of the fragmentation parameters of respectively the uncontrolled and the controlled model. This metric gave us a potential gain (or a loss if negative) in accuracy of the fragmentation effect estimation, expressed in percentage of the uncontrolled accuracy.

As the amount of available data was expected to affect model fits, we assessed whether both eventual bias and gain in accuracy were related to the species commonness, measured using the log of total number of individuals recorded in the dataset for each species.

Results

Time-of-day and weather effect

Among the 97 species considered, the counts of 38 species were significantly affected by time-of-day (Table 3). These responses were as often positive as negative and the global response of the considered species was not significant (Fig. 1a, b). But, "vocal" species ($n = 73$) responded globally negatively to time-of-day (Table 3). Rain had globally the strongest effect on counts, but only 15 species individually responded significantly (Table 3, Fig. 1c). We also found highly significant negative effects of cloudiness and wind on counts (Table 3, Fig. 1d). However, visibility seemed to affect few species counts, without the expected global positive response (Table 3). Altogether, 75 of the 97 species showed at least one significant response to any of the five variables considered.

Bias and accuracy in fragmentation effect estimation

Fragmentation effect slope was highly correlated between uncontrolled and controlled models ($n = 97$, Pearson correlation coefficient: $\rho = 0.997$, see Fig. 2). Paired *t*-test revealed no significant differences between these two estimations ($t = 1.31$, df = 96, $P = 0.194$), and these slight differences were not linked to species commonness ($t = 0.73$, df = 95, $P = 0.47$).

Moreover there was no gain in accuracy in the estimation of fragmentation effect (average gain = −0.7%, $t = -1.33$, df = 96, $P = 0.186$), and there was no significant link between these gains and species commonness ($t = 0.238$, df = 95, $P = 0.812$).

Table 3 Effects of Time-of-day and Weather variables on counts

Variable	Species responses						
	–	(–)	(+)	++	Total significant	Average slope	*P*
Time-of-day							
Total	22	32	27	16	38	–0.001	0.974
Vocal species	19	28	19	7	26	–0.039	**0.014**
Cloudiness	21	43	24	9	30	–0.070	**<0.001**
Rain	9	37	45	6	15	–0.340	**0.013**
Wind	23	44	26	4	27	–0.072	**<0.001**
Visibility	5	35	46	11	16	0.041	0.50

The –, (–), (+) and ++ columns refer to the number of species that respectively respond significantly negatively, non-significantly negatively, non-significantly positively and significantly positively to the corresponding variable. Total significant column refers to the total number of species which respond significantly to each factor (either positively or negatively). Average slope column refers to the average response among species to the corresponding variable, and last column refers to the *P*-value from the *t*-test of the Average slope compared to zero

Bold values are significant test with $P < 0.05$

Discussion

Weather and time-of-day effects on detection

Among the 97 species we studied, 75 responded at least to one of the five variables potentially linked to detectability. Time-of-day seemed to be the less influential variable but the even distribution and large variability of this variable within the dataset showed many significant responses for individual species and, as expected, a global negative trend for vocal species (Lindenmayer et al. 2004; Woltmann 2005). Conversely, the four weather variables showed stronger global effects but affected fewer species, most likely because there were only three categorical values and very unequal sample sizes, as observers were told to avoid rainy, windy and misty conditions as much as possible. This resulted in only 6% of the counts made in both rainy and strong wind conditions and only 1% in poor visibility. Yet, many species still responded significantly to these variables, showing that standardizing field methods in monitoring programs does not still guarantee a constant detectability across sites (Verner 1985; Thompson 2002).

These results also showed that very easily recorded variables can provide valuable information for practical issues. Similar analyses could help to provide strong recommendations to new monitoring schemes, for example by recording time-of-day and weather conditions to find optimal detection conditions of a targeted species. Such variables could also be useful for more theoretical purposes. For example, these monitoring data could be used to test predictions on the time-of-day specialization of song activities (Cody and Brown 1969; Brumm 2006). In this latter case, we show that one should account for the variation in counts induced by variation in the time of the records.

