AVISTEP

The Avian Sensitivity Tool for Energy Planning

Technical Manual Version 2
November 2025

BirdLife INTERNATIONAL

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Acknowledgements

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Funding Partners

ADB Duncan A. Lang, Marianne Villanueva, Victor T. Tumilba
DEG Impulse Anne Schneeweis
Fortescue Jarrod Pittson, Todd Edwards, Louise Ridgeway

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Uzbekistan Society for the Protection of Birds (UzSPB; Uzbekistan) Oleg Kashkarov, Roman Kashkarov, Yuliya Mitropolskaya, Sevara Dekhkankhodjaeva
Nature Conservation Egypt (NCE; Egypt) Khaled Elnoby, Nadia Sherif, Watter AlBahry, Haitham Mossad. We would also like to acknowledge everyone who contributed data and expertise to delineate a migratory corridor over onshore and offshore areas, especially Jethro Gauld, Jonathan Handley, Evan Buechley, Igor Karyakin, Steffen Oppel, Stoyan Nikolov, Alexander Kirschel, Ulrik Lotberg, and all the authors who made data available on Movebank.
Nature Kenya (Kenya) Paul Gacheru, Joshua Sese, Paul Matiku, and members of the Bird Committee of East Africa Natural History Society
BirdLife Australia (Australia) Golo Maurer, Yuna Kim, Grainne Maguire, Glenn Ehmke, Richard Seaton and the broader BirdLife Australia team. We would also like to acknowledge everyone who contributed data and expertise to our onshore maps, including Graham Martin, James Watson, Sreekar Rachakonda, Michael Tarburton, Heather McGinness, Micha V. Jackson, Jon Coleman, David Roshier, Simeon Lisovski, Richard Fuller, David Douglas, and Lainie Berry. For our offshore maps, we are grateful to all who shared data and advice. This includes Jacob Quade and BirdLife Australia for colony data; Barry Baker for flight parameter information; and the many collaborators who provided tracking data, among them Akinori Takahashi, Azwianewi Makhado, Carl G. Jones, Chris Powell, Chris Redfern, Christopher Robertson, the Conservation Service Programme, David Nicholls, David Stewart, David Thompson, Fiona McDuie, Gemma Carroll, Graeme Taylor, Henri Weimerskirch, Jaimie Cleeland, Jean-Claude Stahl, Joanne Morten, Johannes Fischer, Kalinka Rexer-Huber, Karine Delord, Katherine Booth Jones, Ken Norris, Kevin Ruhomaun, Kirsty Franklin, Kris Carlyon, Lachlan Philips, Lucy Hawkes, Luke Halpin, Malcolm Nicoll,

Mark Hindell, Mark Miller, Nicholas Carlile, Nik Cole, Paul Sagar, Richard Phillips, Rosemary Gales, Ross Wanless, Sara Maxwell, Takashi Yamamoto, Vikash Tatayah, Wildlife Management International Ltd, and Yuna Kim. Finally, we thank all those who provided expert advice during our offshore consultation process, and the Australasian Seabird Group for facilitating engagement with local experts.

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Citation: BirdLife International, 2025. *AVISTEP: the Avian Sensitivity Tool for Energy Planning. Technical Manual Version 2.* Cambridge, UK: BirdLife International, 186 pp. DOI: 10.5281/zenodo.17639248

Cover Design: dogeatcog

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Introduction to Avian Sensitivity Mapping

A swift transition from CO_2 emitting fossil fuels to renewable energy sources is essential. However, renewable energy facilities, such as wind and solar farms, and their associated infrastructures, such as power lines, can have a detrimental impact on biodiversity if poorly planned. It is now widely acknowledged that the best way to ensure these impacts are mitigated is to steer development away from high-risk landscapes, composing a strategic biodiversity assessment early in the planning process (Bennun et al., 2021; Bright & Muldoon, 2017). Central to this is wildlife sensitivity mapping, a spatially explicit modelling approach used to identify areas where energy-infrastructure would likely impact wildlife negatively and where it should, therefore, be avoided.

Wildlife sensitivity maps have the following broad characteristics:

- They are used to identify areas at an early stage in the planning process containing ecological values sensitive to a specific influence or activity (typically, this is the construction, operation, and maintenance of energy infrastructure).
- They typically should inform strategic planning decisions during the initial site selection phase of the development process and therefore are intended to operate at a landscape scale. As such, wildlife sensitivity mapping approaches do not replace the need for site-specific Environmental Impact Assessments (EIAs) in the usual permitting process.
- They collect and analyse spatial data, producing spatially explicit information employing spatial biodiversity data relating to species and/or sites.
- They are predictive, providing a forecast of potential sensitivity across a wide landscape. They are based on the best available data and mathematical and graphical modelling exercises. As such, wildlife sensitivity maps should be regarded as providing a preliminary broad-scale assessment. Site-level evaluation through a comprehensive EIA is ultimately required to verify the wildlife composition of an area and the risk that renewable energy development would pose.

Birds are one of the wildlife groups most directly impacted by energy-related infrastructure. Not only can inappropriately sited developments destroy important bird habitat, they can also cause direct mortality through collision with energy infrastructure such as overhead power lines and turbine blades, electrocution on energy pylons and through displacement from their favoured habitats, key flight paths and migration routes. BirdLife International is a world authority on developing maps of avian sensitivity for use in guiding the deployment of energy infrastructure. Sensitivity mapping was first pioneered by the RSPB (BirdLife in the UK) in Scotland, where it played a significant role in influencing the establishment of the region's wind energy sector (Bright et al., 2008). BirdLife has supported many of its Partners to develop national avian sensitivity maps (e.g., Ireland, Mc Guinness et al., 2015; Greece, Dimalexis et al., 2010; South Africa, Retief, 2010) and was responsible for one of the first regional-scale maps, the Soaring Bird Sensitivity Mapping Tool (Allinson, 2017). BirdLife works to establish sensitivity mapping as a cornerstone of sustainable, nature-safe renewable energy development through its role as convener of the Convention on the Conservation of Migratory Species of Wild Animals (CMS) multi-stakeholder Task Force on Reconciling Selected Energy Sector Developments with Migratory Species Conservation (known simply as the CMS Energy Task Force) and as a founding member of the Coalition Linking Energy and Nature for action (CLEANaction).

AVISTEP: the Avian Sensitivity Tool for Energy Planning

AVISTEP: The Avian Sensitivity Tool for Energy Planning is a free-to-access online mapping tool that provides a detailed spatial assessment of avian sensitivity to various types of energy infrastructure, including wind farms (both onshore and offshore), photovoltaic (PV) solar facilities, and overhead power lines (transmission lines and distribution lines). AVISTEP offers assessments at various spatial scales. As such, it can be used across the development process—both in support of national and subnational strategical planning and for a preliminary site level evaluation during the screening phase in the Environmental Impact Assessment. AVISTEP provides biodiversity insights early in the planning cycle when development can be steered towards low-risk sites. An early understanding of potential sensitivity is extremely useful for planners and developers. Forewarned of possible issues, they can ensure that appropriate mitigation measures are factored into project design from the outset. By ensuring that fewer renewable energy projects encounter conflicts with wildlife, AVISTEP can help speed up renewable energy growth whilst ensuring that this expansion is planned strategically and efficiently, optimising available space.

AVISTEP provides users with maps depicting potential avian sensitivity for the following types of energy infrastructure:

- Onshore Wind
- Offshore Wind
- Solar Photovoltaic
- Transmission Powerlines (long-distance, high-voltage)
- Distribution Powerlines (short-distance, low- and medium-voltage)

Overall methodology overview

Onshore wind and Power lines

We develop a spatially explicit approach to create a final map showing how bird sensitivity varies geographically. Our approach can be explained in the five main steps (Figure 1), although there may be slight differences depending on the country mapped.

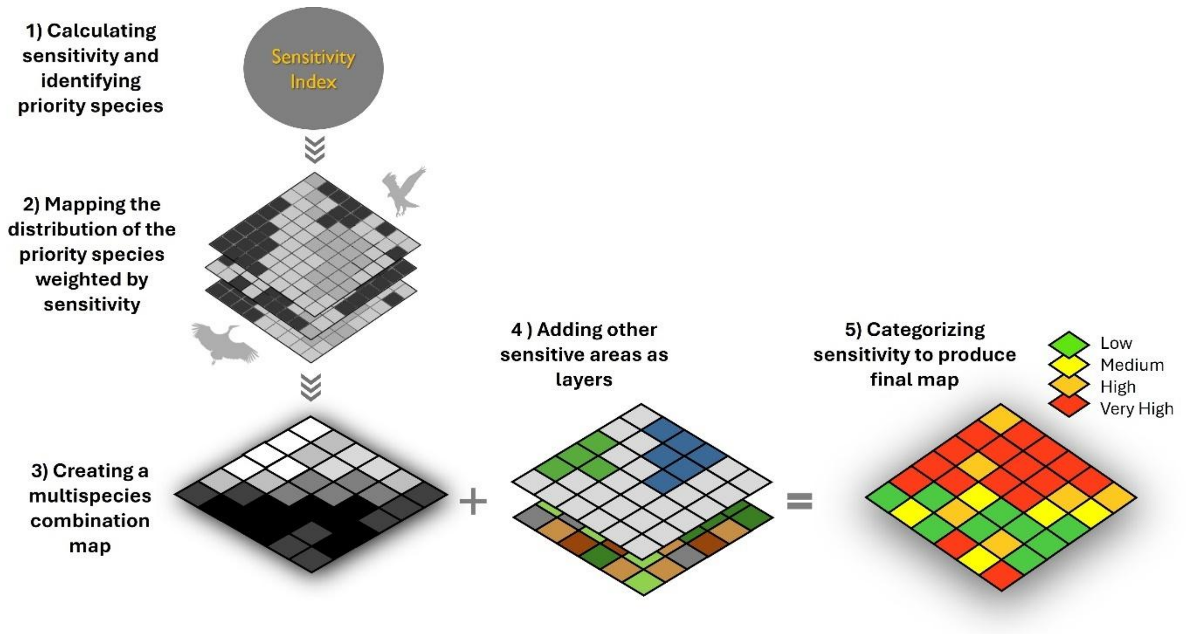

Figure 1. General workflow containing the main steps to calculate bird sensitivity facing different energy infrastructures: 1) Identify species and calculate the species sensitivity index using data on sensitivity to collision with turbines and displacement from preferred areas by the presence of wind farms; 2) produce gridded distribution maps for each selected species; 3) combine maps for all species using the sensitivity index to weight species; 4) add other sensitive areas from additional data sources; 5) categorise the sensitivity into four practical categories.

The first step is to create an index as a sensitivity score for all species regularly occurring at the country level. These indices assess species' sensitivity to a particular type of energy infrastructure (Figure 1, step 1). For instance, the sensitivity index for onshore wind considers factors such as collision susceptibility, displacement susceptibility, conservation status, and life history traits. In contrast, the sensitivity index for solar photovoltaic only considers the latter two. After identifying the at-risk species, we compile and refine their distribution maps, fitting them into a grid with a cell resolution of 5 x 5 km (Figure 1, step 2). The sensitivity scores for all species present within a grid cell are then summed, creating a species cumulative map (Figure 1, step 3). Additional spatial information regarding sensitive areas for bird conservation is also considered, including Land Use and Land Cover data, the Human Footprint Index, Important Bird and Biodiversity Areas, Protected Areas, and main movement corridors when possible. They are all combined with the species cumulative map using Multicriteria Analysis (Figure 1, step 4). The final step is categorising the sensitivity in each grid cell into four practical categories: Very High, High, Medium, and Low sensitivity (Figure 1, step 5).

The methodology is designed to be flexible and adaptable to each country's data availability and biodiversity context. Although the overall procedure for identifying priority species and producing maps follows a common framework (Figure 1), it can be adjusted to incorporate more or less detailed data when available, while maintaining consistency, confidence, and quality. To verify the specific approach used in each country, refer to the Appendix section.

Calculating species sensitivity

The sensitivity is calculated for different energy infrastructures, as each has a distinct impact to be considered. In creating a species sensitivity index, we adapt the sensitivity index developed by Certain et al. (2015) for offshore energy sensitivity mapping. In the equation, we replace the parameters (factors) representing impacts or relevant life history traits for each infrastructure when calculating the indices, while retaining the overall structure. Certain's main innovation has been to differentiate between primary and aggravation factors, where primary factors are species' characteristics that directly control vulnerability, while aggravation factors can increase a vulnerability that already exists due to the primary factors, represented by exponents (Certain et al., 2015). Read Certain et al. (2015) and Garthe & Hüppop, (2004) for more details on parameter combinations.

Onshore Wind

The sensitivity index is calculated for each bird species regularly occurring in each country, excluding flightless, vagrants, or rare sightings. For onshore developments, we also exclude restricted seabirds. The respective national species lists to be assessed are created in agreement with BirdLife International and Partner organisations in each country or with local bird experts. To select the final priority species to be included in the assessment, we rank all species according to their sensitivity values. Overall, we consider around the top ~20% of all species per country per infrastructure, depending on the algorithm used to split species into categories (see Bivand, 2024), selecting the most sensitive ones as priorities (e.g. Very-high, High, and Medium categories). This threshold ensured that the most relevant species are represented and avoid several species with a lower index that could add up to a higher sensitivity than a few species with high sensitivity in the final map. During workshops with local bird experts, we assess the list. It is worth noting that the SI values are specific to each country. Therefore, our final rating provides a value that can only be used for comparisons within the subset of species and cannot be compared among different countries.

The three main impacts of onshore wind energy on birds are 1) direct mortality due to collision with turbines; 2) displacement, and 3) habitat loss (Drewitt & Langston, 2006; Marques et al., 2014; May et al., 2020). Distinct metrics are created to capture collision and displacement susceptibility in calculating a species sensitivity index for onshore wind. Additional metrics relating to conservation status and life history traits, such as annual adult survival and range rarity (endemism), can be included to capture the population implications of these impacts for the species. The impact of potential habitat loss is accounted for by assessing the land cover and other spatial information relevant for bird conservation (see Step 4).

The sensitivity index for onshore wind energy is calculated using the formula below, which comprises three primary factors: collision (Co), displacement (Di), and conservation status (CnS); and two potential aggravation factors (Ag): annual adult survival (Su) and endemism (En), when included. Different aggravation factors could be considered depending on the country’s context and available datasets.

$$Sensitivity\ Index = \left(Co + \left(\frac{DI}{5}\right)\right) \times (CnS)^{\left(1-\left(\frac{(Ag1+Ag2)}{2}\right)/\left(\left(\frac{(Ag1+Ag2)}{2}\right)+0.5\right)\right)}$$

Collision with wind turbines (Co) is the most direct threat and impact on bird populations, and has been reported in many species and locations worldwide (Loss et al., 2013; Marques et al., 2014; Perold et al., 2020; Thaxter et al., 2017). However, multiple factors related to wind farm characteristics (e.g., turbine type, spatial design), and site-specific location (e.g., topology, land use) are also influencing collision risk (Marques et al., 2014).

Different approaches could be used to identify bird susceptibility to collide with wind turbines. Through a modelling approach such as the one developed by Thaxter et al. (2017) considering the ecological characteristics and phylogenetic characteristics that make different taxonomic groups more sensitive to collision, it’s possible to assign a collision probability to most land-bird species worldwide. On the other hand, trait-based approaches can consider other important drivers like flight high and time flying in danger zones, vision and flight abilities, and foraging behaviour, to create a score for each species based on data available and expert opinion. To check which approach was used in each country in detail, see Appendix section.

