

1 **Impacts of onshore wind energy production on birds and bats: recommendations for future life** 2 **cycle impact assessment developments**

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7

8 **Abstract**

9 *Purpose:* Models for quantifying impacts on biodiversity from renewable energy technologies are missing within life
10 cycle impact assessment (LCIA). We aim to provide an overview of the effects of wind energy on birds and bats, with
11 a focus on quantitative methods. Furthermore, we will investigate and provide the necessary background for how these
12 can in future be integrated into new developments of LCIA models.

13 *Methods:* We reviewed available literature summarizing the effects of wind energy developments on birds and bats.
14 We provide an overview over available quantitative assessment methods that have been employed outside of the LCIA
15 framework to model the different impacts of wind energy developments on wildlife. Combining the acquired
16 knowledge on impact pathways and associated quantitative methods, we propose possibilities for future approaches
17 for a wind energy impact assessment methodology for LCIA.

18 *Results and discussion:* Wind energy production has impacts on terrestrial biodiversity through three main pathways:
19 collision, disturbance, and habitat alterations. Birds and bats are throughout the literature considered the most affected
20 taxonomic groups, with different responses to the before-mentioned impact pathways. Outside of the LCIA framework,
21 current quantitative impact assessment prediction models include collision risk models, species distribution models,
22 individual-based models and population modelling approaches. Developed indices allow scaling of species-specific
23 vulnerability to mortality, disturbance and/or habitat alterations.

24 *Conclusion:* Although insight into the causes behind collision risk, disturbance and habitat alterations on bats and birds
25 is still limited, the current knowledge base enables the development of a robust assessment tool. Modelling the impacts
26 of habitat alterations, disturbance and collisions within an LCIA framework is most appropriate using species
27 distribution models as those enable the estimation of species' occurrences across a region. Although local scale
28 developments may be more readily feasible, further up-scaling to global coverage is recommended to allow comparison
29 across regions and technologies, and to assess cumulative impacts.

30

31 **Keywords:** collision, disturbance, habitat alteration, quantitative models, wind turbine, LCIA

32

33 **1. Introduction**

34 Wind energy has emerged as a promising alternative to fossil fuels in an attempt to halt climate change, with an annual
35 average growth rate of 24.3% from 1990 to 2014 (IEA 2016). In 2013 it represented 2.5% of the global electricity
36 supply, and it is expected to grow to between 15-18% by 2050 (International Energy Agency 2013). However, research
37 has shown that wind farms, both onshore and offshore, can cause direct and indirect damage to wildlife (e.g., Edenhofer
38 et al., 2012; Rydell et al., 2012; Schuster, Bulling, & Köppel, 2015). For onshore wind energy, this research describes
39 bats and birds in particular to be vulnerable to collision, disturbance and habitat alterations during the construction and
40 operational stages. Even if this damage may be relatively low today in comparison to other energy sources (Sovacool
41 2013), the cumulative impacts due to the installation of projected wind farms may significantly affect more vulnerable
42 populations (Carrete et al. 2009; Masden et al. 2010a; Schaub 2012). Wind power might also come as an additional
43 impact to already existing environmental impacts, contributing critically to increased impacts upon specific species
44 and populations. For the impacts of wind energy different impact assessments exist, however, these are all site-,
45 species- or impact- specific and a globally applicable tool is still lacking.

46 Life cycle assessment (LCA) is an environmental impact assessment tool, which is widely used to evaluate and
47 compare the environmental performance of products or services through their whole life cycle by using different impact
48 categories, such as climate change, ecotoxicity or land use (Hauschild and Huijbregts 2015). LCA has been used to
49 evaluate and compare environmental impacts associated with different energy production systems, but typically
50 focuses on greenhouse gas emissions (Evans et al. 2009). Martínez et al. (2009) performed a LCA of a multi-megawatt
51 wind turbine, analyzing the manufacturing, use, disposal, and transport stages throughout several impact categories
52 (e.g., global warming carcinogens, acidification). The authors show that manufacturing of the components is the largest
53 contributor to the impacts of a wind turbine, which was supported by a study by Arvesen and Hertwich (2012).
54 However, none of these studies took into account impacts on biodiversity, due to insufficient or lacking impact
55 assessment models. Including biodiversity will likely increase the contribution of the construction and operational
56 stages of a wind farm to its overall impacts, although the magnitude of it is unknown. Even with recent developments
57 in incorporating biodiversity related impacts in LCA (e.g., Azevedo et al. 2013; Chaudhary et al. 2015; Verones et al.
58 2016; Cosme et al. 2017), currently available life cycle impact assessment (LCIA) models do not cover wind energy
59 specific impacts on biodiversity.

60
61 In an attempt to cover the lack of biodiversity impacts from renewable energy production, we aim to summarize the
62 existing knowledge base and its applicability for the future development of LCIA models covering the impacts of wind
63 energy on biodiversity. New developments of LCIA models should take into consideration the varying vulnerability
64 among different species groups to each type of impact. Focusing on onshore wind energy, we provide an overview of
65 the main impact pathways affecting two major taxonomic groups, bats and birds, showing the most relevant state
66 mechanisms and conditional variables that should be considered in the development of an impact assessment model.
67 Although other authors have qualitatively reviewed this topic before, there is yet a lack for a summary of quantitative
68 methods and a link to LCIA. Therefore, we present the most commonly used environmental impact assessment tools
69 in the wind energy sector, as well as recent developments in these. Finally, we explore how these can be used as a basis

70 to develop future LCIA models and provide recommendations for the next steps in the direction of these model
71 developments.