Implication for fragmentation effect estimation

We found no bias induced by weather conditions on the fragmentation effect. Indeed, the fragmentation effect was remarkably robust to time-of-day and weather variables (Fig. 2).

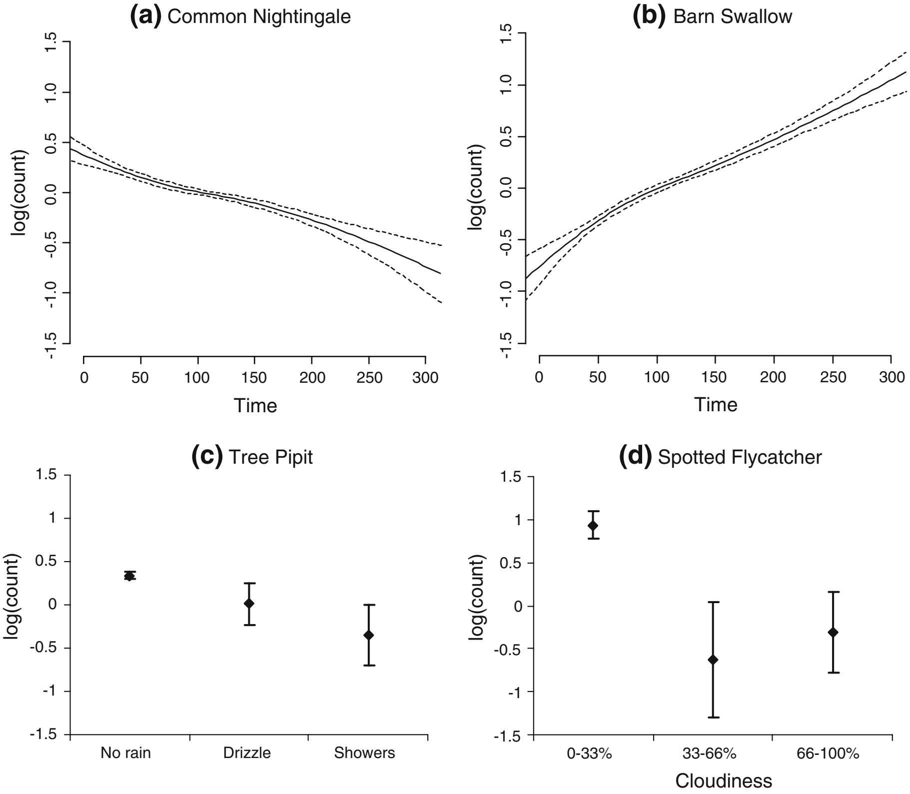
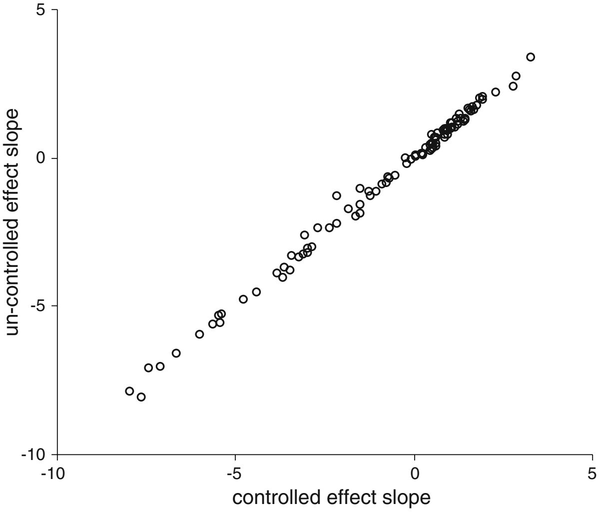