Displacement (Di) refers to the reduction in habitat use within areas influenced by wind energy facilities, which can result in decreased bird densities and, consequently, functional habitat loss over the medium and long term (Bartzke et al., 2015; Drewitt & Langston, 2006). This type of impact has been proven for both sea- and land birds (Marques et al., 2020, 2021; Pearce-Higgins et al., 2009), and after the collision, it is thought to be the primary threat to birds posed by wind farms (Marques et al., 2021;Hötker, 2017). However, its importance and magnitude have been difficult to quantify due to the scarcity of long-term and rigorous studies employing Before-after control-impact (BACI) sampling designs (Hötker, 2017). A study from India has reported that the displacement of raptors had consequences on lower trophic levels, producing cascading effects on food webs (Thaker et al., 2018), highlighting the primarily underestimated effects that displacement could have on ecosystems. To consider displacement, we conduct a literature review to identify articles published on bird displacement, aiming to understand the likelihood of different bird families being impacted. In the formula, the displacement score is downweighed in comparison to collision, based on the scarcity of studies mentioned above.

Conservation status (CnS) is assigned at the species level using manly the IUCN Red List categories Critically Endangered (CR); Endangered (EN); Vulnerable (VU); Near Threatened (NT); Least Concern (LC). The BirdLife database version varied depending on the year the data is assessed. In some cases, the national threat category was also considered to align with the national bird conservation policy. The weighting method concerning the risk of extinction for each category evolved for the countries with exponential logic being applied to the most recent countries instead of a linear one and with consideration of other parameter as population size and trends. Please see the Appendix.

Annual adult survival (Su). The population-level impact of a single individual fatality event depends primarily on the species' life history traits. Specific life history traits, such as fecundity, age of maturity, and adult survival, are particularly relevant. K-selected species are characterised by low fecundity, late ages of maturity and high survival; thus, adult mortality impacts these populations (Niel & Lebreton, 2005; Saether & Bakke, 2000). The species groups with the highest rates of impact from wind development tend to be K-selected species such as Accipitridae, Ciconiidae, or Bucerotidae (Thaxter et al., 2017); thus, it is a factor that must be carefully considered when evaluating impacts on bird conservation. We use annual adult survival calculated for all bird species to include a metric that could capture these life history factors (Bird et al., 2020).

Endemism (En). Previous work on sensitivity mapping has included parameters that reflect the conservation status of species in the global context. Some examples of these parameters are the proportion of the global population present, the annual occurrence (Kelsey et al., 2018) or the percentage of the biogeographic population that occurs in the study area (Bradbury et al., 2014; Critchley & Jessopp, 2019; Furness et al., 2013). Therefore, we create a metric that captures this aspect by calculating the percentage of the global distribution area within each country's territory. Therefore, if a species is endemic to a country, the value of endemism for that country would be 100%, and consequently, the sensitivity of that species would increase. To calculate this parameter, we use the distribution range maps and the global database of political country boundaries (Global Administrative Areas - GADM). We are not considering this metric for some countries, as it was not robust enough to accurately reflect the endemism complexity.

To combine all parameters above in the formula and balance the contribution of them to the sensitivity index, we rescaled all values from 0.01 to 1, following recommendations from (Certain et al., 2015).

Power Line – High voltage

High voltage lines or Transmission lines usually consider the infrastructure with > 60 kV, but the specific designation can vary. Transmission lines impact birds mainly through collision with overhead cables, and except for articles addressing landscape metrics, studies that evidence degradation and habitat loss for susceptible species are scarce or non-existent. Thus, the sensitivity index for Transmission lines follows the formula below, where collision with overhead cables (PwCo) and conservation status (CnS) are the primary factors. Similar to wind farms, different aggravation factors (Ags) could be included depending on the country.

$$Sensitivity\ Index = (PwCo) \times (CnS)^{\left(1-\left(\frac{(Ag1+Ag2)}{2}\right)/\left(\left(\frac{(Ag1+Ag2)}{2}\right)+0.5\right)\right)}$$

Collision with energy cables (PwCo) occurs during bird flight when birds fail to see the overhead wires and represents a significant source of anthropogenic bird mortality (Loss et al., 2014), being responsible for different populations' decline (Alonso et al., 2024; Biasotto et al., 2022; Biasotto & Kindel, 2018). Bird-related taxa typically show similar levels of sensitivity to collision, as they exhibit a strong phylogenetic signal (Prinsen et al., 2011). Different scientific approaches can identify collision-sensitive species, from literature review searching for main groups with published evidence to modelling collision risk based on morphology and behaviour traits, such as wing loading, visual field, and flight behaviour (Bernardino et al., 2018; D'Amico et al., 2018). Trait model approaches can help fill the knowledge gaps regarding understudied species and areas. Refer to the Appendix section to check which approach was used for a specific country.

Conservation status (CnS), Endemism (En), and Annual adult survival (Su) are calculated in the same way as for the onshore wind sensitivity index.

Power Line – Medium and Low voltage

Medium and low voltage lines or Distribution lines usually encompass the infrastructure with < 60 kV, but the specific designation can vary. Distribution lines primarily impact birds through collisions with overhead cables and electrocution on energy pylons and cables. Therefore, in addition to considering the species most sensitive to collision using the formula mentioned for the High-voltage lines **(PwCo)**, a specific formula for calculating and identifying species sensitive to electrocution is also applied separately:

$$Sensitivity\ Index = (PwCo) \times (CnS)^{\left(1-\left(\frac{(Ag1+Ag2)}{2}\right)/\left(\left(\frac{(Ag1+Ag2)}{2}\right)+0.5\right)\right)}$$

$$Sensitivity\ Index = (PwElec) \times (CnS)^{\left(1-\left(\frac{(Ag1+Ag2)}{2}\right)/\left(\left(\frac{(Ag1+Ag2)}{2}\right)+0.5\right)\right)}$$

Electrocution on power lines (PwElec) occurs when a bird simultaneously touches two-phase conductors or a conductor and a grounded structure. Still, other causes, although less frequent, are also possible (see Martín et al., 2022). Except for cases where birds are electrocuted immediately after colliding with cables, electrocution mainly occurs when birds use the pylons and wires for perching or nesting (Biasotto et al., 2021). Several studies indicated that electric shock could be one of the leading causes of population decline (Biasotto et al., 2025; Boshoff et al., 2011; Hernández-Matías et al., 2015). Although we have substantial information reporting the impact of electrocution on raptors, we know that different groups are being impacted worldwide (Biasotto et al., 2022). Various scientific approaches can identify electrocution-sensitive species, from literature review searching for main groups with published evidence to modelling electric shock risk based on morphology and behaviour traits (Biasotto et al., 2021). See the Appendix section to check which approach was used for a specific country.

Conservation status (CnS), Endemism (En), and Annual adult survival (Su) are calculated in the same way as for the onshore wind sensitivity index.

Mapping the distribution area for priority species

Different spatial approaches can be used or combined to map the distribution of priority species (e.g., bird range maps, Area of Habitat maps, Species Distribution Models, etc.). In AVISTEP, we use the Area of Habitat (AOH) approach, for which different versions have been developed for most bird species worldwide at a 100 × 100 m grid resolution. AOH maps represent the suitable habitats within a species' range and are considered an intermediate layer between the Extent of Occurrence (EOO) and the Area of Occupancy (AOO). These maps are generated using a modelling approach that integrates remotely sensed land-cover data translated into species-specific habitat preferences, for example, as defined by the IUCN Red List

Assessments (Lumbierres et al., 2022), and can incorporate additional parameters such as known minimum and maximum elevation limits.

For each species, we generate a raster layer representing the probability of occurrence, expressed as the proportion of suitable habitat (AOH) within each grid cell (Figure 2). Because our assessment is conducted at a 5 × 5 km resolution, the original AOH maps are resampled to this grid size by calculating the proportion of AOH in each cell. Occurrence records from bird experts, monitoring programs, and citizen science platforms are then used to refine the likelihood of occurrence for each species. When a grid cell contains verified records for a species, we assign a very high probability of presence. The time window and frequency of occurrence considered in each country are provided in the Appendix. Finally, each raster layer is weighted by the corresponding species sensitivity value.

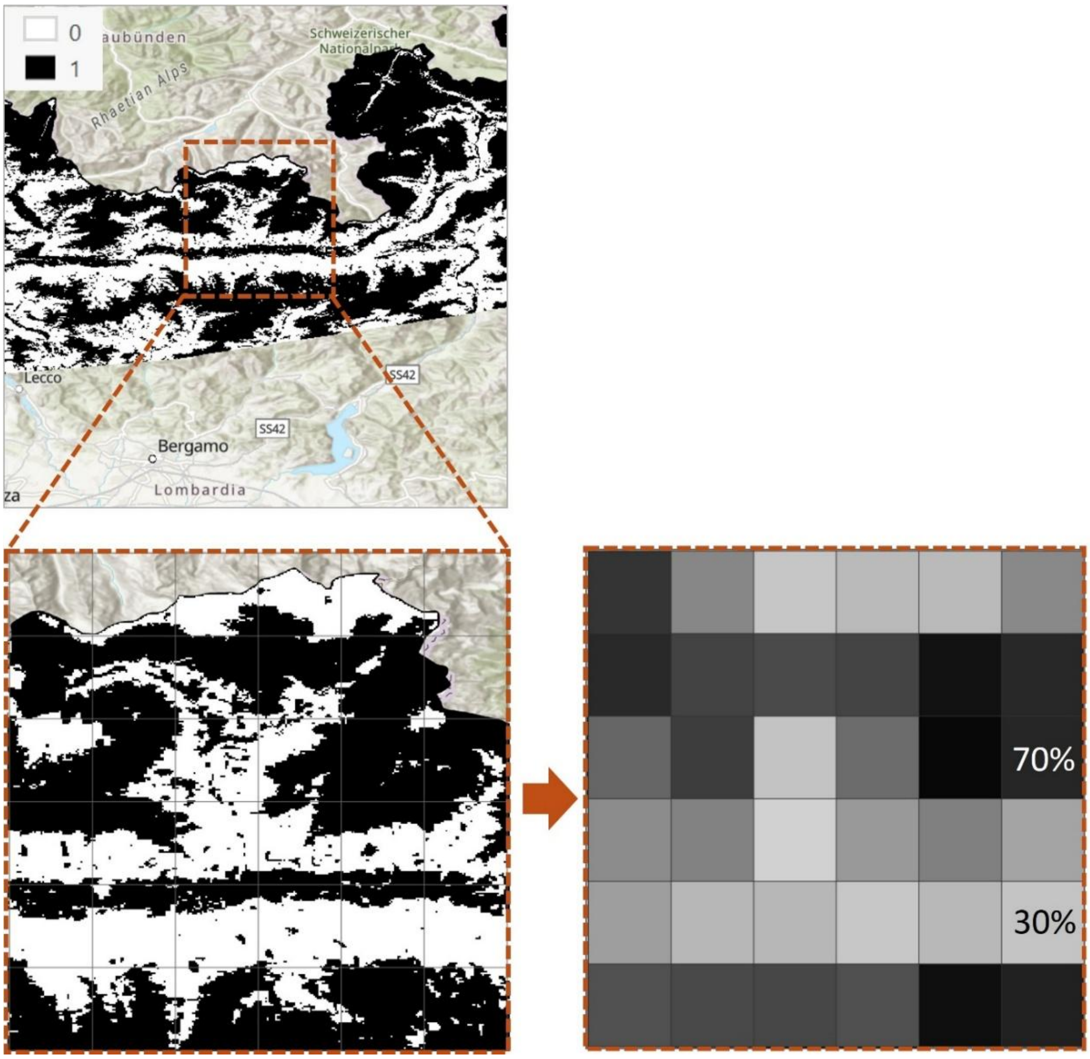

Figure 2. Diagram showing the resampling of the original area of the habitat map (0 is absence, 1 is presence in a grid cell 100x100 m) in a final resolution of 5x5 km, calculating the total percentage of AOH in each cell.

We adapt the Bradbury et al. (2014) formula to weight the raster for each species by its respective sensitivity index. For each grid cell, we apply the formula below:

$$Species\ Sensitivity = ln(species\ occurence\ probability + 1) * SI$$

Species occurrence certainty

To provide information about the likelihood of the species' presence, we create a metric that combines the amount of AOH within and outside the ranges, as well as the confirmed presence of the species in each grid cell. This categorical parameter has values ranging from Low occurrence certainty (1) to Very high occurrence certainty (4) and reflects the level of evidence regarding the species present in that grid cell. The correspondence of the categories could change depending on the country, but overall can be interpreted as follows:

Low occurrence certainty: The percentage of habitat suitable to find the species is < 50% (AOH), but its occurrence is not confirmed by on-the-ground surveys (1).

Medium occurrence certainty: The percentage of habitat suitable to find the species is > 50% (AOH), but its occurrence is not confirmed by on-the-ground surveys (2).

High occurrence certainty: The percentage of habitat suitable to find the species is < 50% (AOH), and the occurrence is confirmed by on-the-ground surveys (3).

Very high occurrence certainty: The percentage of habitat suitable to find the species is > 50% (AOH), and the occurrence is confirmed by on-the-ground surveys (4).

Creating a multispecies combination map

By summing up all species-specific sensitivity maps, we create a multispecies combination map to obtain an overall sensitivity map throughout the country. Thus, this layer captures the cumulative impact over the range of species present in each area (by grid cell).

*Distribution lines combine the map from Collision and Electrocution, conserving the maximum value for each grid cell since it is the only infrastructure with both impacts. Electrocution is very unusual for transmission lines.

Adding other important areas for bird conservation

To limit the impact of energy infrastructure, it is important to target development away from most conserved habitats and towards areas with lower ecological value, such as those already highly modified by human activity (Kiesecker et al., 2019). In addition to mapping bird distribution areas (creating a multispecies map), we also incorporate other relevant spatial layers to represent factors influencing bird conservation. These layers may include land cover and land use data, the human footprint index, key climate variables as water incidence, and information on major bird movement corridors. We integrate information for other sensitive areas from different sources, depending on each country's environmental context and data availability, using Analytic Hierarchy Process (AHP) & expert opinion, and multicriteria analysis (MCA) (Esmail & Geneletti, 2018). Integrating these datasets allows for a more comprehensive assessment of habitat quality, threats, and potential connectivity relevant to bird species.

Identifying final sensitivity categories

Depending on the nature of the data distribution, we classify the results into four categories using Jenks' Natural Breaks algorithm, corresponding to Low, Moderate, High, and Very High bird sensitivity. This classification produces a bird sensitivity map that is easier to interpret and can be readily used by a wide range of stakeholders in decision-making processes.

We also consider Important Bird and Biodiversity Areas (IBAs) or Key Biodiversity Areas (KBAs) and Protected Areas (PAs), which are areas identified as having high priority for bird conservation (BirdLife International, 2025), with the maximum sensitivity. In this way, cells designated as IBAs and PAs automatically received the maximum level of sensitivity (1), while all other cells will vary between 0 and 1. However, not all Protected Area designations have the same relevance for species conservation. We always seek to incorporate the different designations, but with weights that depend on the relevance and motivation for bird conservation. In some countries, we were able to include proposed IBAs/KBAs, as these have already met the criteria but are awaiting confirmation. For more details regarding IBAs and PA designations, please refer to the Appendix section.

Solar Photovoltaic (PV)

The major impact of solar photovoltaic development on ecosystems is caused by habitat loss and degradation produced by direct land occupancy (Ascensão et al., 2023; Hernandez et al., 2014; Turney & Fthenakis, 2011). With a few exceptions (Smallwood, 2022), impacts are still largely understudied (Harrison et al., 2017; Walston et al., 2016). Therefore, the species-specific sensitivity based on different impacts created for the other energy developments does not apply to the context of solar photovoltaic energy. Although some species can indeed coexist with solar PV installations, we have used a precautionary approach, considering that the presence of solar photovoltaics would result in habitat loss and/or degradation for all species occurring in the area.