72

73 2. Methods

74 Several authors (Drewitt and Langston 2006; Kunz et al. 2007b; Rydell et al. 2012; Langston 2013; Marques et al.
75 2014; Dai et al. 2015; Wang et al. 2015; Schuster et al. 2015) have comprehensively reviewed the effects of wind
76 energy on biodiversity from an ecological point of view. These served as a gateway to a more refined search within
77 the subsections covered in each article (e.g., articles focusing on one species or group of species, or on a particular
78 impact pathway). Despite the availability of several reviews, there was only one article focusing on quantitative
79 models; regarding avian collision risk models (Masden and Cook 2016).

80 We searched for available peer-reviewed and “grey” literature on the topic of impacts of wind energy on wildlife
81 published up until the date of final submission. Using mainly Google Scholar (Google 2017) and Oria (Bybysys 2017)
82 we began by using key terms including, but not limited to, “wind energy”, “wind power” “biodiversity”, “LCA”,
83 “impacts”, “assessment”, “birds”, “bats”, “collision”, “displacement”, “disturbance”, “avoidance”, “habitat loss”,
84 “habitat alterations”. For an overview of available quantitative models, we mainly used Google Scholar to conduct our
85 search, using key terms such as “collision risk”, “model”, “quantifying”, “quantitative”, “habitat loss”, “avian”,
86 “displacement”, “bat”, “species distribution” and “wind energy”. When searching for available LCA related
87 methodologies, we also included the key terms “LCA”, “LCIA”, “Life Cycle Assessment”, and “Life Cycle Impact
88 Assessment”, in addition to the previous terms. For each article, we went through its reference list in search for other
89 relevant studies. The most highly cited literature was taken as a basis for understanding the topic. Mendeley (Mendeley
90 Ltd. 2016) and Elsevier (Elsevier 2017) also proved to be valuable sources of knowledge by linking previous searches
91 to related articles and providing recommendations on relevant articles. “Grey” literature was also considered in this
92 review, consisting mainly of technical reports from highly credited institutions or companies working on the topic at
93 hand because of either the reports’ high number of citations or very high relevance to this study. Some articles were
94 excluded from this review, as they were already well described in other reviews and would not contribute any additional
95 content to this article. We also excluded articles describing non-predictive quantitative methods, i.e. those that would
96 not contribute to the development of LCIA models. In total, we reviewed 138 articles.

97

98 3. Effects of wind energy development on biodiversity

99 Knowledge on the effects of wind energy on biodiversity at a species level, and how these reflect impacts on a
100 population level (May et al. 2017), is the first step to adequately quantify impacts, outside and within the LCA
101 framework. Drewitt and Langston (2006), as well as many other authors, identified collision, disturbance, as well as
102 habitat loss and change as the main effects from wind power on birds, both on- and offshore. For bats, Brinkmann
103 (2006) stated that collision is likely the main cause of impacts.. Schuster et al. (2015) consolidated literature on effects
104 from wind power on birds and bats, with a focus on both taxa. We note that disturbance and displacement are two

105 similar terms that may be used interchangeably in wind energy impact assessment literature, and should therefore be
106 clarified. As defined by Furness et al. (2013) disturbance relates to the added expenditure of resources by animals to
107 avoid a wind farm and associated activity. Displacement refers to the reduced number of animals occurring in the wind
108 farm area and its vicinity. We also follow this terminology in this article.

109

110 3.1. Collision

111 Collision risk, or the probability of mortality due to collision of all individuals intersecting with a wind turbine, occurs
112 during the operational life cycle stage of a wind farm. Species that generally do not exercise avoidance behavior
113 towards human-made structures, specifically wind turbines, are at risk of colliding with turbine blades, or the
114 monopoles (Kunz et al. 2007a). Cook et al. (2014), and later May (2015), described three main types of bird avoidance
115 behavior, according to the scale of its occurrence. Two of these, meso- and micro-avoidance, take place inside the
116 wind farm space, and therefore directly affect collision risk. Meso-avoidance is described by May (2015) when birds
117 evade the wind turbines individually by anticipating or reacting to their presence. However, the longer it takes the bird
118 to do this (i.e. the closer it gets to the wind turbine before it responds to the obstacle), the more likely it is to collide.
119 He explains that at this point, birds may still narrowly escape the turbine structure, which the author classifies as a
120 micro-scale avoidance. The bird may also avoid the wind farm altogether (macro avoidance), in which case it will
121 either lead to no response (if the avoidance does not alter the birds' habitat use), or displacement through disturbance.
122 Different variables contribute to the collision risk of birds and bats, and have been observed to be site-, species- and
123 turbine-specific (Drewitt and Langston 2006; Marques et al. 2014; Hein and Schirmacher 2016). Some studies show
124 that wind turbine collisions only account for a considerably small percentage of total bird mortality (Erickson et al.
125 2005; Calvert et al. 2013; Sovacool 2013). This may appear as an argument to reduce efforts to mitigate impacts of
126 wind energy development on wildlife. However, the different authors agree that fatalities from wind energy come in
127 addition to other sources of mortality. In other words, it is not only the main source of a species mortality that should
128 be looked into (while ignoring other causes), as even smaller additions to a population's mortality rate can have severe
129 consequences, especially to species with slow life-history traits (i.e., long lifespans, few offspring and late maturity)
130 such as raptors or bats.