Fig. 1 Examples for differential detectability under different conditions. (**a**, **b**) The relationship between counts and time after sunrise for (**a**) Common Nightingale (*Luscinia megarhynchos* Brehm), a species detected almost exclusively by its song and for (**b**) Barn Swallow (*Hirundo rustica* L.) whose detection is linked to its prey activity (dipterans). Fit from a non-parametric spline function with 4 df, adjusted to habitat, count period and weather; dotted lines show ±1 SE. (**c**) The relationship between counts and rain conditions for Tree Pipit (*Anthus trivialis* L.), a species whose detection is linked to territorial display activity which is strongly inhibited by rain. Note that rain was here considered as a discrete variable, its effect was adjusted to habitat, count period, time-of-day and weather; bars show ±1 SE. (**d**) The relationship between counts and cloudiness for Spotted Flycatcher (*Muscicapa striata* Pallas), a species detected mostly when sallying out from vegetation hunting flying insects (Cramp and Perrins 1993). Cloudiness was here considered as a discrete variable, its effect was adjusted to habitat, count period, time-of-day and weather; bars show ±1 SE

Thus, this result suggests that when heterogeneity in detectability is not correlated to the process of interest, there should be no bias in ecological correlations using raw counts. However, Gu and Swihart (2004) found strong bias in habitat relationships with simulated occurrence data, even when detectability was independent of habitats. We emphasize that this pattern could be induced when considering occurrence data. Indeed, sites with very few individuals should exhibit critically low detection probabilities which may stronger impact occurrence than abundance potential bias. Thus, we argue that although counts may include more sources of unchecked variations, using counts should be more robust than presence-absence data to detectability heterogeneity.

Fig. 2 The relationship between uncontrolled and controlled estimation of the fragmentation effect for the 97 species (points)



Moreover, we also found no gain in accuracy when accounting for time-of-day and weather covariates. Thus in this example, there was no need to account for weather and time-of-day covariates to answer our ecological question.

To conclude, we showed that raw counts can be influenced by weather and time-of-day conditions even if the monitoring design intends to standardize field methods. Yet, we also showed that these variations in detectability did not induce any bias nor any lack of statistical power while estimating species response to habitat fragmentation. We suggest that this example is representative of many ecological analyses performed on large raw counts dataset. Obviously, sources of variation in detectability may be more diverse than weather and time-of-day alone (Bart and Schoultz 1984; Schieck 1997; Norvell et al. 2003) and can give wrong ecological messages if not carefully addressed (Moilanen 2002; Mazerolle et al. 2005). We thus strongly recommend to at least list potential bias induced by heterogeneity in detectability. Then, we suggest that counts from classic monitoring scheme may still be used without any correction when relating species abundance to ecological factor, whenever variations in detectability can be safely considered as independent of the ecological factor of interest.