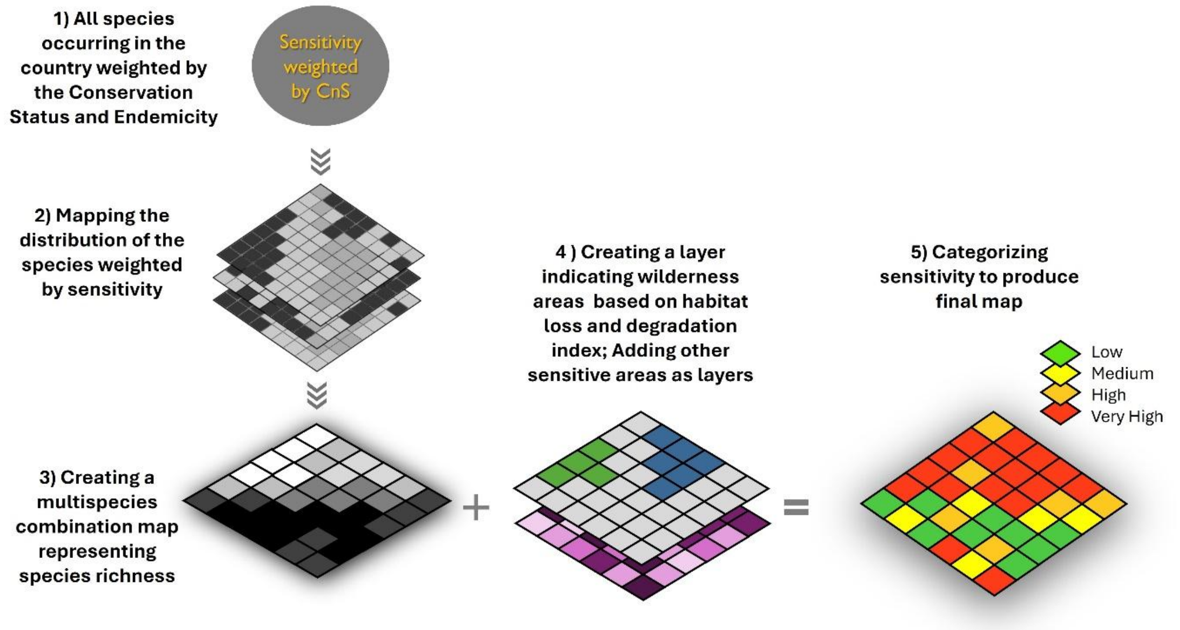

Figure 3. General workflow containing the main steps to create a sensitivity map regarding solar photovoltaic developments: 1) Consider all species occurring and calculate an index based mainly on Conservation Status; 2) Produce gridded distribution maps for all species weighted Conservation Status; 3) Combine maps for all species creating a bird richness map; 4) Create a layer indicating potential wilderness areas and add other sensitive areas; 5) categorise the sensitivity into four practical categories.

Calculating Sensitivity for all species occurring in the country

We consider a list of all species regularly occurring in the country, individually weighted by their respective Conservation Status (CnS - primary factor) and aggravating factor, for example, endemicity, when relevant.

$$Species\ sensitivity = (CnS)^{\left(1-(Ag)/((Ag)+0.5)\right)}$$

Mapping the species distribution according to the Sensitivity

Depending on the country mapped, different spatial data and approaches can be combined to map the distribution of priority species (e.g., bird range maps, Area of Habitat maps, Species distribution models, etc.). In AVISTEP, we use birdlife range maps rasterised in 5 x 5 km resolution or the area of habitat maps representing the probability of occurrence, expressed as the proportion of suitable habitat – AOH - within each 5 x 5 km grid cell. Refers to the prior section regarding *Mapping the distribution area for priority species* for more information. The corresponding species sensitivity value for Solar Photovoltaic weights the final raster for each species.

Creating a species richness map weighted by conservation status

To create a surface representing the cumulative sensitivity, we sum all the rasters in the same grid cell, following the formula.

$$\sum_{species}^{n} (CnS)^{\left(1-(Ag1)/((Ag1)+0.5)\right)}$$

Creating a layer with potentially less disturbed areas and adding important areas for bird conservation

To identify zones where the development of solar farms may negatively impact biodiversity, we usually combine the bird richness surface with a layer informing wilderness sites. Accordingly, areas far from the site with high value for the human footprint index (population density, built infrastructure such as roads, railways, factories, and night-time lights) would be less exposed to disturbance (Ascensão et al., 2023) and, therefore, consist of more relevant areas for bird conservation.

Identifying final sensitivity categories

Depending on the nature of the data distribution, we classify the results into four categories using Jenks' Natural Breaks algorithm, corresponding to Low (1), Moderate (2), High (3), and Very High (4) bird sensitivity. This classification produced a bird sensitivity map that is easier to interpret and can be readily used by a wide range of stakeholders in decision-making processes.

The information for Protected Areas, IBAs, and other high-priority areas for bird conservation is also considered at the top and consists of the same information that was previously used. Therefore, we combine these datasets to create the final sensitivity maps by retaining the maximum value from all overlapping cells. In this way, cells designated as IBAs and PAs automatically received the maximum level of sensitivity (1), while all other cells varied between 0 and 1, depending on their percentage of the trade-off between bird richness and human footprint layers.

Refer to the Appendix section to view the sources of information considered for each country.

Offshore Wind

Offshore wind energy will play a key part in the global transition to renewable energy sources but will also impact marine biodiversity. In this dynamic environment, not all species will be equally at risk from offshore renewables and sensitive species are not evenly distributed. For seabirds, the two main risks from offshore wind development are 1) collision with moving turbines or the static base of the turbine and 2) displacement through avoidance behaviour, barrier effects or habitat alteration (Certain et al., 2015; Bradbury et al., 2014; Furness et al., 2013; Garthe & Hüppop, 2004). How severely a species will be impacted will depend on the following factors; flight height, time spent flying, flight manoeuvrability, nocturnal flight activity, habitat flexibility, disturbance to marine traffic, disturbance to static structure, conservation status and annual adult survival. Where there is the most concentrated risk for development is dependent on the distribution of different species across an area. Building on existing work looking at seabird sensitivity indexes and sensitivity (Certain et al., 2015; Bradbury et al., 2014; Furness et al., 2013; Garthe & Hüppop, 2004) we have established the following approach for estimating areas of seabird sensitivity to offshore wind development.

Delineating Area of Interest (AOI)

For the AVISTEP offshore maps, the area of interest (AOI) is the boundary set for the seabird sensitivity analysis. This is determined prior to collating spatial data and estimating species sensitivity. In most countries, the limits of the national Exclusive Economic Zone (EEZ) are set as the AOI. An EEZ is a well-established and recognised boundary of the marine area within which a country has jurisdiction to explore and exploit natural resources and manage their marine environment (United Nations, 1982). Therefore, the full extent of the EEZ is used to facilitate the incorporation of AVISTEP results into future marine management and spatial planning. The coastal boundaries are taken from the local GADM boundaries (GADM, 2021) and EEZ boundaries are sourced from Flanders Marine Institute (Flanders Marine Institute, 2023). Where using the EEZ is an unsuitable boundary, the AOI is delineated after consultation with local partners.

Establishing a species list

For each country, a list of seabird species for analysis is produced. For offshore sensitivity, all regularly occurring birds with a marine distribution within the AOI are listed. All breeding seabirds are included in the list. For non-breeding species, we investigate the frequency of occurrence. For species which may exhibit both onshore and offshore distribution within their range, marine distribution in the area is reviewed before the species can be added to the list for analysis. This includes some species within the Laridae and Phalacrocoracidae families. The seabird species list is validated with local partners and experts where available.

Calculating species sensitivity

Following the selected species, a sensitivity index is calculated using a trait-based approach. In this analysis, two types of risks are considered. The first type is an individual-level risk to seabirds that includes risks of individual harm from offshore wind development, such as collision and displacement. Following the approach in Furness et al. (2013) these are assessed separately. The second type of risk is the population level risk of additional threats for a given species. This includes the global and/or national red list status of a species. After collision and displacement risks are calculated separately, each are combined with an associated population risk score to produce an overall collision and an overall displacement result.

Individual and population level risks are combined as follows:

$$Overall\ Sensitivity = \ Individual\ Risk\ x\ Population\ Risk$$

Risk Factors

As with the onshore approach, collision, displacement and conservation risk are estimated using a combination of primary and aggravating risk factors. Primary factors are inherently risky behaviours, traits, or other parameters that directly contribute to a species' vulnerability. Aggravating factors exacerbate an existing risk but have no inherent risk of their own when the associated primary risk is not present (Certain et al., 2015). For some countries, an additional risk factor is added where there is a known risk for a species that is not captured by the calculation of primary and aggravating factors.

Conservation Status (CnS) is used to address the disparity in vulnerability of different seabird populations. Certain populations may have very low resilience to new threats when compared to others. Two species with equal individual risk are considered to have different overall sensitivity where one species would be disproportionately impacted on a population level. For example, endangered species collision fatalities will have a larger impact on a population than species with a low extinction risk. Often seabird species that are already at a high-risk for extinction are facing numerous threats such as bycatch and colony predation and already have a small population (Dias, et al. 2019). Any additional loss in individuals would then compound that population's decline.

Red list status (RL) is the primary factor used to estimate population-level risks to offshore wind development. In all countries the same scoring system was applied as onshore, conservation status was assigned at the species level using the IUCN Red List categories Critically Endangered (CR); Endangered (EN); Vulnerable (VU); Near Threatened (NT); Least Concern (LC). The weighting method concerning the risk of extinction for each category evolved for the countries with exponential logic being applied to the most recent countries instead of a linear approach. Please see the Appendix for more details.

Annual adult survival (Su) is used as an aggravating factor to conservation status. There are various life-history factors than can affect a population's ability to recover from additional mortalities or poor breeding success. These include life span, age of first breeding, adult survival, reproductive rate and parental investment. Overall, seabirds are long lived species in comparison to most other birds. They mature later in life and have smaller clutch sizes. We use annual adult survival as a metric to capture these traits (Bird et al., 2020). How this factor has been applied to conservation status has evolved for different countries, with survival being multiplied by the conservation risk in the most recent country. Please see the Appendix for more details.

$$CnS = RL \, x \, Su$$

Collision (Co): Wind turbines are novel structures in the marine environment and can be an obstacle for seabird flight paths. As a result, collision can occur with mobile objects in the rotor swept zone (turbine blades), or with static objects at the base of the turbine during construction, operation and decommissioning. Collision risk modelling has been the focus of windfarm sensitivity analysis in areas with established offshore wind industries (Furness et al. 2013; Garthe & Hüppop, 2004). Despite ongoing research into collision, there is still uncertainty surrounding the drivers and the frequency of collision of seabirds. As a result, risk of collision is estimated by scoring various behavioural and morphological traits of individual species.

Exposure (Exp) is the primary factor used calculate the risk of collision with turbines offshore. This is a categorisation based off estimates of flight height and time spent flying combined or off evidence of flight behaviour such as flight height and foraging type. Relevant information is collected and categorised according to available data and expert elicitation.

Flight behaviours are categorised as follows:

- 0- No Risk
- 1- Very Low Risk
- 2- Low Risk
- 3- Moderate Risk
- 4- High Risk
- 5- Very High Risk

Flight Manoeuvrability (FM) and **Nocturnal Flight Activity (Noc)** are aggravating factors for exposure that incorporate the physical characteristics or behaviours of a species which influence the ability avoid last moment collisions. Flight manoeuvrability is calculated by dividing recorded body mass (Dunning, 2007) by wing length from AVONET (Tobias et al., 2022) as a proxy for wing loading. Nocturnal flight activity is categorised based on estimates of overall time spent flying at night, or categorised based on evidence of overall nocturnal activity type. Where no information is available, partial nocturnal activity is assumed. As these two aggravating factors may operate independently, the average is calculated and multiplied with the exposure score.

Extra Risk Factor (ExR)

Where there has been evidence of recorded collisions with wind turbines, an additional risk factor is added to their overall sensitivity. As we cannot establish from event records alone why these collisions are occurring, this factor is additive. Since this applies to probability of a collision occurring, it is added to the exposure factor. This factor is weighted by strength of the evidence of collisions occurring for offshore structures.

Collision (Co) was calculated as follows:

$$Co = Exp\ x\ \left(\frac{FM + Noc}{2}\right) + ExR$$

Overall sensitivity to collision (CoSI) is then calculated by combining the collision score with the associated conservation status score:

$$CoSI = Co\ x\ Cns$$

Displacement (Di): The presence of offshore development may also deter seabirds from areas or force them to alter their movements and behaviours. Post construction, changes in distribution of seabirds in response to windfarm development has often been recorded (Lamb et al., 2024). The strength of this response often varies between taxa, breeding seasons, spatial and temporal extent of the disturbance and this response can be attraction or avoidance. Avoidance behaviour may adversely impact seabirds the most where it displaces them from key foraging areas or notably changes their time-energy budgets.

Disturbance from Marine Traffic (MtD) and Static Structures (StD) are the primary factors for calculating displacement for seabirds. In line with the onshore approach, we applied a literature review looking for articles published regarding bird displacement to understand how likely different bird families are to be impacted. Some authors do not distinguish between types of disturbances. However, since marine traffic (i.e., vessels and helicopters) is expected to increase during construction and operation of offshore wind farms, we include them separately. For some species we did not find information about both disturbance types, but only for fixed structures; on those occasions, we scored both parameters equally. As these factors may operate independently, an average of the two is used to estimate disturbance.

For each factor, disturbance was categorised into from 1 (low disturbance response) to 5 (high disturbance response).

Habitat Flexibility (HbF) is the aggravating factor used for displacement. While the marine environment is dynamic and habitats often change overtime, the flexibility of foraging habitats or a specialisation of feeding for seabirds varies from species to species. This aspect of their ecology directly influences a risk or impact of displacement. A review of available data on diet and foraging is used to categorise species. Where no data was available for the species, proxy species were used to estimate factors.

Habitat flexibility was categorised into from 1 (high habitat flexibility) to 5 (low habitat flexibility).

Displacement was calculated as follows:

$$Di = \left(\frac{MtD + StD}{2}\right) x\ HbF$$

Overall sensitivity to displacement (DiSI) is then calculated by combining the displacement score with the associated conservation status score:

$$DiSI = Di\ x\ Cns$$

Mapping the distribution area for priority species

Seabirds have a varied distribution during of their annual cycle, and a variety of spatial information is available to create an estimation of areas used across the year (for example, breeding colony information, known core migratory areas, tracking data and at-sea observations). For AVISTEP offshore sensitivity mapping, spatial data is split into areas of breeding and non-breeding or all-year distributions. The resolution of data available varies from country to country, so approaches to mapping distributions have been adjusted over time. All spatial data is rasterised on a 5x5km grid.

Range Maps

Range maps from the BirdLife DataZone are used to establish a base for the species distribution. These range maps are then checked against other sources and edited where necessary. Species are mapped by season, with resident species contributing more to the final maps than species only present in the non-breeding season. When available, range maps delineated by local experts are given preference for species distribution. Where data is reliable, core areas are identified within range maps and given a higher weighting in analysis.

Breeding colony buffers

During the breeding period, seabirds are central-place foragers constrained to the areas around their nesting sites (Schreiber & Burger, 2002). The high use of these areas during this critical period makes them highly sensitive to anthropogenic impacts. In recent years, different approaches have been developed to identify these high use areas for seabirds. The “foraging radius approach” uses information about foraging ecology to predict foraging areas around breeding colonies (BirdLife International, 2010; Soanes et al., 2016). In this method, foraging radii are drawn around a breeding colony based on the distance travelled by breeding birds, which grid cells inside the radius receiving a value of 1. It can be applied to any central-place forager and requires little a-priori data on at-sea distribution (BirdLife International, 2010; Grecian et al., 2012). For countries containing very numerous colonies and/or species with very large foraging ranges, we modelled density around seabird colonies as gradient (Critchley et al. 2019). This approach uses the best estimate a colony size and foraging range to calculate the number of individuals extending out from the site using a log decay function. A log decay function assumes that the use of the surrounding waters reduces with increased distance from the colony. This seaward extension is computed for each colony for all listed breeding species and summed together to create a layer. If no foraging information was available for a given species, we use data from the most closely related species.