131

132 3.2. Disturbance

133 Displacement can be considered as reduced flight activity within the wind farm area due to a functional loss in habitat
134 (May 2015). This is true for not only resident species, but also migratory species through loss of stopover sites. It may
135 also lead to a higher expenditure of energy for species that need to alter their flight path to avoid the wind farm (also
136 known as "barrier effect"), which may potentially have consequences on population health if a high number of wind
137 farms is to be avoided (Masden et al. 2009; Masden et al. 2010b). The extent and severity of disturbance and consequent
138 displacement is dependent on site and species characteristics (Drewitt and Langston 2006), and some authors consider
139 displacement to be potentially more threatening for birds than collision (Kuvlesky et al. 2007). Pearce-Higgins et al.
140 (2012) show how the construction stage of wind farms may have a greater displacement impact on bird populations

141 than the operational stage. Nevertheless, indirect impacts of wind energy production remain greatly understudied,
142 making their quantification very challenging (May 2015). Bird displacement from wind farms has been shown to
143 translate into the avoided habitat effectively being lost (Pedersen and Poulsen 1991; Larsen and Madsen 2000; Pearce-
144 Higgins et al. 2008; Pearce-Higgins et al. 2009; Garvin et al. 2011; Petersen et al. 2011; May et al. 2013). However,
145 some species may return to their original habitat with time, becoming habituated to the presence of the wind farm
146 (Madsen and Boertmann 2008). Masden et al. (2009) evaluated this deviation and concluded that although avoidance
147 of a single wind farm may be negligible in terms of energy cost, there may be a harmful cumulative effect over the
148 avoidance of several wind farms.

149 Bats, on the other hand, appear to either be undisturbed by wind turbines and even in some cases attracted to them,
150 which thereby can increase the number of collisions (Rydell et al. 2012). Kunz et al. (2007b) present several hypotheses
151 that may explain bat attraction to turbines. Most of these are related to a potential attraction to insects drawn to the
152 wind turbines or associated altered landscape, which is also supported by other authors (Brinkmann 2006; Rydell et
153 al. 2010a). Another hypothesis presented by Kunz et al. (2007b), is that tree-roosting bats are attracted to the turbines
154 that they perceive as potential roosts. This is further described in the work of Cryan et al. (2014), as well as other
155 observed bat behaviors around wind turbines in an experimental setting. Nevertheless, Rydell et al. (2012) note that
156 indirect effects of wind energy on bats are relatively small, while possible the most relevant on birds.

157

158 **3.3. Habitat alterations**

159 Construction of wind turbines, like any infrastructure development, alters habitats at and surrounding the construction
160 sites. However, the extent of this effect may vary depending on the original setting. For instance, habitat alteration
161 effects may be more pertinent in e.g. forested and/or pristine wilderness areas, versus multiple-use landscapes with
162 pre-existing anthropogenic influences. Specialist species, i.e. species with a narrow range of usable habitats (high
163 habitat specificity) are more vulnerable (Swihart et al. 2003; Munday 2004; de Baan et al. 2013), and therefore
164 potentially suffer a higher impact than more wide-ranging and generalist species.

165 Apart from the direct loss of habitat for certain species where the turbines are placed, the tall structure of the turbines
166 may be mistaken for previous natural structures such as trees, which, as described in the previous section, may attract
167 certain species and lead to increased collision risk (i.e., an ecological trap; May 2015). In addition, roads and power
168 lines associated with the wind farm may cause habitat fragmentation, which can be particularly damaging in previously
169 unaltered areas (Rydell et al. 2012). Although these alterations can reduce habitat suitability for some species, other
170 species may find these new conditions more favorable (Hötker et al. 2006). In turn, increased densities of benefiting
171 species may attract predators, such as bats or birds of prey, which may end up suffering higher collision rates while
172 hunting. Smallwood et al. (2007), for instance, showed how increased densities of ground squirrels near the base of
173 wind turbines attracted burrowing owls closer to the blades, consequently increasing collision risk.

174

175 **3.4. Conditions influencing effects of wind farms on wildlife**

176 *Species-specific conditions*

177 Bat behavior towards wind farms and turbines can be explained with the concept of guilds. Denzinger and Schnitzler
178 (2013) group different bat species based on their use of echolocation, foraging habitats and modes, as well as sensory
179 and motor adaptations. They identify three main guild types, namely open space, edge space and narrow space, which
180 forage at different distances from background structures (such as wind turbines) and may be more or less apt to avoid
181 them. The authors conclude that the foraging and echolocation behaviors of all species within a guild are so similar
182 that a small number of species or observations can be used as proxy for the whole guild with high certainty.

183 Birds' sensory capabilities, as well as behavior, may play a significant role in their response to a wind farm or turbine
184 (e.g., Marques et al. 2014; May et al. 2015). Moreover, the morphology of birds appears to be a determinant parameter
185 for collision risk (e.g., Bevanger 1994; Janss 2000; Herrera-Alsina et al. 2013). Rayner (1988) grouped flying birds
186 according to their size, aspect ratio and wing loading and described how these relate to different flight behaviors. The
187 mechanisms behind bird (and bat) flight, and how this in turn reflects in their flight behavior, are further described by
188 Lindhe Norberg (2007).

189

190 *Environmental conditions*

191 Topographical features of the region influence bat and bird activity. Migrating bats use linear aspects of the landscape
192 for navigation/movement, such as river valleys, tree rows or forest edges (e.g., Ahlén et al. 2009; Furmankiewicz and
193 Kucharska 2009), which could increase collision rates with wind turbines placed in the proximity of these features
194 (Rydell et al. 2010b). Similarly, Johnson et al. (2004) determined a negative correlation between bat activity and
195 distance to woodlands. This knowledge is particularly important for the conservation of tree roosting bats, which may
196 mistake wind turbines to be potential roosting or mating sites (Cryan et al. 2008), as these activities typically take place
197 in tall trees (Cryan et al. 2014). Certain birds, such as raptors, are also known to utilize landscape features enhancing
198 thermal or orographic lift, such as ridgelines or slopes, in order to save energy, making their passages predictable to a
199 certain extent (Duerr et al. 2012). An analysis by Hötker et al. (2006) on collision risk factors showed that habitat type
200 has a significant influence on bird casualty rates, particularly mountain ridges and wetlands.