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Appendix

List of the 97 species used in the analysis

Scientific name	Vocal	Time-of-day	Cloudiness	Rain	Wind	Visibility
Aegithalos caudatus	0	0.118 ± 0.062	0.059 ± 0.068	−0.109 ± 0.076	0.01 ± 0.065	−0.04 ± 0.062
Alauda arvensis	1	0.093 ± 0.018	0.018 ± 0.02	−0.038 ± 0.023	0.015 ± 0.018	−0.024 ± 0.019
Alectoris rufa	1	−0.053 ± 0.08	−0.021 ± 0.084	0.144 ± 0.07	−0.362 ± 0.097	−0.067 ± 0.071
Anthus campestris	1	−0.158 ± 0.083	−0.366 ± 0.114	−5.477 ± 314	−0.075 ± 0.083	5.693 ± 292
Anthus pratensis	1	−0.247 ± 0.08	−0.197 ± 0.089	−0.061 ± 0.094	0.386 ± 0.065	−0.022 ± 0.084
Anthus trivialis	1	0.042 ± 0.037	0.005 ± 0.04	−0.136 ± 0.05	−0.078 ± 0.04	−0.032 ± 0.036
Apus apus	0	0.188 ± 0.094	−0.591 ± 0.162	0.27 ± 0.093	0.089 ± 0.098	−0.088 ± 0.138
Burhinus oedicnemus	1	0.083 ± 0.129	−0.029 ± 0.146	0.167 ± 0.115	−0.47 ± 0.167	−0.144 ± 0.111
Buteo buteo	0	0.158 ± 0.059	−0.059 ± 0.068	−0.15 ± 0.096	−0.094 ± 0.066	0.064 ± 0.074
Carduelis cannabina	1	0.127 ± 0.047	−0.032 ± 0.054	0.04 ± 0.048	0.092 ± 0.045	−0.001 ± 0.05
Carduelis carduelis	1	0.02 ± 0.034	−0.017 ± 0.037	−0.002 ± 0.035	−0.018 ± 0.034	−0.017 ± 0.035
Carduelis chloris	1	−0.096 ± 0.026	−0.006 ± 0.027	−0.003 ± 0.025	−0.015 ± 0.026	0.027 ± 0.027
Certhia brachydactyla	1	−0.092 ± 0.031	0 ± 0.032	−0.013 ± 0.032	−0.103 ± 0.034	−0.023 ± 0.029
Certhia familiaris	1	−0.17 ± 0.111	−0.294 ± 0.134	−0.116 ± 0.151	0.366 ± 0.104	−0.178 ± 0.098
Cettia cetti	1	−0.557 ± 0.086	−0.003 ± 0.085	0.034 ± 0.073	−0.003 ± 0.076	−0.205 ± 0.061
Cisticola jucundis	1	−0.038 ± 0.064	−0.028 ± 0.075	−0.188 ± 0.101	−0.05 ± 0.062	−0.201 ± 0.06
Coccothraustes coccothraustes	0	−0.202 ± 0.093	0.183 ± 0.087	−0.152 ± 0.112	−0.278 ± 0.114	−0.077 ± 0.07
Columba livia	1	−0.208 ± 0.086	−0.369 ± 0.122	0.117 ± 0.075	0.066 ± 0.094	−0.094 ± 0.112
Columba oenas	1	−0.082 ± 0.189	−0.178 ± 0.218	−0.25 ± 0.4	−0.308 ± 0.251	−0.054 ± 0.213
Columba palumbus	1	−0.107 ± 0.021	0.008 ± 0.023	0.015 ± 0.021	−0.074 ± 0.022	−0.006 ± 0.022
Corvus corone	0	0.021 ± 0.036	−0.005 ± 0.039	0.021 ± 0.036	−0.01 ± 0.036	−0.005 ± 0.036
Corvus frugilegus	0	0.207 ± 0.141	−0.442 ± 0.22	0.115 ± 0.186	0.074 ± 0.14	−0.009 ± 0.207
Corvus monedula	0	0.249 ± 0.104	−0.166 ± 0.129	0.116 ± 0.106	−0.216 ± 0.126	−0.118 ± 0.112