Tracking Data

To investigate high use areas both inside and out of the breeding season, tracking data is collated and analysed. Platforms such as the Seabird Tracking Database and Movebank are used to search for tracking data along with a literature review. GLS, GPS and PTT data are requested for analysis, and used according to their data accuracy and representativeness of species movements. Tracks from breeding and non-breeding periods are analysed separately. Where sufficient breeding GPS data is available for identified colonies, kernel densities are used instead of seaward extensions. Due to the very large error associated with GLS tracking, GLS tracks are only used as corroborative data for other spatial information or expert advice (Phillips et al., 2004; Halpin et al., 2021).

Bird Migration

Marine areas that are used for onshore bird migration are analysed where data is available. This was done for Australia and Egypt. There were two analyses used for migratory maps. The first approach uses tracking data and ebird observations to create kernel densities estimates of key stopover sites for migrating birds. The other approach uses bird observations to calculate hotspot areas along the coast used for open water migration and estimates potential movement corridors between these hotspots using a least-cost paths analysis.

Creating multispecies combination map

Following the methodology for onshore wind energy, sensitivity maps are produced by multiplying the values in the species distribution rasters by the species' sensitivity index (SI), making this value spatially explicit in a 5 x 5 km grid cell. We combine the SI with the distribution layers using one of two approaches. The first approach is to creates a separate collision and displacement sensitivity layer for each species using the CoSI and DiSI. Each of these two layers are then summed with the other species sensitivity layers of their associated risk to form a cumulative collision sensitivity map and a cumulative displacement map. The two cumulative maps are then merged, with the maximum value used from each overlapping cell. The second approach is to attribute the maximum overall sensitivity result (CoSI or DiSI) to the cells of the individual species distribution layers. This creates a single sensitivity layer which either contains collision (CoSI) or displacement (DiSI) values for each species. Then, all the individual species sensitivity layers are summed to create a final cumulative species sensitivity layer.

Identifying final sensitivity categories

After obtaining each grid cell's final seabird sensitivity value, we classified the results into four categories using Jenks Natural Breaks algorithm using the *ClassInt* package in R Studio (Bivand, 2024). These four categories correspond to Low, Moderate, High, and Very High sensitivity, represented by green, yellow, orange and red cells on the map. This classification produced a map that is easier to interpret and can be readily used by a wide range of stakeholders in decision-making processes. For some countries, the assignment of each cell to one of the four categories was applied before considering the known areas most important for bird conservation, and which therefore should have maximum sensitivity. For countries with a very large AOI, two additional subcategories were input into the existing four categories. These subcategories were calculated using Jenks natural breaks again to produce eight overall categories from green to red (very low risk, low risk, low to moderate risk, moderate risk, high risk, high to very high risk, very high risk and extremely high risk).

Adding other important areas for bird conservation

Other important areas for bird conservation are also incorporated, including sensitivity habitats (e.g. coral reefs, seagrass and mangroves), conservations areas (such as protected areas and KBAs or IBAs) and migratory areas for non-marine birds. Areas are considered in three ways:

1) Combined using a weighted average before or after the Jenks natural breaks classification. This approach is typically used if areas are very large so cannot be attributed the highest level of sensitivity across their extent within the AOI.
2) Overlayed with the species sensitivity layer by the maximum value from each cell before the Jenks natural breaks classification. This is generally used when layers vary in value and are unlikely to interact with other layers (for example onshore bird migratory layers).
3) Rasterised at the highest level of sensitivity (value of one) and are added on top of the classified sensitivity map. This approach does not impact the relative sensitivity of other cells as it is applied after the Jenks natural breaks classification.

Understanding the final sensitivity categories

The assessment of avian sensitivity presented in AVISTEP is intended to provide a broad scale understanding of the potential risks posed to birds by certain types of energy infrastructure. Evaluating spatial risk is key to improv early-stage renewable energy planning. However, it is important to recognize our imperfect knowledge of avian distribution and incomplete understanding of the factors that make certain bird species more susceptible to impacts from energy infrastructure. Furthermore, the maps show relative sensitivity within each country, so the sensitivity categories and values are only comparable between grid cells inside the country's territory. Both bird sensitivity parameters and data normalisation on individual layers are relative to each country's intrinsic minimum and maximum values.

By design, the assessments are precautionary and intended to provide an awareness of the at-risk bird species present within an area and what such a species composition might mean for developing renewable energy infrastructure and power lines. This information is intended to inform, rather than replace, subsequent site-scale evaluation. It is possible that an area predicted to be of low avian sensitivity could, following further local assessment, be shown to have a greater degree of sensitivity. Equally, areas deemed highly sensitive could ultimately be shown to be less sensitive. It is also the case that a highly sensitivity area could still be suitable for development if the correct mitigation measures are implemented. Therefore, those areas depicted as being highly sensitive should not be automatically assumed to be "go" or "no-go" areas for development.

The sensitivity scores were grouped into four categories of sensitivity — Low, Moderate, High and Very High that should be interpreted as follows:

Low	*Development is considered to pose a low risk to bird populations. However, comprehensive site-level assessment is necessary to confirm the absence of significant risk.*
Moderate	*Development is considered to pose a moderate risk to bird populations. However, comprehensive site-level assessment is necessary to confirm this level of risk.*
High	*Development is considered to pose a high risk to bird populations. However, comprehensive site-level assessment is necessary to confirm this level of risk. This area may be unsuitable for development and will certainly require mitigation measures.*
Very High	*Development is considered to pose a very high risk to bird populations. However, comprehensive site-level assessment is necessary to confirm this level of risk. This area is likely to be unsuitable for development and will certainly require mitigation measures.*

Most regions are likely to have sufficient available land of Low and Moderate sensitivity to meet their solar and wind targets, and therefore development of these technologies in High and Very High sensitivity areas should be discouraged. In contrast, it may be less easy to locate power lines away from areas of higher risk as they are typically required throughout the landscape.

A universal colour-coding convention

It is a universally recognised convention to communicate the status of something, especially risk, using a colour-coded system based on traffic lights known as the traffic-light or RAG rating. Traffic-light ratings are commonly used to rate performance, progress, risk, or overall status and are broadly utilised in different fields. The colour palette used in the final maps is colourblind-friendly.

Wind and Solar Resources

Wind resource

To visualise the availability of wind resource for onshore and offshore wind energy development, we map areas suitable for wind farms and display them on the website, allowing users to choose to view the sensitivity of areas with good wind potential only. We use data from the Global Wind Atlas, which provides wind parameters tailored to the wind energy industry (World Bank Group, globalwindatlas.info/en/). The original data comes from the ERA5 dataset from the European Centre for Medium-Range Weather Forecasts (ECMRWF) from 2008–2017 and through a modelling system, they produce a final dataset at 250 m of spatial resolution at several heights (i.e., 10m, 50m, 100m, 150m, 200m). For our study, we use the dataset at 100 m height and recalculate the mean average speed to a 5 x 5 km cell size. A common standard applied in the industry is that for onshore utility scale development mean wind speed must be ≥ 5 m/s onshore and ≥ 5 m/s offshore (Esmap, 2019). We considered all those areas above this threshold to be potentially suitable for development.

Solar resource

To visualise the availability of solar resources for photovoltaic energy development, we map areas suitable for solar PV and display them on the website, allowing users to choose to view only areas with good solar potential according to the Global Solar Atlas (World Bank Group, globalsolaratlas.info/map). From the parameters available for solar energy assessment, we used global horizontal irradiance (GHI), specifically the long-term yearly average of GHI (kWh/m2). This metric is commonly used in solar PV research (Baruch-Mordo et al., 2019). We defined suitable areas for solar PV utility-scale development as those with a GHI ≥ 1400 kWh/m2/year (He & Kammen, 2016). Setting this threshold was less straightforward than for wind resources, as different economic and geographical factors affect it (Suri et al., 2020) and can vary widely (Baruch-Mordo et al., 2019). However, we believe the value chosen represents a good compromise between resource availability and energy production efficiency.

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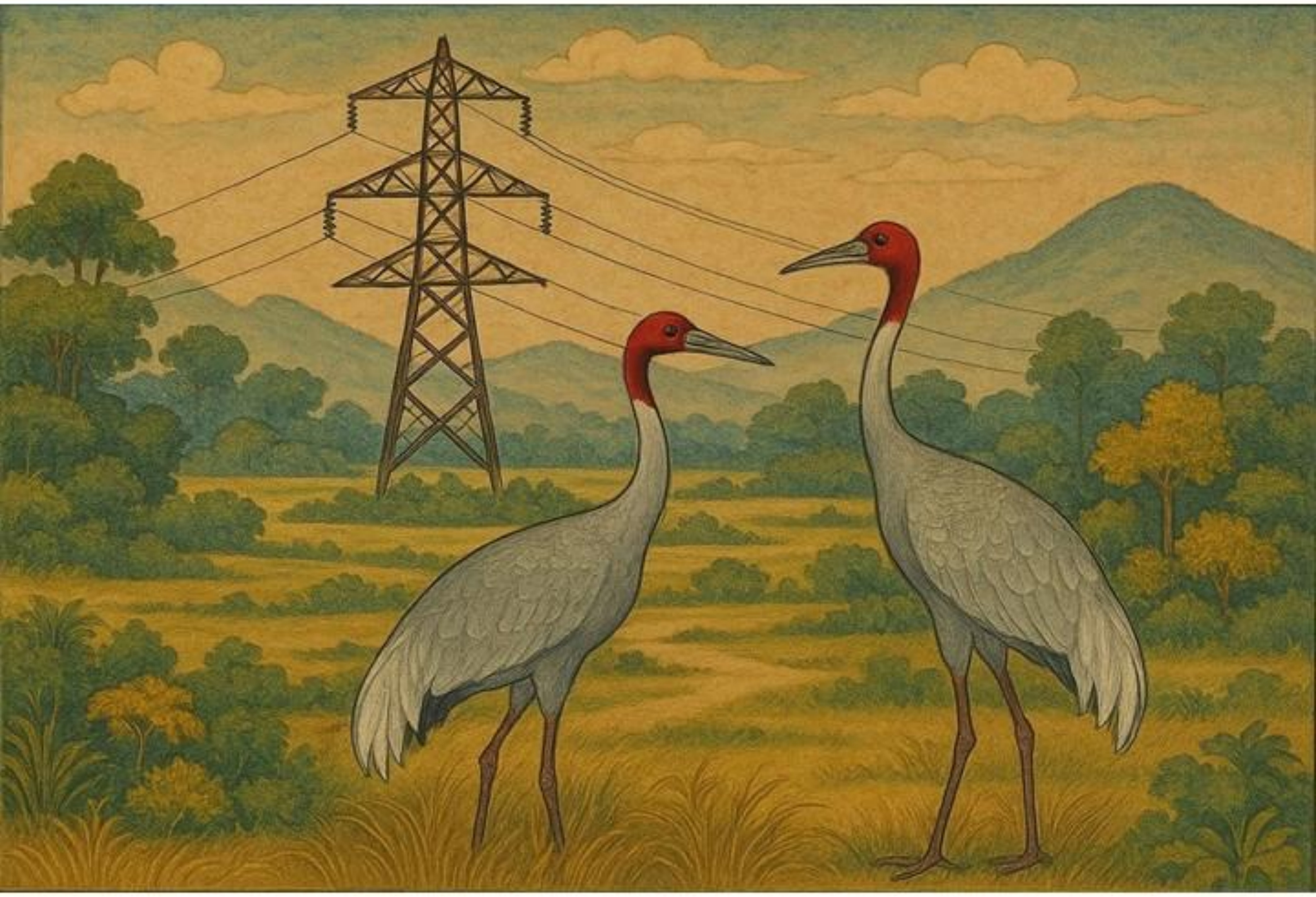
AVISTEP

The Avian Sensitivity Tool for Energy Planning

Appendix I – India, Nepal, Thailand, Vietnam

November 2025



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Wind Farm Onshore

Calculating species sensitivity – STEP 1

In creating a species sensitivity index for onshore wind, we used a modified version of the sensitivity index developed by Certain et al. (2015) for offshore energy sensitivity mapping. We adapted this methodology for land birds by modifying the metrics in the calculation of the indices whilst retaining their overall structure. The main innovation in the methodology has been to differentiate between primary and aggravation factors. Primary factors are species characteristics that directly control the vulnerability, while aggravation factors are those that can increase a vulnerability that already exist (Certain et al., 2015). These differences between factors are therefore incorporated in the mathematical formulation of the indices.

The three main impacts of onshore wind energy on birds are collision, displacement, and habitat loss (Drewitt & Langston, 2006; Marques et al., 2014; May et al., 2020). In creating a species sensitivity index for onshore wind, separate metrics were created to capture collision and displacement susceptibility. Additional metrics relating to conservation status, annual adult survival, and range rarity were included to capture the population implications of these impacts for the species. The impact of habitat loss was accounted for through an assessment of land cover and land use data. The sensitivity index for onshore wind energy followed the formula:

$$Sensitivity\ Index = \left(Co + \left(\frac{Di}{5}\right)\right) \times (CnS)^{\left(1-\left(\frac{(Su+En)}{2}\right)/\left(\left(\frac{(Su+En)}{2}\right)+0.5\right)\right)}$$

Where there are three primary factors: Co = collision, Di = displacement, and CnS = conservation status and two aggravation factors: Su = annual adult survival, and En = endemism.

A detailed explanation of the different metrics employed is as follows:

Collision (Co) is the most direct threat to bird populations, and it has been reported in multiple species and locations across the world (Loss et al., 2013; Marques et al., 2014; Perold et al., 2020; Thaxter et al., 2017). However, multiple factors related to wind farm characteristics (e.g., turbine type, spatial design), and site location (e.g., topology, land use) have been found to influence collision risk (Marques et al., 2014).

To develop a metric that could identify the sensitivity of different taxonomic groups, we used a study by Thaxter et al., 2017. In this study, the authors analysed the ecological traits and phylogenetic characteristics that make different taxonomic groups more sensitive to collision. Through a modelling approach they assigned a collision probability to most land-bird species worldwide. Based on the authors recommendations, we summarised this value at the family level (average value). After that we categorised this value between 1 and 4. These categories were calculated following a natural break classification, the corresponding values for reach category were:

- 1 = < 0.023
- 2 = > 0.023 - 0.036
- 3 = > 0.036 - 0.06
- 4 = > 0.06

Following advice from local experts (including from BirdLife partners) and recent published literature about collisions of migratory Pittidae with man-made infrastructures (Kumar et al., 2019; Low et al., 2017), we upgraded all migratory members of the Pittidae family to a value of 3.

Displacement (Di) refers to the reduction in the habitat use of areas under the influence of wind energy facilities, which in the long-term produce a decrease in bird density and functional habitat loss (Drewitt & Langston, 2006; May, 2015). This type of impact has been proven for both sea- and land-birds (Marques et al., 2021, 2020; Pearce-Higgins et al., 2009), and after collision it is thought to be the major threat to birds posed by wind farms (Hötker, 2017; Marques et al., 2021). However, its importance and magnitude has been difficult to quantify due to the scarcity of long-term and rigorous studies employing BACI methodologies (i.e., Before-after control-impact) (Hötker, 2017). A recent study from India has reported that displacement of raptors had consequences on lower trophic levels, producing cascading effects on food webs (Thaker et al., 2018), highlighting the largely underestimated effects that displacement could have on ecosystems.

To produce a displacement metric, we referred to the work done by Hötker, 2017. In this study, the author reviewed all the evidence from the scientific and grey literature reporting displacement in bird species in Europe. The author divided this impact into two categories: negative – when displacement was reported to reduce species abundance; and positive – when there was no change or a positive effect was found in species abundance. Surprisingly, different studies report different responses for the same species depending on several factors. Through the literature review, the author was able to report the number of times a positive or negative effect had been found per species and, for those groups with enough samples, the statistical significance of this difference (binomial test). To transform these values into a metric that we could be employed in our equation, we assigned the following values:

- 1 = Displacement never reported for the species.
- 2 = Displacement reported for the species in at least one study.
- 3 = Displacement more often reported, but differences not statistically significant.
- 4 = Displacement more often reported and differences statistically significant.