201 Season also affects bird and bat behavior, particularly in terms of habitat use and flight activity, and consequentially
202 collision risk. The highest bat fatality rates due to collision are observed during late summer and autumn, during which
203 bat activity is typically at its peak (due to, among other factors, migration periods) (e.g., Brinkmann 2006; Rydell et
204 al. 2010; Baerwald and Barclay 2011a). May et al. (2010, 2011) determined that the white-tailed eagle (*Haliaeetus*
205 *albicilla*) had considerably higher flight activity in the spring, as well as more fatal collisions with wind turbines.
206 Barrios and Rodríguez (2004) also noted a seasonal variation in the flight frequency of vultures in wind farms, with
207 higher counts, but also variance, during the winter-autumn period. These findings are supported by Smallwood et al.
208 (2009), who evaluated different bird species flying in wind farms at the Altamont Pass Wind Resource Area, USA.
209 Relatively large seasonal variations in bird numbers are associated with migratory behavior, although some of these
210 also coincide with post-breeding periods, when there is an increase of young and inexperienced birds (Drewitt and
211 Langston 2008).

212 Meteorological conditions, particularly wind speed and direction as well as temperature, are essential in determining
213 the probability of negative effects of a specific site (e.g., by creating orographic and thermal updrafts), influencing the

214 flight behavior and activity of different species (Richardson 1998; Langston 2013; May et al. 2015). In particular,
215 wind, fog and rain have a direct impact on birds' maneuverability, flight height and sensory perception (Langston and
216 Pullan 2003; Arnett et al. 2007). Furthermore, temperature (Arnett et al. 2006) and low wind speeds are positively
217 correlated with bat activity, near wind turbines, and therefore a useful parameter in determining the areas of highest
218 collision risk (e.g., Rydell et al. 2010; Baerwald and Barclay 2011a; Cryan et al. 2014). Brinkmann et al. (2006) report
219 that operating wind turbines only at wind speeds above 5.5 m/s can be an effective measure to reduce bat collision
220 rates with wind turbines. This was also tested and confirmed by Baerwald et al. (2009), at the same start-up speed,
221 with only marginal costs from the decreased electricity production. Similarly, Barrios and Rodríguez (2004) show that
222 wind speed also affects bird collision risk of raptors, with the highest being at wind speeds between 4.6-8.5 m/s, which
223 is consistent with the observations of Smallwood et al. (2009). However, some species are able to fly at speeds
224 considerably higher than these observed limits (Winter 1999), which needs to be taken into consideration when
225 planning such mitigation strategies.

226
227 *Technological conditions*
228 Finally, type, size and number of wind turbines, as well as layout of wind farms are considered by some authors to be
229 relevant aspects in determining avian and bat collision risk. Smallwood and Thelander (2004) identified tower size,
230 blade tip speed and wind farm layout to be the most relevant factors contributing to golden eagle (*Aquila chrysaetos*)
231 mortality at the Altamont Pass Wind Resource Area (APWRA). Barclay et al. (2007), on the other hand, reported that
232 turbine height did have a significant effect on bats, but not birds, while rotor blade length had no effect on bird or bat
233 fatality rates. de Lucas et al. (2008) also found taller turbines to be linked to a higher number of fatalities, although
234 they could not conclude on the effect of the wind farm layout. Hötker et al. (2006) drew opposing conclusions,
235 determining a statistically insignificant effect of turbine hub height on collision rates. Nevertheless, Hötker et al. (2006)
236 recommend that wind farms should be arranged with turbine arrays parallel to the main flight direction to decrease the
237 risk of collision. Rotor speed has also been identified as a determinant collision risk factor by model developers (e.g.,
238 Tucker 1996), such that more rotations per minute imply a higher chance of a bird or bat colliding if it traverses the
239 rotor swept area. This makes turbine designs of inherent slower blade rotation (e.g., vertical axis wind turbine
240 (VAWT)) potentially less deadly to birds and bats (Islam et al. 2013, Santangeli & Katzner 2015). Furthermore, designs
241 that can cause a lower degree of motion smear of the blades may potentially be more detectable by avian species
242 (Hodos 2003).

243

244 **4. Impact assessment modelling approaches**

245 Integrating wind energy impacts on biodiversity in LCIA not only depends on knowledge on the impacts, but also on
246 how these can be assessed using currently available models. Therefore, and given the current lack of a literature review
247 on the matter, we compiled different predictive modelling approaches used in assessing collision, disturbance and
248 habitat alterations on bird and bat species. We grouped these models by type of method used, noting that each type
249 may cover more than one effect. Table 1 summarizes our findings, and provides an overview on the inputs required

250 for each model type to cover the relevant conditions as described in the previous section. All model types are further
251 detailed in the following paragraphs. At the end of this section, Table 2 summarizes a critical comparison between the
252 different model types, showing the different advantages and disadvantages of each model type for inclusion in LCIA.

253

254 [Table 1 here](#)

255

256 **4.1. Collision Risk Models (CRMs)**

257 Masden and Cook (2016) recently reviewed available avian collision risk models. Tucker (1996b) presented the first
258 of these models, calculating collision risk as a ratio between the time spent by a bird flying through the rotor swept
259 area over the time taken by one single rotation of the rotor blades. Similarly, Band et al. (2007) developed a model for
260 onshore wind turbines which associates the risk of collision with the probability of the bird occupying the same space
261 as the turbine blade during its flight through the rotor swept area. This model was then extended to take into account
262 the variable distribution of birds with height within the rotor swept area (Masden and Cook 2016). Also other models
263 have been developed (e.g., Podolsky 2008; Holmstrom et al. 2011; Eichhorn et al. 2012), but in general these take a
264 similar approach to Tucker (1996b) and Band et al. (2007). Bird size, flight characteristics, as well as rotor blade length
265 and speed are typical inputs in this type of models and are combined with the expected number of birds flying within
266 rotor swept height. In another approach, Korner-Nievergelt et al. (2013) used a combination of carcass searches and
267 animal density indices in a mixture model to determine collision rates, yielding results “at least as precise as
268 conventional estimates” from carcass search data. New et al. (2015) developed a predictive CRM based on the
269 assumption of a relationship between pre-construction avian exposure and subsequent fatalities. Among other
270 differences, this model distinguishes itself for the direct inclusion of uncertainty, as well as considering the entire
271 turbine height when calculating the total hazardous volume of a wind turbine. This means that birds in this model are
272 considered to be able to collide when flying under the rotor area, as opposed to most CRMs which only consider rotor
273 blade length. Chamberlain et al. (2006) assessed the effects of estimating and using avoidance rates in the development
274 of a collision risk model, based on the original Band model (Band et al. 2007). Fatality rates derived from estimated
275 avoidance rates may be used for comparative purposes, but the authors underline the urgent need for more specific and
276 empirical avoidance rate studies. Lastly, Calvert et al. (2013) estimated avian mortality, in Canada, due to different
277 sources. The authors developed a stochastic simulation model and compared the effects of mortality at different life
278 stages of different species, as well as across different mortality sources. This model also allowed the assessment of the
279 effects at a population level.