Appendix continued

Scientific name	Vocal	Time-of-day	Cloudiness	Rain	Wind	Visibility
Coturnix coturnix	1	−0.278 ± 0.071	0.031 ± 0.075	−0.036 ± 0.094	−0.007 ± 0.063	−0.26 ± 0.121
Cucculus canorus	1	−0.09 ± 0.035	−0.074 ± 0.038	0.015 ± 0.035	−0.131 ± 0.039	−0.153 ± 0.029
Delichon urbicum	0	−0.073 ± 0.132	−0.338 ± 0.179	−0.425 ± 0.403	−0.207 ± 0.157	−0.104 ± 0.166
Dendrocopos major	1	−0.038 ± 0.032	0.057 ± 0.034	−0.058 ± 0.039	−0.169 ± 0.037	0.036 ± 0.035
Dendrocopos medius	1	0.15 ± 0.073	−0.137 ± 0.081	−0.399 ± 0.18	−0.289 ± 0.105	−0.31 ± 0.051
Dendrocopos minor	1	0.073 ± 0.118	−0.014 ± 0.13	−0.015 ± 0.132	−0.218 ± 0.141	0.004 ± 0.127
Dryocopos martius	1	−0.063 ± 0.121	0.133 ± 0.123	0.012 ± 0.123	−0.019 ± 0.131	0.112 ± 0.141
Emberiza cia	1	−0.291 ± 0.163	0.283 ± 0.157	−0.318 ± 0.226	−0.045 ± 0.164	−0.111 ± 0.135
Emberiza cirlus	1	−0.066 ± 0.039	−0.117 ± 0.043	0.046 ± 0.04	−0.071 ± 0.039	0.003 ± 0.04
Emberiza citrinella	1	−0.047 ± 0.027	−0.013 ± 0.029	−0.028 ± 0.031	0.007 ± 0.026	0.018 ± 0.028
Emberiza hortulana	1	0.234 ± 0.168	−0.19 ± 0.228	−5.607 ± 623	0.213 ± 0.164	−0.081 ± 0.213
Erithacus rubecula	1	−0.08 ± 0.015	0.036 ± 0.016	−0.01 ± 0.015	0.005 ± 0.016	−0.002 ± 0.015
Falco tinnunculus	0	0.116 ± 0.062	0.046 ± 0.068	0.017 ± 0.066	0.068 ± 0.06	0.096 ± 0.075
Fringilla coelebs	1	0.044 ± 0.01	0.02 ± 0.011	0.015 ± 0.01	0.01 ± 0.01	0.021 ± 0.011
Galerida cristata	1	−0.117 ± 0.103	−0.459 ± 0.133	−5.375 ± 265.9	−0.576 ± 0.15	−0.193 ± 0.092
Garrulus glandarius	0	0.041 ± 0.035	−0.089 ± 0.039	0.019 ± 0.037	−0.05 ± 0.038	0.08 ± 0.041
Hippolais polyglotta	1	−0.128 ± 0.036	−0.117 ± 0.043	−0.023 ± 0.047	−0.061 ± 0.037	−0.063 ± 0.041
Hirundo rustica	0	0.341 ± 0.043	0.138 ± 0.048	0.034 ± 0.042	−0.164 ± 0.048	0.076 ± 0.051
Jynx torquilla	1	0.052 ± 0.124	−0.307 ± 0.149	0.062 ± 0.127	−0.125 ± 0.138	−0.093 ± 0.114
Lanius collurio	0	0.17 ± 0.068	−0.108 ± 0.093	−0.006 ± 0.105	−0.136 ± 0.076	0.119 ± 0.125
Locustella naevis	1	−0.123 ± 0.107	0.063 ± 0.106	−0.039 ± 0.101	−0.01 ± 0.104	−0.116 ± 0.084
Lullula arborea	1	0.067 ± 0.048	−0.131 ± 0.055	0.042 ± 0.054	−0.159 ± 0.053	0.058 ± 0.056
Luscinia megarhynchos	1	−0.193 ± 0.023	−0.064 ± 0.024	0.011 ± 0.023	−0.078 ± 0.023	−0.039 ± 0.021
Merops apiaster	0	1.182 ± 0.15	−0.454 ± 0.272	−5.473 ± 629	−0.613 ± 0.287	0.167 ± 0.375
Miliaria calandra	1	−0.028 ± 0.039	−0.007 ± 0.043	0.004 ± 0.046	−0.015 ± 0.037	−0.017 ± 0.041