These scores were given at the family level. The whole family received the value of the highest scoring species included in that family. This precautionary approach was taken to ensure that similar species that have not been directly studied could be evaluated. This was especially important given the limited scientific evidence directly available for the project area.

Scoring was modified for several families due to the availability of more recent research. This was the case for the following:

- Accipitridae received a value of 4. Recent studies suggest that this impact is more severe that previously acknowledged (Fielding et al., 2021; Law et al., 2020; Marques et al., 2021, 2020; Santos et al., 2021; Thaker et al., 2018).
- Otididae received a value of 3. This group was not included in Hötker, 2017, but some studies (Raab et al., 2014) and expert opinion suggested this was a more appropriate value.
- Gruidae received a value of 3. On top of the evidence in Hötker, 2017 new studies from the USA suggest a stronger effect than previously acknowledged (Navarrete, 2011; Pearse et al., 2021, 2016; Veltheim et al., 2019).

Conservation status (CnS) was assigned at the species level using the IUCN Red List categories (BirdLife International, 2020) as follows:

- 5 = Critically Endangered (CR)
- 4 = Endangered (EN)
- 3 = Vulnerable (VU)
- 2 = Near Threatened (NT)
- 1 = Least Concern (LC) and Data Deficient (DD)

Annual adult survival (Su). The population-level impact of a single individual mortality event depends on the life history traits of the species involved. Some life history traits like fecundity, age of maturity, and adult survival are especially relevant. K-selected species are characterised by low fecundity, late ages of maturity and high survival; thus, adult mortality has high impacts on these populations (Niel & Lebreton, 2005; Sæther & Bakke, 2000). The species groups with the highest rates of impact from wind development tend to be K-selected species such as Accipitridae, Ciconiidae or Bucerotidae (Thaxter et al., 2017); thus, it is a factor that must be carefully considered when evaluating impacts on bird conservation. To include a metric that could capture these life history factors, we employed annual adult survival (Su) which has been recently calculated for all bird species (Bird et al., 2020). This value ranges from 0.31 to 0.98. To transform these values to categories from 1 to 5, we used a natural breaks classification algorithm implemented in the RStudio package *classInt* (Bivand et al., 2022).

Endemism (En). Previous work on sensitivity mapping have included parameters that reflect the conservation status of species in the global context. Some examples of these parameters are the proportion of the global population present, the annual occurrence (Kelsey et al., 2018) or the percentage of the biogeographic population that occurs in the study area (Bradbury et al., 2014; Critchley & Jessopp, 2019a; Furness et al., 2013). Therefore, we created a metric that would capture this aspect through a calculation of the level of endemism. Endemism (En) was calculated at the country level as the percentage of the total distribution range area that falls within the country's boundaries. So, if a species were endemic to a country, the value of the endemism for that country would be 100% and consequently increase the sensitivity of that species. To calculate this parameter we used the distribution range maps (BirdLife International & The Handbook of the Birds of the World, 2019) and the global database of political boundaries GADM (Global Administrative Areas, 2021) in ArcGIS Pro (ESRI, 2021). To transform these values to categories from 1 to 5, we used the following conversion criteria:

- 1 = 0-20%
- 2 = >20-40%
- 3 = >40-60%
- 4 = >60-80%
- 5 = >80-100%

To standardise all metrics and make them comparable, we divided each of them by the maximum category value following recommendations from Certain et al., 2015. Sensitivity indices were calculated for each species separately for the four focal countries and then used to rank the most sensitive species per country.

To choose the final list of species to be included in the assessment, we ranked all species by country according to their sensitivity values. Then we chose only those species with a sensitivity index of ≥ 0.3885 (See tables in Supp. material). We found that this threshold ensured that the most sensitive species were represented, with it roughly corresponding to the top 15% of all species per country. To produce the final sensitivity scores, we normalised the values to a 0.01 to 1 scale in order to emphasise the much greater sensitivity of species in the top part of the list compared to the species at the bottom (Critchley & Jessopp, 2019a).

Mapping the distribution area for priority species – STEP 2

To incorporate the species geographic distribution, we used area of habitat (AOH) maps (Brooks et al., 2019). These maps represent the utilised habitats within the range of a species and can be considered an intermediate step between Extent of Occurrence (EOO) and Area of Occupancy (AOO). They have been created through a modelling approach based on remotely sensed land cover and elevation data and the habitat preferences of each species according to the IUCN (Lumbierres et al., 2022). These maps are available for most bird species worldwide in raster format with a spatial resolution of ~100 meters. Since our assessment was in a ~5x5 km grid cells resolution, we needed to transform the original AOH maps to our resolution. To do so, we calculated the total percentage of AOH that was present in each cell and retain, as part of the species distribution, only those cells where the percentage was ≥ 30%.

To assess the accuracy of the new species distribution created using the AOH maps, and to complement these, we employed information about species presence from field surveys. Two main sources of information were used:

- BirdLife's local partners compiled observational records for their respective countries from a range of sources (i.e., published, and unpublished literature, survey and project data, and a range of other sources).
- Additional observational records came from the citizen science project eBird (https://ebird.org/home). To download and curate the datasets we used the RStudio package *auk* (Strimas-Mackey et al., 2018). To guarantee the accuracy of the data, we only included observations that were recent (i.e., 2010 – 2020) and came from protocols stationary or travelling. The maximum distance travelled was set to 7 km to ensure that all records were contained within the final ~ 5x5 km cells.

With these datasets, we calculated two metrics per species: point prevalence and surface reduction. Point prevalence was calculated by dividing the total number of locations that fell within the new species distribution by the total number of locations present within the distribution range of that species (Dahal et al., 2022). While surface reduction was the total reduction in area between the range maps and the new species distribution based on the AOH maps.

Several exceptions had to be made to this general methodology. On these occasions we had to use the BirdLife range maps as a base information and transform them directly into the ~ 5x5 km grid. This was the case for:

- Species whose point prevalence was ≤ 60% or where we did not have an AOH map.
- Species for which we did not have information from field surveys or where their presence was only confirmed outside the range. We only used those distribution maps based on AOH that had a surface reduction smaller than 60%. We chose this value because it was the average surface reduction for species with a low accuracy (i.e., point prevalence ≤ 60%).
- Species with a migratory passage distribution in the country. The original AOH maps were created without considering the passage range.

The final point prevalence and surface reduction values of the AOH maps after removing those species that did not meet the criteria mentioned above were:

- India: Average point prevalence = 90.33% and surface reduction = 17.28%
- Nepal: Average point prevalence = 91.19% and surface reduction = 24.86%
- Thailand: Average point prevalence = 93.39% and surface reduction = 20.62%
- Vietnam: Average point prevalence = 91.08 % and surface reduction = 18.38%

Finally, for a few species we found out that there was strong evidence of presence outside the original range maps. To incorporate this information and complement the new distribution maps, we decided to add those cells outside the range maps where the species had been reported in more than 10 surveys during the period from 2010 to 2021.

Species occurrence certainty

To add extra information about the species presence and distribution, we created a metric based on the amount of AOH and the confirmed presence of the species in each grid cell. This categorical parameter has values from 1 to 4 and reflects the evidence of the presence of the species in that grid cell. The correspondence of the values is as follows:

- 1 = AOH between 30% and 50%, but presence not confirmed by on the ground surveys.
- 2 = AOH > 50%, but presence not confirmed by on the ground surveys.
- 3 = AOH between 30% and 50% and presence confirmed by on the ground surveys.
- 4 = AOH > 50% and presence confirmed by on the ground surveys.

For those distribution maps that were based just on the BirdLife range maps, we created a classification that was comparable but based on the information available for those species. On these occasions, we gave a generic value of 1 to the range area and a value of 3 to those grid cells where the species presence was confirmed by surveys.

Creating multispecies combination map – STEP 3

We created a multispecies combination map by summing the sensitivity maps for all species. To do so, we transferred the calculated sensitivity index value per species to their geographic distribution, making this value spatially explicit in a ~ 5x5 km grid cell. After that, we overlapped all the species geographic distributions and added the sensitivity values from all the species. Thus, the final score for each cell is the result of the summed values of all the species present in that cell. The bird sensitivity map captures the cumulative impact over the range of species present in each area. To make these maps comparable with the rest of sources of information, we normalised the values from 0 to 1.

Adding other important areas for bird conservation – STEP 4

Land Cover Land Use

To limit the impact of renewable energy, it is important to target development away from natural habitats and towards areas with low ecological value, such as those already highly modified by human activity (Kiesecker et al., 2019). For this purpose, we used land cover data to identify cropland and urban areas with low ecological value. Specifically, we used the Copernicus global land- cover product for 2019 (https://lcviewer.vito.be/2019) and the discrete land cover classification, which includes 23 classes at a ~100 m spatial resolution (Buchhorn et al., 2020). We chose to use this dataset for its high accuracy (average ~80%) and its suitability for conservation (Jung et al., 2020). First, we reclassified all land cover classes to have a value of 1 except for cropland and urban/built up areas which received a value of 0. We then calculated the percentage of natural areas present in each 5x5 km cell. In our scoring, cells with a higher percentage of natural areas will result in a higher sensitivity score. To to give a greater importance to the bird sensitivity maps, we established that the land cover value would contribute only 20% to the final score. We did so by multiplying the land cover score by 0.2.

Important Bird and Biodiversity Areas (IBAs)

Important Bird and Biodiversity Areas (IBAs) are a global dataset of areas of greatest significance for the conservation of the world's birds. They cover about 6.7% of terrestrial areas, 1.6% of marine areas and 3.1% of the total surface area of the Earth (Donald et al., 2019). This dataset is curated by BirdLife International and available through their website (http://datazone.birdlife.org/site). The most up-to-date version of this data from 2022 was used for all four countries (BirdLife International, 2022). In some instances, areas not identified as IBAs but nonetheless known to be of global significant for at-risk bird species were also included. Cells overlapping with these areas received the maximum value of sensitivity.

Protected Areas

We used the World Database on Protected Areas (WDPA) from the Protected Planet website (www.protectedplanet.net). This database is updated by governments and curated by the UN Environment Programme World Conservation Monitoring Centre (UNEP-WCMC) and includes the most up-to-date information on protected areas. The latest version from 2022 was used, except for India where this dataset was under revision and the 2019 version was used instead. All protected areas were included, regardless of their IUCN management category. As with IBAs, cells overlapping with these areas automatically received the maximum level of sensitivity.

Identifying final sensitivity categories – STEP 5

The final sensitivity maps range from 0 to 1, and to classify the levels of sensitivity into four categories – from low to very high – we used the natural breaks algorithm implemented in ArcGIS Pro.

Powerlines

The calculation of the powerline sensitivity maps follows the same general approach used for onshore wind energy, with the exception that land cover information was not incorporated into the calculations. Whilst utility scale wind energy development and solar PV are known to be spatially intensive, it is not the case for powerlines infrastructure, which occupy much smaller areas.

Calculating species sensitivity – STEP 1

Powerlines are responsible for two main impacts on birds: collision and electrocution (Martín Martín et al., 2019; Prinsen et al., 2011). However, the magnitude of these two impacts depends on certain technical characteristics of the powerline itself. Transmission lines (voltages > 60 kV) have been found to impact mainly through collision, while distribution lines (voltages from ~1 kV to 60 kV) can cause both collisions and electrocutions (Prinsen et al., 2011).

Two indices based on both impacts were calculated:

Powerline Collision

$$Sensitivity\ Index = (PwCo) \times (CnS)^{\left(1-\left(\frac{(Su+En)}{2}\right)/\left(\left(\frac{(Su+En)}{2}\right)+0.5\right)\right)}$$

Powerline Electrocution

$$Sensitivity\ Index = (PwElec) \times (CnS)^{\left(1-\left(\frac{(Su+En)}{2}\right)/\left(\left(\frac{(Su+En)}{2}\right)+0.5\right)\right)}$$

Where there are three primary factors: PwCo = powerline collision, PwEC = powerline electrocution, and CnS = conservation status, and two aggravation factors: Su = annual adult survival, and En = endemism.

A detailed explanation of the different metrics employed is as follows:

Powerline collision (PwCo) and **powerline electrocution (PwEc)**. To assess the species sensitivity to these two impacts, and apply a scoring system, we used three published reviews from Africa and Eurasia (Haas et al., 2003; Martín Martín et al., 2019; Prinsen et al., 2011). These reviews provide a classification at the family level of the main species affected by both impacts. Collision and electrocution have a strong phylogenetical signal, so related taxa typically show similar levels of sensitivity (Prinsen et al., 2011).

Four categories were used by these authors to measure sensitivity:

- Category 0 = no casualties reported or likely.
- Category I = casualties reported, but no apparent threat to the bird population.
- Category II = regionally or locally high casualties, but with no significant impact on the overall species population.
- Category III = casualties are a major mortality factor, threatening a species with extinction, regionally or at a larger scale.

Slight differences were found in the classification for certain families between the three publications. To unify this information, we decided to retain the most common value (mode). In some cases, the values assigned to the families corresponded to an intermediate value between categories (i.e., I-II, II-III). To transform these categories to values that could be fitted in the sensitivity index score we used the following conversion scheme:

- Category 0 = 1
- Category I = 2
- Category I-II = 3
- Category II = 4
- Category II-III = 5
- Category III = 6

Some bird families present in our study area were not assessed in any of these reviews and others had more recent information available. On those occasions, a literature review was made using Google Scholar including the formula: ("genus" OR "common name") AND ("collision" OR "electrocution").

After this review was made and using the same criteria applied by Prinsen et al., 2011, we applied the following scoring:

- Family Burhinidae was scored as Category II (Garcia-del-Rey & Rodriguez-Lorenzo, 2011).
- Family Glareolidae was scored as Category I (Garcia-del-Rey & Rodriguez-Lorenzo, 2011).
- Family Jacanidae was scored as Category I (De La Zerda & Rosselli, 2003).
- Family Phoenicopteridae was scored as Category III (BirdLife International, 2019; Picazo Talavera, 2014; Tere & Parasharya, 2011).

For Families for which no information could be found that were potentially sensitive to collision or electrocution based on their morphology or behaviour, we assigned scores of similar related families. For instance, family Anhingidae received the same scores as Phalacrocoracidae, family Heliornithidae received the same scores as Anatidae, family Turnicidae received the same score as Phasianidae, and families Dromadidae, Ibidorhynchidae, and Rostratulidae received the same scores as Scolopacidae. Families where no information was available were included as Category 0 for both collision and electrocution.

Finally, for some families, we found that behavioural and ecological differences at the species level could severely affect the sensitivity to these threats. For instance, some species from the Phasianidae family in Asia have a high dependency on forested habitats which they rarely abandon, making them less likely to collide with powerlines when compared to European species which mostly occupy more open landscapes. Since the score for the whole family was mostly based on European and African species, we decided to downgrade species that showed a different habitat preference. Thus, species with high forest dependency belonging to families Tytonidae, Strigidae, and Phasianidae were downgraded to category I for collision and electrocution.

Conservation status (CnS), **endemism (En)**, and **annual adult survival (Su)** were calculated in the same way as for the onshore wind sensitivity index.

To standardise all metrics and make them comparable, we divided each of them by the maximum category value following recommendations from Certain et al. (2015). Sensitivity indices were calculated for each species separately for the four focal countries and consequently used to rank the most sensitive species per country.

To choose the final list of species to be included in the assessment, we ranked all species by country according to their sensitivity values for collision and electrocution. In the case of collision, we included species with a sensitivity value ≥ 0.3297, while for electrocution we included species with a value ≥ 0.251. In both cases, these values approximately correspond to the top 15% of the most sensitive species per country (see tables and in Supp. Material). We found that this threshold ensured that the most sensitive species were represented. To produce the final sensitivity scores, we normalised the values to a 0.01 to 1 scale in order to emphasise the much greater sensitivity of species in the top part of the list compared to the species at the bottom (Critchley & Jessopp, 2019a).