280

281 **4.2. Species distribution models (SDMs)**

282 Species distribution models are used to determine the probability of occurrence of a species in a given location.
283 Therefore, these can be used to predict avian and bat activity and, together with posterior effect modelling, the
284 likelihood of a negative effect. One interesting application of SDMs is seen in a recent study by Santos et al. (2013),
285 who applied a maximum entropy model (MaxEnt; Phillips et al. 2006), using presence-only data to determine the

286 collision risk associated with wind farms of four different bat species in Portugal. Given a small number of occurrences
287 and a given set of environmental conditions, MaxEnt can be used to identify regions where a species is likely to be
288 present (Pearson et al. 2007), and therefore delineate areas of higher conflict probability. Roscioni et al. (2014) also
289 applied the MaxEnt approach, but rather to determine the impacts of wind energy developments on habitat connectivity
290 for bats. Rebelo and Jones (2010) compared this approach with the ecological niche factor analysis (ENFA) (Hirzel et
291 al. 2002), a similar model which also uses presence-only data, for modelling the potential distribution of a bat species
292 in Portugal. The authors conclude that the differences between the two models make ENFA more appropriate for
293 determining a species' potential distribution, while MaxEnt is better suited for determining a species' realized
294 distribution. Hayes et al. (2015) created seasonally dynamic SDMs to study the impacts on migratory hoary bats
295 (*Lasiurus cinereus*). Apart from MaxEnt, the authors used four other SDM approaches to model the species'
296 distribution. Bastos et al. (2016) assess the local impacts of wind energy on the skylark (*Alauda arvensis*) populations
297 in Portugal via an index derived from a SDM, showing how this combined framework can be used for predictive impact
298 assessments Elith et al. (2006) summarizes and compares other different modelling methods used in predicting species'
299 distributions from occurrence data.

300 Bright et al. (2008) presents a bird sensitivity map of 16 protected species in Scotland, in which species distribution
301 data were buffered and rated taking into account foraging ranges, collision risk and susceptibility to disturbance. The
302 SDM was then overlapped with a map of existing or planned wind farm locations in order to provide a proportion of
303 affected bird species by these developments. Similarly, Reid et al. (2015) modelled the movements of bearded vultures
304 (*Gypaetus barbatus*) in southern Africa in terms of habitat use. Other behavior-inclusive SDMs focus on migratory
305 species. Pocewicz et al. (2013) mapped important migratory areas for birds in Wyoming, US, including stopover
306 habitats. The authors combined different geographical features, (such as ridges, streams and likely thermal updraft
307 locations), which directly correlate to increased activity of migratory bird species. Similarly, Liechti et al. (2013)
308 developed a model enabling the determination of areas with predictable high concentration of migratory bird species
309 in Switzerland, which translate to a higher collision risk. Also, with a focus on soaring birds, BirdLife International
310 (2017) developed a sensitivity mapping tool for migratory soaring birds in the Middle East. If migratory paths are
311 known or predictable, siting new wind farms away from them could potentially decrease collisions and displacement
312 effects on those species. These and other applications of species distribution models are further analyzed by Guisan
313 and Thuiller (2005). May et al. (2013) evaluated habitat utilization and displacement of white-tailed eagles using
314 Resource Utilization Functions (RUF), which correlate a species space use to its resource utilization. Other authors
315 also used RUFs to assess potential negative effects on birds from wind energy developments (Mcnew et al. 2014;
316 Miller et al. 2014).

317 Two models have been developed to quantify the spatial implications of "barrier effects". Masden et al. (2012) details
318 models used to described birds' movement in response to wind farms, based on bird movement data collected post-
319 construction of the wind farm. Masden et al. (2010a) had previously modelled the energy cost of avoidance by several
320 seabirds due to offshore wind farm placement, using the model developed by Pennycuick (2008). The study concluded
321 that the additional energy costs of avoiding the wind farm may be insignificant for some species, but a species-specific
322 approach should be taken when assessing the effects of wind farms on seabirds.

323

324 4.3. Individual Based Models (IBMs)