Appendix continued

Scientific name	Vocal	Time-of-day	Cloudiness	Rain	Wind	Visibility
Milvus migrans	0	−0.207 ± 0.139	−0.141 ± 0.153	0.142 ± 0.117	0.046 ± 0.128	0.158 ± 0.177
Motacilla alba	1	−0.011 ± 0.041	0.062 ± 0.043	0.047 ± 0.036	0.016 ± 0.039	−0.001 ± 0.041
Motacilla flava	1	−0.031 ± 0.05	0.035 ± 0.054	−0.075 ± 0.068	0.008 ± 0.046	0.055 ± 0.059
Muscicapa striata	0	0.286 ± 0.104	−0.467 ± 0.167	−5.22 ± 299.411	−0.082 ± 0.126	0.067 ± 0.199
Oenanthe oenanthe	0	0.192 ± 0.085	−0.046 ± 0.098	0.065 ± 0.084	−0.073 ± 0.09	−0.216 ± 0.064
Oriolus oriolus	1	−0.017 ± 0.045	−0.051 ± 0.051	0.005 ± 0.054	−0.113 ± 0.049	0.132 ± 0.063
Parus ater	1	0.175 ± 0.041	−0.082 ± 0.051	0.05 ± 0.047	0.09 ± 0.047	0.031 ± 0.047
Parus caeruleus	1	0.03 ± 0.019	−0.018 ± 0.02	−0.015 ± 0.02	−0.037 ± 0.02	0.028 ± 0.02
Parus cristatus	0	0.243 ± 0.061	−0.04 ± 0.077	−0.29 ± 0.144	−0.05 ± 0.079	−0.08 ± 0.071
Parus major	1	−0.025 ± 0.015	0.027 ± 0.016	0.028 ± 0.014	−0.095 ± 0.016	0.041 ± 0.016
Parus montanus	1	−0.045 ± 0.114	0.067 ± 0.128	0.117 ± 0.095	−0.028 ± 0.122	0.141 ± 0.096
Parus palustris	1	0.109 ± 0.062	0.122 ± 0.066	0.019 ± 0.063	−0.274 ± 0.08	0.001 ± 0.062
Passer domesticus	0	0.001 ± 0.021	−0.092 ± 0.024	0.072 ± 0.02	0.028 ± 0.021	0.028 ± 0.025
Passer montanus	0	−0.246 ± 0.104	−0.343 ± 0.125	0.067 ± 0.12	−0.207 ± 0.112	−0.165 ± 0.093
Perdix perdix	0	0.012 ± 0.058	0.074 ± 0.062	0.013 ± 0.065	−0.087 ± 0.057	0.003 ± 0.061
Phasianus colchicus	1	−0.286 ± 0.061	−0.053 ± 0.061	0.02 ± 0.059	−0.085 ± 0.06	−0.009 ± 0.056
Phoenicurus ochruros	1	−0.06 ± 0.031	−0.004 ± 0.033	0.047 ± 0.029	−0.116 ± 0.033	0.118 ± 0.038
Phoenicurus pheonicurus	1	0.027 ± 0.057	−0.13 ± 0.066	−0.085 ± 0.075	−0.062 ± 0.063	−0.001 ± 0.063
Phylloscopus bonelli	1	0.091 ± 0.05	−0.254 ± 0.064	0.034 ± 0.066	−0.249 ± 0.066	0.018 ± 0.061
Phylloscopus collybita	1	−0.006 ± 0.015	0.031 ± 0.016	−0.053 ± 0.016	0.007 ± 0.016	−0.013 ± 0.015
Phylloscopus sibilatrix	1	−0.014 ± 0.108	0.175 ± 0.109	0.118 ± 0.098	−0.348 ± 0.146	0.092 ± 0.118
Phylloscopus trochilus	1	0.223 ± 0.047	0.243 ± 0.05	−0.149 ± 0.059	−0.063 ± 0.054	−0.075 ± 0.044
Pica pica	0	−0.045 ± 0.032	−0.005 ± 0.035	−0.064 ± 0.039	−0.046 ± 0.033	0.003 ± 0.037
Picus viridis	1	−0.002 ± 0.039	−0.001 ± 0.042	0.041 ± 0.036	−0.101 ± 0.042	−0.015 ± 0.038
Prunella modularis	1	−0.058 ± 0.028	−0.048 ± 0.03	0.023 ± 0.026	0.076 ± 0.027	−0.027 ± 0.027