Species geographical distribution, Important Bird Areas, and Protected Areas were the same datasets used for the onshore wind energy sensitivity analysis.

Mapping the distribution area for priority species – STEP 2

Species geographical distribution were the same datasets used for the onshore wind energy sensitivity analysis. Following the same methodology, we first transferred the sensitivity indices values per species to their geographic distribution, making this value spatially explicit in a ~5x5 km grid cell.

Creating multispecies combination map – STEP 3

We created a multispecies combination map by overlapping all the species geographic distributions and added the sensitivity values from all the species. Thus, the final score for each cell was the result of the summed values of all the species present in that cell. We did this separately for the collision and electrocution sensitivity index; thus, two different maps were created, one for collision and one for electrocution sensitivity. To make these maps comparable with the rest of sources of information, we normalised the values from 0 to 1.

Transmission powerlines (voltages > 60 kV) affect birds mainly through collision; thus, the collision sensitivity maps could be used for this powerline type. However, distribution powerlines (voltages from ~1 kV to 60 kV) affect birds through both collision and electrocution, so the sensitivity maps for collision and electrocution needed to be combined. To do so, we overlapped both maps so that the final score of each cell was the maximum value of either sensitivity indices. In this way we ensured that the final sensitivity score for that area was calculated based on the most sensitive species present, regardless of the type of impact.

Adding other important areas for bird conservation – STEP 4

Important Bird Areas and Protected Areas were the same datasets used for the onshore wind energy sensitivity analysis. For both collision and electrocution sensitivity maps, we incorporated the IBAs and Protected Areas by giving a score of 1 to all overlapping cells with these areas, the maximum level of sensitivity.

Identifying final sensitivity categories – STEP 5

The final sensitivity maps ranged from 0 to 1. For the transmission lines, to classify the levels of sensitivity into four categories – from low to very high – we used the natural breaks algorithm implemented in ArcGIS Pro (ESRI, 2021). For the distribution lines, to do this same classification and make both maps comparable, we used the same breakdown values.

Solar Photovoltaic (PV)

A different approach was taken when considering Solar PV. The major impact on ecosystems of this form of energy development is caused by habitat loss and degradation produced by direct land occupancy (Hernandez et al., 2014; Turney & Fthenakis, 2011). A limited number of studies have reported the impact of bird collision for certain geographic areas, mainly from the USA (Smallwood, 2022), but the impacts are still largely unknown (Harrison et al., 2017; Walston et al., 2016). Therefore, creating indices reflecting species-specific sensitivity was not possible. We considered that the presence of this type of infrastructure would result in habitat loss and/or degradation for all species present in that area equally. Although it is true that some species can coexist with solar PV installations, we have applied a precautionary approach.

The methodology for creating this assessment followed that used for onshore wind energy, with the exception of the inclusion of the species indices. The information for land cover data, protected areas, and IBAs was the same as previously used. To create the final sensitivity maps, we combined these datasets by retaining the maximum value from all overlapping cells. In this way, cells catalogued as IBAs and Protected Areas automatically received a value of 1 (maximum level of sensitivity), while all other cells will vary between 0 and 1 depending on their percentage of natural habitat cover. To produce the sensitivity categories, we used Natural breaks classification.

Wind Farm Offshore

The methodology for offshore wind sensitivity mapping followed a similar structure to that of onshore wind energy. First, to determine the list of species that will be included in the analysis per country, we overlapped the distribution range maps (BirdLife International & The Handbook of the Birds of the World, 2019) for all seabird species within the respective exclusive economic zone (EEZ) for each country. All species catalogued as seabirds by BirdLife International were included in the analysis regardless of being considered coastal or pelagic. The final list of species per country can be found in the Supplementary Material.

Calculating species sensitivity – STEP 1

We used a modified version of the sensitivity index developed by Certain et al. 2015 for sensitivity mapping in relation to offshore energy. This methodology has been used in similar exercises for Ireland (Critchley & Jessopp, 2019b) and Scotland (Searle et al., 2019). In turn, this index is a renewed version of one created by Garthe & Hüppop, 2004 who pioneered this field of work. The main innovation of this methodology is the differentiation between primary and aggravation factors. Primary factors are species characteristics that directly control the vulnerability, while aggravation factors are those that can increase a vulnerability that already exists (Certain et al., 2015). These differences between factors are therefore incorporated in the mathematical formulation of the indices. Although we mostly based our work on this methodology, we incorporated concepts, information and methods from other works like Bradbury et al. (2014), Furness et al. (2013), and Kelsey et al. (2018). Moreover, most of the information for scoring the different parameters by species came from Bradbury et al. (2014), Certain et al. (2015), Critchley & Jessopp (2019a), Furness et al. (2013), Kelsey et al. (2018) and, Robinson Willmott et al. (2013). When we could not find information from these sources, we conducted a literature review to extract the necessary information. If no information was available to estimate a metric value for a given species, we used data from similar species. Finally, when several sources disagreed, we used the most recent values. Information about parameter values and sources of information can be found in the Supplementary Material.

As with onshore wind energy development, collision and displacement are two of the main impacts described for offshore wind energy (Furness et al., 2013; Garthe & Hüppop, 2004). Collision has been mostly related to flight characteristics of the species, while displacement has been traditionally linked to habitat flexibility and disturbance metrics.

Two different sensitivity indices were created:

Offshore Wind Collision

$$Sensitivity\ Index = (A1 \times A2)^{\left(1-\left(\frac{(A3+A4)}{2}\right)/\left(\left(\frac{(A3+A4)}{2}\right)+0.5\right)\right)} \times (CnS)^{((1-Su)/(Su+0.5)}$$

Where there are three primary factors: A1 = % of time flying at blade height, A2 = % of time spent flying, and CnS = conservation status, and three aggravation factors: A3 = nocturnal flight activity, A4 = flight manoeuvrability, and Su = annual adult survival.

A detailed explanation of the different metrics employed is as follows:

Percentage of time flying at blade height (A1). This parameter is directly related to the species flight height, and it is one of the main factors influencing collision. The height range selected to represent the blade height was between 20-150 meters.

We assigned values from 1 to 5 where:

- 1 = 0 – 5%
- 2 = > 5 – 10%
- 3 = > 10 – 15%
- 4 = > 15 – 20%
- 5 = > 20 – 100%

Percentage of time spent flying (A2). Percentage of time in flight during a complete day (24h; day and night). Robinson Willmott et al. (2013) and Kelsey et al. (2018) did not include this specific parameter, but instead they calculated diurnal flight activity and nocturnal flight activity separately. To use these sources, we calculated the average of the nocturnal and diurnal flying activity. We assigned values from 1 to 5 where:

- 1 = 0 – 20%
- 2 = > 20 – 40%
- 3 = > 40 – 60%
- 4 = > 60 – 80%
- 5 = > 80 – 100%

Nocturnal flight activity (A3). Percentage of time in flight during night. We assigned values from 1 to 5 where:

- 1 = 0 – 20%
- 2 = > 20 – 40%
- 3 = > 40 – 60%
- 4 = > 60 – 80%
- 5 = > 80 – 100%

Flight manoeuvrability (A4). Aerial agility of species and hence their potential to micro-avoid collision with wind turbines at sea. We assigned values from 1 to 5 where:

- 1 (very high manoeuvrability) to 5 (very low manoeuvrability)

Conservation status (CnS) was the same parameter used in the onshore sensitivity assessment. Most previous studies have included information about population and conservation status at the national or regional level (e.g., Bradbury et al., 2014; Kelsey et al., 2018). The lack of this information for our study area, obliged us to employ a simplified version of this score.

- 1 = Least Concern (LC)
- 2 = Near threatened (NT)

- 3 = Vulnerable (VU)
- 4 = Endangered (EN)
- 5 = Critically Endangered (CR)

Annual adult survival (Su) was the same parameter considered in the onshore sensitivity assessment. However, in this case we followed the classification proposed by Critchley & Jessopp (2019a), specifically for seabirds.

- 1 = < 0.75
- 2 = > 0.75 – 0.8
- 3 = > 0.8 – 0.85
- 4 = > 0.85 – 0.9
- 5 = > 0.9

Offshore Wind Displacement

$$Sensitivity\ Index = ((B1 + B2)/2)^{(1-B3)/(B3+0.5)} \times (CnS)^{((1-Su)/(Su+0.5)}$$

Where there are three primary factors: B1 = disturbance by vessels & helicopters, B2 = disturbance by structures, and CnS = conservation status, and two aggravation factors: B3 = habitat flexibility, and Su = annual adult survival.

A detailed explanation of the different metrics employed is as follows:

Disturbance by vessels & helicopters (B1). This parameter measures the escape response produced by vessel and helicopter traffic.

- From 1 (low disturbance response) to 5 (high disturbance response)

Some authors do not distinguish between disturbance produced by fix ed structures and marine traffic. However, since marine traffic (i.e., vessels and helicopters) is expected to increase during construction and operation of offshore wind farms, we included them separately. For some species we did not find information about both disturbance types, but only for fixed structures; on those occasions, we scored both parameters equally.

Disturbance by structures (B2). Macro-avoidance behaviour from fixed structures on the sea (i.e., offshore wind farms) and possible displacement from areas under the influence of these structures.

- From 1 (low disturbance response) to 5 (high disturbance response)

Habitat flexibility (B3). Ability of the species to feed on a variety of food sources and/or forage within multiple habitat types, or if, on the contrary, the species is restricted in their diet and/or forages in very particular habitats.

- From 1 (high habitat flexibility) to 5 (low habitat flexibility)

Conservation status (CnS) and **annual adult survival (Su)** were the same parameters calculated for the offshore wind collision sensitivity index.

To standardise all metrics and make them comparable, we divided each on them by the maximum category value following recommendations from Certain et al. (2015). Sensitivity indices were calculated for each species separately for the three focal countries with EEZs (India, Thailand and Vietnam).

Mapping the distribution area for priority species – STEP 2

For species geographical distributions, we used distribution range maps (BirdLife International & The Handbook of the Birds of the World, 2019). Following the same methodology we used for onshore wind energy, we first transferred the sensitivity indices values per species to their geographic distribution, making this value spatially explicit in a ~5x5 km grid cell.

Creating multispecies combination map – STEP 3

We overlapped all the species geographic distributions and added the sensitivity values from all the species. Thus, the final score for each cell was the result of the summed values of all the species present in that cell. We did this separately for the collision and displacement sensitivity index; thus, two different maps were created, one for collision and one for displacement.

To make these maps comparable with the rest of sources of information, we normalised the values from 0 to 1. We then overlapped both maps so that the final score of each cell was the maximum value of either sensitivity indices. In this way, we ensured that the final sensitivity score for an area was calculated based on the most sensitive species present, regardless of the type of impact.

Adding other important areas for bird conservation – STEP 4

Seabird Colonies

Most seabirds show wide home ranges during most of their annual cycle; however, during the breeding period they are central-place foragers constrained to the areas around their breeding grounds (Schreiber & Burger, 2002). The high use of these areas during this critical period makes them highly sensitive to the presence of anthropogenic impacts. Thus, identifying areas of high use around colonies can help us to identify sensitive areas for offshore wind energy development.

In recent years, different approaches have been developed to delineate important areas for seabirds. The "foraging radius approach" is one of these and uses information about foraging ecology to predict foraging areas around breeding colonies (BirdLife International, 2010; Soanes et al., 2016). In this method, one or more foraging radii are drawn around a breeding colony based on the distance travelled by breeding birds. It can be applied to any central-place forager and requires little a-priori data on at-sea distribution (BirdLife International, 2010; Grecian et al., 2012).

To delineate these areas, we first compiled a database of seabird colonies in the region. Through an exhaustive literature review and expert consultation, we georeferenced all the seabird colonies known within the exclusive economic zones (EEZs) of the focal countries. We then reviewed available information on foraging distance parameters, and we prioritised the "mean maximum distance" defined as "the maximum range reported in each study averaged across studies" (BirdLife International, 2010; Thaxter et al., 2012). For some species, we could only find information from one study, thus the value used was the maximum range reported in that study. If no information was available for a given species, we used data from the closest related species.

In the foraging radius approach, foraging habitat preferences are often used to refine areas around colonies (Soanes et al., 2016). However, due to the lack of information about habitat use from most of our focal species, we simplified the methodology and created a circular buffer around each colony with the mean maximum distance as the radius. When colonies were multi-species, we used the radius of the species with the largest mean maximum distance. Finally, for more pelagic species, the maximum foraging ranges were extraordinarily large (hundreds to thousands of kilometres). Some authors have stated that site-based conservation actions are not suitable for highly pelagic species (Oppel et al., 2018). Moreover, the foraging radius approach is thought to be more suitable/accurate for less pelagic species (BirdLife

International, 2010). Following these recommendations, we eliminated from this part of the analysis those species belonging to the families Sulidae and Phaethontidae.

Ocean Habitats

The analysis also contains information on the distribution of marine habitats that are of special importance for marine organisms and ecosystems. Three habitat types were considered.

- *Mangroves*. This dataset was created mostly from satellite imagery and shows the global distribution of mangroves. It was produced as a joint initiative of several international organizations (Spalding et al., 2010).
- *Coral reefs*. This dataset shows the global distribution of coral reefs in tropical and subtropical regions. It is the most comprehensive global dataset of warm-water coral reefs to date (UNEP-WCMC et al., 2021).
- *Seagrasses*. This global dataset of seagrass distribution was created from multiple sources (in 128 countries and territories), including maps (of varying scales), expert interpolation and point-based samples (UNEP-WCMC & FT Short, 2021).

This information is curated by UNEP-WCMC and available through the Ocean Data Viewer on their website (https://data.unep-wcmc.org/).

Overlapping cells with any of these three habitats were given the maximum sensitivity value.

Marine Protected Areas

We used the World Database of Protected Areas (WDPA) from the Protected Planet website (www.protectedplanet.net). This database is updated regularly by governments and curated by UNEP-WCMC and includes the most up-to-date information on protected areas. For India we used the 2019 version since some updates on the latest versions were in progress and the dataset was not available. The latest version from 2022 was used for the remaining countries. All protected areas classified as coastal or marine were included, regardless of their IUCN management category. Cells overlapping with these areas automatically received the maximum level of sensitivity.

Important Bird and Biodiversity Areas (IBAs)

Important Bird and Biodiversity Areas (IBAs) are a global dataset of areas of greatest significance for the conservation of the world's birds. They cover about 6.7% of terrestrial area, 1.6% of marine area and 3.1% of the total surface area of the Earth (Donald et al., 2019). This dataset is curated by BirdLife International and available through their website (http://datazone.birdlife.org/site). All countries included the most up-to-date version of this data from 2022 (Birdlife International, 2022). We included all IBAs catalogued as marine by BirdLife International plus those coastal IBAs which had ≥5% overlap with the oceans following the classification applied in the Sustainable Development Goals (Goal 14.5 - Indicator 14.5.1) (United Nations Environment Programme, 2021). A buffer of ~5 km was applied to all IBA polygons to ensure that coastal grid cells were properly included. Cells overlapping with a marine or coastal IBA automatically received the maximum level of sensitivity.

Identifying final sensitivity categories – STEP 5

The final sensitivity maps ranged from 0 to 1 and to classify the levels of sensitivity into four categories – from low to very high – we used the natural breaks algorithm implemented in ArcGIS Pro (ESRI, 2021).