325 Several individual-based models (IBMs) have been developed for avian impacts. IBMs allow researchers to simulate
326 interactions of individuals with the surrounding environment, as well as their adaptations to environmental changes.
327 Grimm et al. (2006) further describe the concepts behind this tool, potential applications and provide a protocol for
328 further developments, named ODD ('Overview', 'Design concepts' and 'Details'). Eichhorn et al. (2012) followed this
329 protocol in their collision risk model of red kites (*Milvus milvus*). They used landscape grid cells (with habitat
330 characteristics based on West Saxony, Germany), a red kite and a wind turbine as entities in their model, each with
331 their own particular variables. The bird entity is based essentially on its behavior and flight characteristics, as well as
332 probability of collision (based on the Band model) and avoidance. For the wind turbine, position, hub height and rotor
333 blade length were used as inputs. Schaub (2012) also based his model on the red kite species, although not following
334 the same protocol, but nevertheless modelling the effect of a varying number and layout of wind turbines on the
335 population dynamics of the species. Ferreira et al. (2015), also followed the protocol proposed by Grimm et al. (2006),
336 for estimating bat mortality risk at wind farms. As with the model produced by Eichhorn et al. (2012), three entities
337 were selected, referring to landscape, the bat and the wind turbines. Soil-use and altitude of the landscape were included
338 in the first entity, taking into consideration the use for foraging and/or roosting by bats. Wind speed, temperature and
339 species behavior determined the inputs of the bats entity. As for the turbines, the authors also included the variable of
340 blade length, but not height. Masden (2010) developed an IBM following the ODD protocol to evaluate changes in
341 collision mortality and habitat-related productivity in hen harriers (*Circus cyaneus*) due to technological conditions.
342 From her results, the author concludes that the impacts of wind turbines on hen harriers depended not only on the
343 number of turbines, but also their location, suggesting the need for knowledge on a species' ecology in wind energy
344 development planning. A recent work by Warwick-Evans et al. (2017) shows the use of the ODD protocol to study the
345 effect of wind turbines on body mass, mortality rate and breeding success of Northern gannets (*Morus bassanus*). The
346 authors state that this is the most complex and comprehensive model of its kind yet, and has the potential to be adapted
347 for other seabird populations and other types of impacts from spatial change.

348

349 4.4. Population models

350 Widely used in ecology, population viability analyses (PVA) estimate the probability of a population or species
351 becoming extinct in a given period of time, and based on a number of case-dependent variables together with
352 demographic parameters (Beissinger and McCullough 2002). Multiple authors have used the program VORTEX (Lacy
353 and Pollak 2014), an IBM used for PVA, to simulate the effects of avian mortality from wind farms on population
354 dynamics of different species (Hötcker et al. 2006; Carrete et al. 2009; García-Ripollés and López-López 2011;
355 Rushworth and Krüger 2014). This type of modeling is mainly based on demographic parameters (e.g., mortality rates,
356 population size, age at first reproduction), although some environmental variables such as carrying capacity can be
357 incorporated. Sanz-Aguilar et al. (2015) designed a PVA without using VORTEX, using instead linear regression and

358 R based scripts to determine stochastic population growth. Nevertheless, their model is based on demographic
359 parameters. Erickson et al. (2015), using branching process models, delivered a predictive model for the probability of
360 extinction of four representative species: two bats and two birds. Although branching process models are in essence
361 individual-based models, this output is characteristic of PVAs, and based on population dynamics. Rydell et al. (2012)
362 presented a simple, deterministic population model based on population size, survival rates, fecundity and number of
363 turbines. The mortality from wind turbines is a simple subtractive factor in the equation, dependent only on the annual
364 mortality at each turbine and the number of turbines. Bellebaum et al. (2013) estimated mortality thresholds for red
365 kites in Germany using a potential biological removal (PBR) model. They affirm that PBR models are needed to enable
366 more precise estimations of thresholds for the added mortality from wind energy developments. In his PhD thesis,
367 Dahl (2014) used a different approach and presented an age-structured matrix-based population model for the white-
368 tailed eagle in Smøla, Norway. This model focused on the demographic parameters of the population in study,
369 including not only survival rates but also reproductive success. In a report by Grünkorn et al. (2016), matrix and
370 elasticity models were used to identify consequences of bird mortality at a population level, for three raptor species,
371 taking into account age-specific mortality and reproduction rates. Lastly, Cook and Robinson (2017) recently published
372 an article where they present a framework for assessing wind energy impacts at a population level using Leslie matrix
373 models. These models consider a generic seabird species with characteristics derived from literature. Of note is the
374 evaluation of decision criteria previously summarized by Green et al. (2016). The authors highlight the need for
375 transparency when it comes to the use of demographic values of populations. However, it would be very difficult, if
376 not impossible at the moment, to obtain demographic data for a large number of species at scales relevant to LCIA.

377



378 **4.5. Index-based models**

379 Data scarcity can be a constraint when modelling ecological processes, especially at higher scales when many different
380 species are involved. To overcome this obstacle, index-based models can potentially be used as proxies, delivering
381 score-based outputs on effects rather than, for instance, a number of individuals affected. Data requirements are lower,
382 and often based on what is known of a species in terms of e.g., behavior, morphology, habitat use. Garthe and Hüppop
383 (2004) developed a vulnerability index for species affected by offshore wind power farms, with a focus on German
384 seas, based on different seabird characteristics as well as their conservation status. More recently, Furness et al. (2013)
385 constructed similar indexes for collision and displacement impacts on Scottish marine birds. Although somewhat
386 simplistic in its nature, this type of sensitivity indexes can be used to identify important impact sources, as well as map
387 areas of higher risk, even when experimental data is not widely available. Using the indexes from these publications,
388 Busch and Garthe (2016) developed a novel method for assessing displacement combining a matrix of potential
389 displacement and mortality levels of seabirds from offshore wind farms with a potential biological removal (PBR)
390 model (Wade 1998). Perhaps one of the methodologies that encompasses the most impacts of wind energy on bats and
391 birds to date was designed by Diffendorfer et al. (2015). The methodology prioritizes species based on previously
392 gathered data, combining each species' conservation status, as well as its relative risks from collision fatalities and
393 habitat modification. The consequent impacts at a population level are then evaluated with the methodology's

394 demographic and PBR models. The authors followed-up on this work, this time focusing on prioritizing bird taxonomic
395 orders according to their impact risk indexes (Beston et al. 2016).