Appendix continued

Scientific name	Vocal	Time-of-day	Cloudiness	Rain	Wind	Visibility
Pyrrhula pyrrhula	0	0.098 ± 0.077	0.012 ± 0.087	0.02 ± 0.08	0.014 ± 0.082	0.003 ± 0.082
Regulus ignicapillus	1	−0.013 ± 0.051	−0.028 ± 0.056	0.078 ± 0.046	−0.147 ± 0.06	−0.056 ± 0.047
Regulus regulus	1	0.028 ± 0.054	−0.041 ± 0.062	0.061 ± 0.057	−0.157 ± 0.066	0.055 ± 0.06
Saxicola rubetra	1	−0.275 ± 0.113	−0.238 ± 0.129	−0.042 ± 0.139	0.112 ± 0.1	0.072 ± 0.132
Saxicola torquatus	1	0.024 ± 0.039	−0.009 ± 0.042	0.059 ± 0.039	−0.092 ± 0.039	0.028 ± 0.041
Serinus serinus	1	−0.09 ± 0.036	−0.016 ± 0.038	−0.024 ± 0.038	−0.053 ± 0.037	−0.016 ± 0.037
Sitta europaea	1	0.058 ± 0.034	−0.034 ± 0.038	−0.095 ± 0.048	−0.141 ± 0.04	0.052 ± 0.041
Streptopelia decaocto	1	−0.064 ± 0.025	0.029 ± 0.026	0.042 ± 0.022	−0.092 ± 0.026	−0.001 ± 0.025
Streptopelia turtur	1	−0.014 ± 0.032	0.015 ± 0.035	−0.085 ± 0.042	−0.072 ± 0.033	−0.064 ± 0.035
Sturnus vulgaris	1	0.025 ± 0.045	0.117 ± 0.048	0.039 ± 0.04	−0.03 ± 0.045	−0.075 ± 0.043
Sylvia atricapilla	1	−0.019 ± 0.011	0.009 ± 0.011	−0.008 ± 0.011	−0.037 ± 0.011	0.016 ± 0.011
Sylvia borin	1	0.06 ± 0.045	0.125 ± 0.049	−0.175 ± 0.067	0.033 ± 0.046	−0.018 ± 0.052
Sylvia cantillans	1	−0.121 ± 0.093	−0.791 ± 0.158	0.456 ± 0.08	−0.235 ± 0.114	0.236 ± 0.158
Sylvia communis	1	0.004 ± 0.028	−0.004 ± 0.031	−0.069 ± 0.035	0.039 ± 0.027	−0.072 ± 0.028
Sylvia curruca	1	0.029 ± 0.128	−0.282 ± 0.166	0.258 ± 0.111	−0.099 ± 0.135	0.215 ± 0.196
Sylvia melanocephala	1	−0.106 ± 0.067	−0.033 ± 0.072	−0.033 ± 0.072	−0.231 ± 0.079	−0.136 ± 0.059
Sylvia undata	1	0.049 ± 0.097	0.188 ± 0.112	−5.568 ± 383	−0.117 ± 0.116	0.261 ± 0.153
Troglodytes troglodytes	1	−0.138 ± 0.014	0.063 ± 0.014	−0.023 ± 0.014	0.025 ± 0.014	0.013 ± 0.014
Turdus merula	1	−0.062 ± 0.011	0.035 ± 0.011	0.029 ± 0.01	−0.044 ± 0.011	−0.003 ± 0.011
Turdus philomelos	1	−0.141 ± 0.023	0.097 ± 0.023	−0.046 ± 0.023	−0.029 ± 0.024	−0.036 ± 0.021
Turdus pilaris	1	−0.013 ± 0.137	−0.034 ± 0.152	0.072 ± 0.104	0.34 ± 0.122	−0.252 ± 0.097
Turdus viscivorus	1	−0.023 ± 0.05	−0.13 ± 0.056	0.085 ± 0.044	0.029 ± 0.051	−0.131 ± 0.042
Upupa epops	1	−0.237 ± 0.068	−0.252 ± 0.074	0.021 ± 0.065	0.029 ± 0.064	−0.278 ± 0.046
Vanellus vanellus	0	0.396 ± 0.161	−0.301 ± 0.236	0.234 ± 0.164	−0.321 ± 0.2	−0.022 ± 0.197

Vocal column shows which species have been considered as "vocal" (1) or not (0), i.e. whose detections are mainly due to territorial vocalizations. The last five columns show species response slopes (±SE) to the five weather and time-of-day z-transformed variables in the controlled model

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