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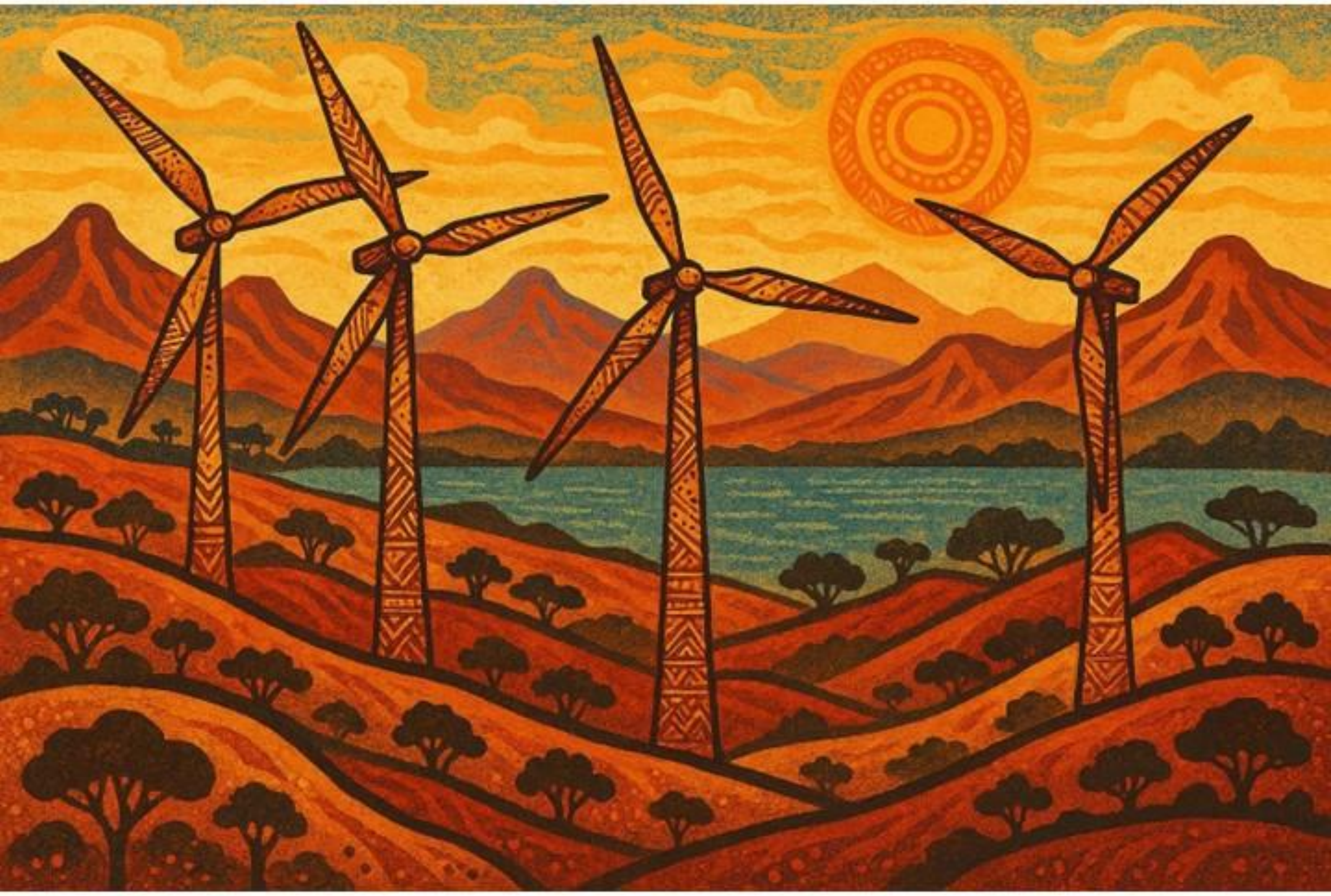
AVISTEP

The Avian Sensitivity Tool for Energy Planning

Appendix II – Kenya

November 2025



BirdLife INTERNATIONAL

NatureKenya The East Africa Natural History Society

KFW DEG Impulse

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Wind Farm Onshore

Calculating species sensitivity – STEP 1

The respective national species lists to be assessed were created in agreement with BirdLife International, and bird experts from Nature Kenya, a BirdLife International partner. The sensitivity index was calculated for each regularly occurring bird species, excluding flightless, vagrant, rare sightings, and restricted seabirds. For Kenya, we calculated the sensitivity index for 990 bird species.

$$Sensitivity\ Index = \left(Co + \left(\frac{Di}{5}\right)\right) \times (CnS)^{\left(1-\left(\frac{Su+En}{2}\right)/\left(\left(\frac{Su+En}{2}\right)+0.5\right)\right)}$$

Collision (Co): To develop a metric that could identify the sensitivity of different taxonomic groups, we used a study by Thaxter et al. (2017). In this study, the authors analysed the ecological traits and phylogenetic characteristics that make different taxonomic groups more sensitive to collision. They assigned a collision probability to most land-bird species worldwide through a modelling approach. Based on the author's recommendations, we summarised this value at the family level based on global number of species (average value). After that, we categorised this value in four categories (ranging from 1 and 4). These categories were calculated following a natural break classification algorithm, the corresponding values for each category were: 1($x < 0.028$); 2 ($0.028 < x < 0.043$); 3 ($0.043 < x < 0.059$); 4 ($x > 0.059$).

Displacement (Di): To classify the displacement, we referred to Hötker (2017), who reviewed all the evidence from scientific sources and 148 grey literature reports on displacement in birds to produce a metric for European birds. The paper reported the number of times a negative effect (e.g. displacement reported to reduce species abundance) or a positive effect or no effect had been found per species and, for those groups with enough samples, the statistical significance of this difference (binomial test). To produce a relevant metric, we assigned the following values to each species: 1 = Displacement never reported; 2 = Displacement reported in at least one study; 3 = Displacement more often reported, but differences not statistically significant; 4 = Displacement more often reported and differences statistically significant. The whole family received the value of the highest-scoring species included in that family. This precautionary approach was taken to ensure that phylogenetically closer species, which are more similar and have not been directly studied, could also be evaluated. To complement the assessment regarding bird families different from Europe, a systematic review looking for articles published about bird displacement was conducted on Web of Science using the terms: ((TS=("wind*farm*" OR "onshore" OR "offshore" OR "wind*turbine*")) AND TS=("birds" OR "avian")) AND TS=("displacement" OR "avoidance" OR "space*use*") from 2000 to 2024. In total, 24 families had displacement evidence at different levels. Accipitridae, Muscicapidae, Scolopacidae, Anatidae, and Charadriidae were the families with the highest displacement category. The Supplementary Material contains bird families with their respective displacement assessments.

Conservation Status (CnS) was assigned at the species level using the IUCN Red List categories (2021) as follows: 5 = Critically Endangered (CR); 4 = Endangered (EN); 3 = Vulnerable (VU); 2 = Near Threatened (NT); 1 = Least Concern (LC) or Data Deficient (DD).

Annual adult survival (Su). We employed annual adult survival calculated for all bird species to include a metric that could capture life history factors (Bird et al., 2020). To transform these values into categories from 1 to 5, we used a natural breaks classification algorithm implemented in the RStudio package classes (Bivand, 2022). The corresponding values for each category were: 1 ($x < 0.466$); 2 ($0.466 \leq x < 0.559$); 3 ($0.559 \leq x < 0.655$); 4 ($0.655 \leq x < 0.775$); 5 ($x > 0.911$).

Endemism (En): We consider the level of endemism for each species as the percentage of the global distribution area inside each country's territory. To calculate this parameter, we used the distribution range maps (BirdLife International & The Handbook of the Birds of the World, 2019) and the global database of

political boundaries GADM (Global Administrative Areas, 2021) in ArcGIS Pro (ESRI, 2023). To transform these values into categories from 1 to 5, we used the following conversion criteria: 1 = 0-20%, 2 = >20-40%, 3 = >40-60%, 4 = >60-80%, 5 = >80-100%.

To combine the five parameters above in the formula, balancing their contribution to the sensitivity index, we standardized all values from 0 to 1 by dividing each parameter by its maximum value, following recommendations from Certain et al. (2015).

To choose the final list of species to be included in the assessment, we ranked all species by country according to their sensitivity values. To avoid that considering several species with a lower index could add up to a greater sensitivity than a few species with high sensitivity, we decided to work with only those species with a sensitivity index of ≥ 0.321 (See "AVISTEP_Kenya_Onshore.xlsx" in Supplementary Material), corresponding to the top ~20% of all species per country. This threshold ensured that the most sensitive species were represented. Additionally, conducting workshop with bird experts, we assessed the list, uplisting or downlisting species, if necessary, according to their relevance to the national context for bird conservation. For Kenya, we included 161 species as priority species regarding the wind farms onshore impacts. To produce the final sensitivity scores, we normalised the values to a 0.01 to 1 scale in order to emphasise the much greater sensitivity of species in the top part of the list compared to the species at the bottom (Critchley & Jessopp, 2019).

The Supplementary Material contains 161 priority species with their respective information for different parameters.

Mapping the distribution area for priority species – STEP 2

We used the area of habitat (AOH) maps created for most bird species worldwide in 100x100m grid cells as resolution. The AOH maps represent the utilized habitats within a species' range and can be considered an intermediate step between the Extent of Occurrence (EOO) and Area of Occupancy (AOO). These maps were created using a modelling approach based on remotely sensed land cover data translated to species' habitat preferences according to the IUCN Red List Assessments (Lumbierres et al., 2022) and known maximum and minimum elevation. The AOH maps were created using binary information representing presence and absence, and only based on breeding, non-breeding, and resident distribution (more details in https://github.com/BirdLifeInternational/code_for_AOH). A raster layer for each species was created, representing the species occurrence probability described by the proportion of area of suitable habitat in each grid cell. More specifically, since our assessment was in a 5x5 km grid cell resolution, we transformed the original AOH maps to our resolution, calculating the total percentage of AOH present in each cell. We also used occurrence points to refine the likelihood of occurring in each grid cell for each species from different sources: 1) Local bird experts compiled observational records for their respective countries from a range of sources (i.e., published, and unpublished literature, survey and project data, and a range of other sources) and 2) eBIRD data. To guarantee the accuracy of the data, we only included recent observations (2013 to 2024) that came from eBIRD's protocol, whether stationary or travelling. The maximum distance travelled was set to 7 km to ensure that all records were contained within the final ~ 5x5 km cells.

Due to the scarcity of observational data for Kenya, we assume the species has a very high probability of occurring in a grid cell if it has at least one occurrence of evidence spatially overlapping it. In these cases, we upgraded the cell value to the maximum value (=1), regardless of the amount of habitat available in the AOH surface.

For 16 species without AoH maps (species with just passage area inside the country) but still regularly occurring, we used the BirdLife range maps instead. We rasterised the polygons into a 5x5 km grid resolution. Due to the uncertainty about the occurrence of species in the ranges in their broad scale, we weighted all grid cells equally = 0.5, representing the 50% change to have or not the species occurring there. We also upgraded the grid cell to a maximum value when a survey point overlaps the raster surface.

We adapted the Bradbury et al. (2014) formula to weight the raster for each species by its respective sensitivity index and amount of habitat in each grid cell. The final species sensitivity value (SI) was assigned for each grid cell following the formula below:

$$Species\ Sensitivity = \ln(species\ occurence\ probability\ in\ the\ grid\ cell + 1) * SI$$

Species occurrence certainty

To provide information about the species' presence likelihood, we created a metric combining the amount of AOH and the confirmed presence of the species in each grid cell. This categorical parameter has values ranging from 1 to 4 and reflects the evidence of the presence of the species in that grid cell. The correspondence of the categories follows:

Low occurrence certainty. The percentage of AOH is < 50%, and the occurrence is not confirmed by on-the-ground surveys (1).

Medium occurrence certainty. The percentage of AOH is > 50%, and the occurrence is not confirmed by on-the-ground surveys (2).

High occurrence certainty. The percentage of AOH is < 50%, and the occurrence is confirmed by on-the-ground surveys (3).

Very high occurrence certainty. The percentage of AOH is> 50%, and the occurrence is confirmed by on-the-ground surveys (4).

For those distribution maps based just on the BirdLife range maps, we created a comparable classification based on the information available for those species. On these occasions, we gave the range area a generic value of 1 (low occurrence certainty) and a value of 3 (high occurrence certainty) to those grid cells where surveys confirmed the species' presence.

Creating multispecies combination map – STEP 3

We created a multispecies combination map by summing up all species-specific sensitivity maps. For Kenya, we combined 161 priority species' rasters. Thus, the final score for each grid cell is the result of the summed values of all the species present in that cell. The bird sensitivity map captures the cumulative impact over the range of species present in each area. To make these maps comparable with the rest of the sources of information, we normalised the values from 0 to 1.

$$\sum_{species}^{n} \ln(species\ occurence\ probability\ in\ the\ grid\ cell + 1) * SI$$

** Distribution lines considered maps from Collision and Electrocution, combining them and conserving the maximum value in each grid cell. That means if a grid cell has a value of 1 for electrocution but 0.5 for collision, the final grid cell value is 1.

Adding other important areas for bird conservation – STEP 4

Land Cover/Land Use

To limit the impact of renewable energy, it is important to target development away from natural habitats and towards areas with low ecological value, such as those already highly modified by human activity (Kiesecker et al., 2019). For this purpose, we used land cover data to identify human-altered areas with lower ecological value. Specifically, we used the Copernicus global land-cover and the discrete land cover classification, which includes 23 classes at a ~100 m spatial resolution (Buchhorn et al., 2020). We chose to use this dataset for its high accuracy (average ~80%) and its suitability for conservation (Jung et al., 2020). First, we reclassified all land cover classes to have a value of 1 except for cropland and urban/built up areas which received a value of 0. We then calculated the percentage of natural areas present in each 5x5 km cell following a similar procedure as for distribution areas. In our scoring, cells with a higher percentage of natural areas will result in a higher sensitivity score. We combined the resulting land cover proxy map with the species cumulative map (step 3) using a Multicriteria Analysis (MCA) (Adem Esmail & Geneletti, 2018), weighting land cover proxy and species sensitivity according to bird expert opinion. So, land cover was weighted as 0.2 (contributing with 20% for the final layer) and priority species sensitivity as 0.8 (contributing with 80% for the final layer). This final outcome was then normalised between zero and 1.

Important Bird and Biodiveristy Areas (IBAs)

Important Bird and Biodiversity Areas (IBAs) are a global dataset of areas of greatest significance for the conservation of the world's birds. This dataset is curated by BirdLife International and available through website (https://datazone.birdlife.org/country/factsheet/kenya). The most up-to-date version of this data was used (BirdLife International, 2024a). In some instances, proposed IBAs and areas not identified as IBAs but nonetheless known to be of global significance for at-risk bird species were also included. Cells overlapping with these areas received the maximum value of sensitivity.

Protected Areas

We used the World Database on Protected Areas (WDPA) from the Protected Planet website (www.protectedplanet.net). This database is updated by governments and curated by the UN Environment Programme World Conservation Monitoring Centre (UNEP-WCMC) and includes the most up-to-date information on protected areas. We used the latest version from 2024. All protected areas were included for Kenya, regardless of their IUCN management category. As with IBAs, cells overlapping with these areas automatically received the maximum level of sensitivity.

Identifying final sensitivity categories – STEP 5

We categorised geographical sensitivity by applying the Jenk's Natural Breaks algorithm (Natural breaks function, ArcGIS Pro (ESRI, 2023)) to identify four categories, which we interpret as Low, Medium, High, and Very High bird sensitivity. Natural Breaks minimize the squared deviations of a group's means and are a standard method for splitting spatial datasets. This produced a final bird sensitivity map in a format that provides meaningful visualization and is easier to interpret for a range of stakeholders in decision-making processes.

Power Line – High voltage

Calculating species sensitivity – STEP 1

The sensitivity index was calculated for each regularly occurring bird species, excluding flightless, vagrant, rare sightings, and restricted seabirds. For Kenya, we calculated the sensitivity index for 990 bird species.

$$Sensitivity\ Index = (PwCo) \times (CnS)^{\left(1-\left(\frac{(Su+En)}{2}\right)/\left(\left(\frac{(Su+En)}{2}\right)+0.5\right)\right)}$$

Collision with energy cables (PwCo). Bird collisions occur during flight when birds fail to see the overhead wires. They represent a significant source of anthropogenic bird mortality (Loss et al., 2014) and are responsible for the decline of different populations (Biasotto & Kindel, 2018). Bird-related taxa typically show similar levels of sensitivity to collisions since they have a strong phylogenetic signal (Prinsen et al., 2011).