396

397 [Table 2 goes here](#)



398

399 **5. On modeling biodiversity impacts from wind energy production in LCIA**

400 The integration of wind energy impacts on biodiversity in LCIA should include all three aforementioned impact
401 pathways: collision, disturbance and habitat alterations. Figure 1 illustrates how the impact pathways can conceptually
402 be integrated into a logical assessment flow (conditions – state – effect – impact), and the potential contribution of the
403 different prediction models to quantify these. We propose that separate characterization factors should be developed
404 for the three impact pathways and both birds and bats. All bat and bird species should be grouped into guilds or groups
405 depending on their morphology and behavior, in order to cover as many species as possible without requiring all
406 information for every individual species (which may not be available). However, a final impact score should include
407 all the impacts on all species groups together, expressed in common LCIA units such as potentially disappeared fraction
408 of species (PDF) as recommended by the UNEP-SETAC Life Cycle Initiative (Verones et al. 2017). Verones et al.
409 (2015) propose four different options to aggregate land and water use impact scores into a single score: equal weight
410 for species, equal weight for taxa and two options with special consideration of species' vulnerability. Similar
411 approaches could be used to combine impact scores for bats and birds, over the main impact pathways, into one score
412 compatible with current LCIA methodologies. These options are particularly relevant when deciding if and which
413 taxonomic groups between birds and bats should be given a higher impact score from wind energy developments.

414 The three impact pathways generally affect a species' probability of occurrence at a specific site. Whereas habitat
415 alterations may lead to the loss of presence of a species at a site, displacement and collision reduce the number of
416 individuals and thereby indirectly the probability of occurrence. Spatial estimation of species probability of occurrence
417 can be done using SDMs. Harte et al. (2009) presents an approach on species-area relationships that estimates the
418 number of species in a certain area through correlation of species richness with probability of occurrence. With such
419 estimates, and knowing at which sites wind turbines are located, GIS tools can be used to quantify effects from wind
420 energy developments in a spatially explicit manner. Estimating an altered probability of occurrence due to the expected
421 effect, e.g. using respectively flight initiation distances (Blumstein 2006) and collision risk models (e.g. Tucker 1996,
422 Band 2007), the expected loss of occurrence at a site can be determined. MaxEnt, for instance, is a SDM that derives
423 a score in each map cell proportional to the probability of occurrence of a species. Summing scores across species
424 renders insight into the species richness at a site, allowing the calculation of regional and potentially global PDFs. An
425 impact score can then be derived by applying species-area relationship models (SARs), which are already used in
426 LCIA. Unlike classical SARs, which consider all biodiversity to be lost when habitat is changed, countryside SARs
427 (Pereira and Daily 2009) factor in habitat suitability for a given species. This habitat suitability factor is analogous to
428 the proposed use of MaxEnt scores. In addition, estimating a species distribution rather than directly using binary
429 presence-absence range map is an improvement in terms of ecological significance.

430 Only in cases where population size and species distribution are known (either empirically or through estimation), can
431 the number of affected individuals in each cell be determined. With such data, other approaches such as PVAs and
432 IBMs also become feasible for developing (regional) LCIA models. Furthermore, if a relation between the area (or
433 number of individuals) lost and probability of extinction is known, one can potentially quantify results directly in terms
434 of PDF and therefore easily integrate the results in LCIA. However, to our knowledge, such relations are not known,
435 and population data is scarce for a large number of species. As a generic approach for inclusion within the LCIA
436 framework, such models are therefore deemed less appropriate. Although IBMs would give the most detail, they are
437 in general too complex and data intensive to be able to cover a large number of species and spatial distribution.
438 Nevertheless, future research can be done to further develop or adapt CRMs or index-based models in order to obtain
439 a descriptive result of a fraction of species lost, or another justifiable unit in LCIA.

440 It is important to note that the three identified impact pathways are hierarchical. Displacement of individuals only
441 occurs outside the area of habitat alteration. Only individuals which were not displaced face the risk of collision with
442 turbines. This hierarchy should be taken into account to avoid double counting. However, species are known to respond
443 behaviorally to these risks through avoidance, reducing the risk of an impact to occur (May 2015). Attraction of bats,
444 or birds, towards wind turbines may on the contrary lead to increased occurrence and thereby a higher risk of collisions.
445 Such pertinent avoidance and attraction effects should therefore also be taken into account.

446 Furthermore, it is necessary to take into consideration that different species or populations may be more vulnerable to
447 an effect than others. Understanding a species' or species group's behavior and population dynamics is key to
448 adequately integrating vulnerability at an impact level. (Verones et al. 2013) added a vulnerability score to their LCIA
449 characterization factors for biodiversity impacts from water consumption. The authors developed this score from
450 species geographical distribution ranges together with IUCN threat levels. More variables could be added in order to
451 adapt this method to other types of impacts on biodiversity, such as those from onshore wind energy on bats and birds.
452 It is also important to keep the spatial scale that the methodologies are developed for in mind. Characterization factors
453 developed for a certain region may not be applicable in another, due to differences in species composition,
454 vulnerability, as well as technical and environmental characteristics. Furthermore, data may not be available for every
455 region in the same quantity or quality, which therefore adds uncertainty to methodologies developed at a global scale.
456 In addition, scaling up or down (i.e., going from a local to a global spatial scale, or vice-versa) must take into
457 consideration that species composition, as well as environmental variables, may change in the process. Wessman
458 (1992) further develops on the issues of scaling, discussing the matter of extrapolation of environmental or ecological
459 information in modelling approaches.

460 Irrespective of the approach used to quantify the impacts in question, various types of data are required (Table 1).
461 Several existing databases cover some of these information needs (e.g., species data, turbine characteristics and
462 locations, environmental data), while other types of data may require the use of allometric relationships (e.g., bird
463 wing loading from body mass). Empirical species-related data at a global level can be obtained from BirdLife
464 International (2016) on birds, while IUCN (2016) provides data on many other species groups, including threat status
465 and range maps. For occurrence data, GBIF (2016) provides an open access database describing more than 1.6 million

466 species. In addition, Wilman et al. (2014) compiled a great amount of data on animal diet and mass for all extant bird
467 and mammal species, which can potentially be used to estimate important morphological parameters such as wing
468 loading and aspect ratio using allometric relationships (Lindhe Norberg 2007). Lack of species data can also potentially
469 be coped with by using better-known species, with similar characteristics, as proxies for a larger group (Denzinger and
470 Schnitzler 2013). Such data can be used to, for instance, rank species according to characteristics that render them
471 more vulnerable to the different effects of wind energy developments. Environmental data, such as wind speed and
472 topography, may be required to predict a species' occurrence, especially when using SDM software such as MaxEnt.
473 Temperature and wind speed data can be acquired from databases such as the NASA Langley Research Center
474 Atmospheric Science Data Center Surface meteorological and Solar Energy (SSE) web portal (NASA 2016), among
475 others. The U.S. Geological Survey (2016) provides remote sensing data, including digital terrain models.
476 Technological data may be available through direct contact with the operating company, or local datasets. Remote
477 sensing databases such as the CORINE Land Cover (Heymann et al. 2000) can provide information for present land
478 cover types, which can also aid in the prediction of a species' preferred habitat. Knowledge on a species' flight
479 initiation distance allows the determination of the extent of area disturbed for that species, although no database
480 currently exists to provide these distances for a large number of bird species (but see Blumstein 2006). Lastly, although
481 many of these databases provide relatively generic data, local datasets may also exist with higher resolution or more
482 accurate data (e.g., in Norway: Artsdatabanken 2017; Kartverket 2017; NVE 2017) to complement larger databases.

483

484 **Figure 1 goes here**

485

486 **6. Conclusions and recommendations**

487 Available literature on the impacts of wind energy on biodiversity allowed this article to focus on two main research
488 gaps: a lack of a review on predictive quantitative methods on the topic, and a lack of attempts to develop a
489 methodology for LCIA to address this type of impacts. This is a first effort to provide the necessary background
490 knowledge for the development of said LCIA methodology, in terms of the effects of wind energy on birds and bats
491 and how these are modelled outside of LCA. Based on the results in this study, we can now start to develop LCIA
492 models for assessing impacts of onshore wind power on birds and bats.

493 Collision, displacement and habitat alterations have been identified as the main impacts of wind energy on wildlife in
494 numerous articles. According to current research, birds and bats are the most susceptible species groups to these effects
495 for onshore wind turbines. As their responses to wind energy developments are considerably different, models should
496 be developed separately for each of the two species groups. In addition, assessment of these species should take into
497 consideration that within the two taxonomic groups there is considerable behavioral and morphological variation,
498 especially among bird species.

499 Existing predictive models for the three main impact pathways show that quantitative estimations can be performed.
500 GIS tools and remote sensing have proven invaluable in spatially differentiating areas of variable risk. More
501 specifically, SDMs are widely used for determining areas of higher probability of conflict with biodiversity. This type
502 of modelling has proven especially important in collision risk modelling, given the existing scarcity of data usually
503 required by the more complex CRMs. However, an application of SDMs at a global scale for estimating wind energy
504 impacts on biodiversity is still lacking. Index-based models offer a clear, simplistic approach to not only scale impacts
505 according to the species' sensitivity, but to include certain aspects that are often excluded from assessments,
506 particularly those related to a species vulnerability (e.g., life-history traits, behavior).

507 Inclusion of the three main pathways for impacts of wind energy on biodiversity in LCIA requires adaptation of these
508 quantitative methods to the methodologies used in the LCA framework. In other words, results must be compatible
509 with those of other ecosystem-related impact categories, which should be communicated in units of PDF (Verones et
510 al. 2017). As an example, in order for a number of fatalities to be integrated, knowledge of a total number of individuals
511 would be needed, so that a percentage loss of each species is obtained. This integration must be spatially explicit, with
512 the support of GIS tools, given the variability between regions or countries in terms of ecosystem composition and
513 wind energy technology. We suggest local characterization factors be constructed first, as data requirements should be
514 lower and more accessible. Once a working model is in place, it should then be followed by an attempt of upscaling to
515 a global level, taking into consideration data and technological constraints of up-scaling models. In either case, we
516 point out that modelling habitat alterations, together with or followed by disturbance, is more readily feasible compared
517 to collision. Modelling the first two impact pathways relies strongly on available GIS tools and remote sensing data,
518 as well as knowledge of each species group's general behavior towards wind turbines. SDMs show promise in their
519 ability to tackle this set of impacts, and can be combined with currently used SARs in order to directly obtain
520 characterization factors in units of PDF, as described before. Vulnerability should be introduced at this point for
521 instance by means of indexes, in order to weigh species according to how strongly they are affected.

522 The proposed LCIA development is not only a step towards more comprehensive impact assessments in LCA, but also
523 outside of it. Most of the reviewed quantitative methods focused on only one or two of the three main impact pathways
524 and at relatively small scales. Also, many studies are based on small samples or on few species that are not
525 representative for all birds or bats (Sovacool 2013). This underlines the importance of grouping species after e.g.
526 morphological similarities and creating archetypes for environmental conditions when data for all species and
527 conditions is not available. Furthermore, there is still a lack of impact quantification relative to the energy produced
528 by each turbine or wind farm. This hinders the possibility of an adequate comparison between wind energy production
529 and other types of energy production, as well as between wind farms with variable production efficiencies. LCA has
530 the potential to, in future, cover all these gaps, as well as integrate impacts on biodiversity from other energy sources.

531

532 **Acknowledgements**

533 This work was funded by the Research Council of Norway through the SURE project (project number 244109). We
534 thank John Woods for support as a native English speaker and for valuable insight and discussions. We also thank
535 Bram van Moorter for very constructive and insightful thoughts that helped us improve our ideas. Finally, we thank
536 Greg Something for proof-reading this article on the quality of a native English speaker.

537

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