To assess the species' sensitivity to overhead collision, we used three main published reviews from Africa and Eurasia (Haas et al., 2003; Martín Martín et al., 2019; Prinsen et al., 2011). These reviews provide a classification at the family level of the main avifauna affected by collision. Four broad categories were used to measure sensitivity: **Category I** = casualties reported, but no apparent threat to the bird population. **Category II** = regionally or locally high casualties, but with no significant impact on the overall species population. **Category III** = casualties are a major mortality factor, threatening a species with extinction, regionally or at a larger scale. To complement the assessment regarding global bird families, a systematic review looking for articles published about bird collisions with power lines was conducted on Web of Science. Slight differences were found in the classification for certain families, so we included each family in the following subcategories: **6** (III) = casualties are a major mortality factor, threatening a species with extinction, regionally or at a larger scale. **5** (between category II and III). **4** (II) regionally or locally high casualties, but with no significant impact on the overall species population. **3** (between category II and I). **2** (I) casualties reported, but no apparent threat to the bird population. **1** No casualties reported or likely. The Supplementary Material contains bird families with their respective assessments.

Conservation status (CnS), endemism (En), and annual adult survival (Su) were calculated in the same way as for the onshore wind sensitivity index.

To combine the parameters in the formula and balance their contribution to the sensitivity index, we standardized all values from 0 to 1 by dividing each parameter by its maximum value, following recommendations from Certain et al. (2015).

To choose the final list of species to be included in the assessment, we ranked all species by country according to their sensitivity values. To avoid that considering several species with a lower index could add up to a greater sensitivity than a few species with high sensitivity, we decided to work with only those species with a sensitivity index of ≥ 0.244 (see "AVISTEP_Kenya_PW_Collision.xlsx" in Supplementary Material), corresponding to the top ~20% of all species per country. This threshold ensured that the most sensitive species were represented. Additionally, conducting workshop with local bird experts, we assessed the list, uplisting or downlisting species, if necessary, according to their relevance to the national context for bird conservation. For Kenya, we included 152 species as priority species regarding the collision with power lines. To produce the final sensitivity scores, we normalised the values to a 0.01 to 1 scale in order to emphasise the much greater sensitivity of species in the top part of the list compared to the species at the bottom (Critchley & Jessopp, 2019).

The Supplementary Material contains 152 priority species with their respective information for different parameters.

Mapping the distribution area for priority species – STEP 2

We used the area of habitat (AOH) maps created for most bird species worldwide in 100x100m grid cells as resolution. The AOH maps represent the utilized habitats within a species' range and can be considered an intermediate step between the Extent of Occurrence (EOO) and Area of Occupancy (AOO). These maps were created using a modelling approach based on remotely sensed land cover data translated to species' habitat preferences according to the IUCN Red List Assessments (Lumbierres et al., 2022) and known maximum and minimum elevation. The AOH maps were created using binary information representing presence and absence, and only based on breeding, non-breeding, and resident distribution (more details in https://github.com/BirdLifeInternational/code_for_AOH). A raster layer for each species was created, representing the species occurrence probability described by the proportion of area of suitable habitat in each grid cell. More specifically, since our assessment was in a 5x5 km grid cell resolution, we transformed the original AOH maps to our resolution, calculating the total percentage of AOH present in each cell. We also used occurrence points to refine the likelihood of occurring in each grid cell for each species from different sources: 1) Local bird experts compiled observational records for their respective countries from a range of sources (i.e., published, and unpublished literature, survey and project data, and a range of other sources) and 2) eBIRD data (https://ebird.org). To download and curate the datasets, we used the RStudio package *auk* (Strimas-Mackey et al., 2018). To guarantee the accuracy of the data, we only included recent observations (2013 to 2024) that came from eBIRD's protocol, whether stationary or travelling. The maximum distance travelled was set to 7 km to ensure that all records were contained within the final ~ 5x5 km cells.

Due to the scarcity of observational data for Kenya, we assume the species has a very high probability of occurring in a grid cell if it has at least one occurrence of evidence spatially overlapping it. In these cases, we upgraded the cell value to the maximum value (=1), regardless of the amount of habitat available in the AOH surface.

For 14 species without AoH maps (species with just passage area inside the country) but still regularly occurring, we used the BirdLife range maps instead. We rasterised the polygons in a 5x5 km grid resolution. Due to the uncertainty about the occurrence of species in the ranges in their broad scale, we weighted all grid cells equally = 0.5, representing the 50% change to have or not the species occurring there. We also upgraded the grid cell to a maximum value when a survey point overlaps the raster surface.

We adapted the Bradbury et al. (2014) formula to weight the raster for each species by its respective sensitivity index and amount of habitat in each grid cell. The final species sensitivity value (SI) was assigned for each grid cell following the formula below:

$$Species\ Sensitivity = \ln(species\ occurence\ probability\ in\ the\ grid\ cell + 1) * SI$$

Species occurrence certainty

To provide information about the species' presence likelihood, we created a metric combining the amount of AOH and the confirmed presence of the species in each grid cell. This categorical parameter has values ranging from 1 to 4 and reflects the evidence of the presence of the species in that grid cell. The correspondence of the categories follows:

Low occurrence certainty. The percentage of AOH is < 50%, and the occurrence is not confirmed by on-the-ground surveys (1).

Medium occurrence certainty. The percentage of AOH is > 50%, and the occurrence is not confirmed by on-the-ground surveys (2).

High occurrence certainty. The percentage of AOH is < 50%, and the occurrence is confirmed by on-the-ground surveys (3).

Very high occurrence certainty. The percentage of AOH is> 50%, and the occurrence is confirmed by on-the-ground surveys (4).

For those distribution maps based just on the BirdLife range maps, we created a comparable classification based on the information available for those species. On these occasions, we gave the range area a generic value of 1 (low occurrence certainty) and a value of 3 (high occurrence certainty) to those grid cells where surveys confirmed the species' presence.

Creating multispecies combination map – STEP 3

We created a multispecies combination map by summing up all species-specific sensitivity maps. For Kenya, we combined 152 priority species' rasters. Thus, the final score for each grid cell is the result of the summed values of all the species present in that cell. The bird sensitivity map captures the cumulative impact over the range of species present in each area. To make these maps comparable with the rest of the sources of information, we normalised the values from 0 to 1.

$$\sum_{species}^{n} \ln{(species\ occurence\ probability + 1)} * SI$$

Adding other important areas for bird conservation – STEP 4

Land Cover Land Use

To limit the impact of renewable energy, it is important to target development away from natural habitats and towards areas with low ecological value, such as those already highly modified by human activity (Kiesecker et al., 2019). For this purpose, we used land cover data to identify human-altered areas with lower ecological value. Specifically, we used the Copernicus global land-cover and the discrete land cover classification, which includes 23 classes at a ~100 m spatial resolution (Buchhorn et al., 2020). We chose to use this dataset for its high accuracy (average ~80%) and its suitability for conservation (Jung et al., 2020). First, we reclassified all land cover classes to have a value of 1 except for cropland and urban/built up areas which received a value of 0. We then calculated the percentage of natural areas present in each 5x5 km cell following a similar procedure as for distribution areas. In our scoring, cells with a higher percentage of natural areas will result in a higher sensitivity score. We combined the resulting land cover proxy map with the species cumulative map (step 3) using a Multicriteria Analysis (MCA) (Adem Esmail & Geneletti, 2018), weighting land cover proxy and species sensitivity according to bird expert opinion. So, land cover was weighted as 0.2 (contributing with 20% for the final layer) and priority species sensitivity as 0.8 (contributing with 80% for the final layer. This final outcome was then normalised between zero and 1.

Important Bird and Biodiversity Areas (IBAs)

Important Bird and Biodiversity Areas (IBAs) are a global dataset of areas of greatest significance for the conservation of the world's birds. This dataset is curated by BirdLife International and available through website (https://datazone.birdlife.org/country/factsheet/kenya). The most up-to-date version of this data was used (BirdLife International, 2024a). In some instances, proposed IBAs and areas not identified as IBAs but nonetheless known to be of global significance for at-risk bird species were also included. Cells overlapping with these areas received the maximum value of sensitivity.

Protected Areas

We used the World Database on Protected Areas (WDPA) from the Protected Planet website (www.protectedplanet.net). This database is updated by governments and curated by the UN Environment Programme World Conservation Monitoring Centre (UNEP-WCMC) and includes the most up-to-date information on protected areas. We used the latest version from 2024. All protected areas were included for Kenya, regardless of their IUCN management category. As with IBAs, cells overlapping with these areas automatically received the maximum level of sensitivity.

Identifying final sensitivity categories – STEP 5

We categorised geographical sensitivity by applying the Jenk's Natural Breaks algorithm (Natural breaks function, ArcGIS Pro (ESRI, 2023)) to identify four categories, which we interpret as Low, Medium, High, and Very High bird sensitivity. Natural Breaks minimize the squared deviations of a group's means and are a standard method for splitting spatial datasets. This produced a final bird sensitivity map in a format that provides meaningful visualization and is easier to interpret for a range of stakeholders in decision-making processes.

Power Line – Medium and Low voltage

Calculating species sensitivity – STEP 1

Distribution lines impact birds mainly through collision with overhead cables and electrocution on energy pylons. Therefore, in addition to considering the species most sensitive to collision using the formula mentioned for the High-voltage lines (PwCo), a specific formula for calculating and identifying species sensitive to electrocution was also applied separately:

$$Sensitivity\ Index = (PwElec) \times (CnS)^{\left(1-\left(\frac{(Su+En)}{2}\right)/\left(\left(\frac{(Su+En)}{2}\right)+0.5\right)\right)}$$

To assess the species' sensitivity to electrocution, we used three main published reviews from Africa and Eurasia (Haas et al., 2003; Martín Martín et al., 2019; Prinsen et al., 2011). These reviews provide a classification at the family level of the main avifauna affected by electrical shock. Four broad categories were used to measure sensitivity: **Category I** = casualties reported, but no apparent threat to the bird population. **Category II** = regionally or locally high casualties, but with no significant impact on the overall species population. **Category III** = casualties are a major mortality factor, threatening a species with extinction, regionally or at a larger scale. To complement the assessment regarding global bird families, a systematic review looking for articles published about bird electrocutions with power lines was conducted on Web of Science. Slight differences were found in the classification for certain families, so we included each family in the following subcategories: **6** (III) = casualties are a major mortality factor, threatening a species with extinction, regionally or at a larger scale. **5** (between category II and III). **4** (II) regionally or locally high casualties, but with no significant impact on the overall species population. **3** (between category II and I). **2** (I) casualties reported, but no apparent threat to the bird population. **1** No casualties reported or likely. The Supplementary Material contains bird families with their respective assessments.

Conservation status (CnS), endemism (En), and annual adult survival (Su) were calculated in the same way as for the onshore wind sensitivity index.

To combine the parameters above in the formula and balance their contribution to the sensitivity index, we standardized all values from 0 to 1 by dividing each parameter by its maximum value, following recommendations from Certain et al. (2015).

To choose the final list of species to be included in the assessment, we ranked all species by country according to their sensitivity values. To avoid that considering several species with a lower index could add up to a greater sensitivity than a few species with high sensitivity, we decided to work with only those species with a sensitivity index of ≥ 0.17 (see "AVISTEP_Kenya_PW_Electrocution.xlsx" in Supplementary Material), corresponding to the top ~20% of all species per country. This threshold ensured that the most sensitive species were represented. Additionally, conducting workshop with local bird experts, we assessed the list, uplisting or downlisting species, if necessary, according to their relevance to the national context for bird conservation. For Kenya, we included 149 species as priority species regarding the electrocution with power lines. To produce the final sensitivity scores, we normalised the values to a 0.01 to 1 scale in order to emphasise the much greater sensitivity of species in the top part of the list compared to the species at the bottom (Critchley & Jessopp, 2019).

The Supplementary Material contains 149 priority species with their respective information for different parameters.

Mapping the distribution area for priority species – STEP 2

We used the area of habitat (AOH) maps created for most bird species worldwide in 100x100m grid cells as resolution. The AOH maps represent the utilized habitats within a species' range and can be considered an intermediate step between the Extent of Occurrence (EOO) and Area of Occupancy (AOO). These maps were created using a modelling approach based on remotely sensed land cover data translated to species' habitat preferences according to the IUCN Red List Assessments (Lumbierres et al., 2022) and known maximum and minimum elevation. The AOH maps were created using binary information representing presence and absence, and only based on breeding, non-breeding, and resident distribution (more details in https://github.com/BirdLifeInternational/code_for_AOH). A raster layer for each species was created, representing the species occurrence probability described by the proportion of area of suitable habitat in each grid cell. More specifically, since our assessment was in a 5x5 km grid cell resolution, we transformed the original AOH maps to our resolution, calculating the total percentage of AOH present in each cell. We also used occurrence points to refine the likelihood of occurring in each grid cell for each species from different sources: 1) Local bird experts compiled observational records for their respective countries from a range of sources (i.e., published, and unpublished literature, survey and project data, and a range of other sources) and 2) eBIRD data (https://ebird.org). To download and curate the datasets, we used the RStudio package auk (Strimas-Mackey et al., 2018). To guarantee the accuracy of the data, we only included recent observations (2013 to 2024) that came from eBIRD's protocol, whether stationary or travelling. The maximum distance travelled was set to 7 km to ensure that all records were contained within the final ~ 5x5 km cells. Due to the scarcity of observational data for Kenya, we assume the species has a very high probability of occurring in a grid cell if it has at least one occurrence of evidence spatially overlapping it. In these cases, we upgraded the cell value to the maximum value (=1), regardless of the amount of habitat available in the AOH surface.

For 6 species without AoH maps (species with just passage area inside the country) but still regularly occurring, we used the BirdLife range maps instead. We rasterised the polygons in a 5x5 km grid resolution. Due to the uncertainty about the occurrence of species in the ranges in their broad scale, we weighted all grid cells equally = 0.5, representing the 50% change to have or not the species occurring there. We also upgraded the grid cell to a maximum value when a survey point overlaps the raster surface. We adapted the Bradbury et al. (2014) formula to weight the raster for each species by its respective sensitivity index and amount of habitat in each grid cell. The final species sensitivity value (SI) was assigned for each grid cell following the formula below:

$$Species\ Sensitivity = \ln(species\ occurence\ probability\ in\ the\ grid\ cell + 1) * SI$$

Species occurrence certainty

To provide information about the species' presence likelihood, we created a metric combining the amount of AOH and the confirmed presence of the species in each grid cell. This categorical parameter has values ranging from 1 to 4 and reflects the evidence of the presence of the species in that grid cell. The correspondence of the categories follows:

Low occurrence certainty. The percentage of AOH is < 50%, and the occurrence is not confirmed by on-the-ground surveys (1).

Medium occurrence certainty. The percentage of AOH is > 50%, and the occurrence is not confirmed by on-the-ground surveys (2).

High occurrence certainty. The percentage of AOH is < 50%, and the occurrence is confirmed by on-the-ground surveys (3).

Very high occurrence certainty. The percentage of AOH is> 50%, and the occurrence is confirmed by on-the-ground surveys (4).

For those distribution maps based just on the BirdLife range maps, we created a comparable classification based on the information available for those species. On these occasions, we gave the range area a generic value of 1 (low occurrence certainty) and a value of 3 (high occurrence certainty) to those grid cells where surveys confirmed the species' presence.

Creating multispecies combination map – STEP 3

We created a multispecies combination map by summing up all species-specific sensitivity maps. We create one map specific for collision (combining 152 species) and another for electrocution (combining 149 species). Thus, the final score for each grid cell is the result of the summed values of all the species present in that cell. The bird sensitivity map captures the cumulative impact over the range of species present in each area. To make these maps comparable with the rest of the sources of information, we normalised the values from 0 to 1.

$$\sum_{species}^{n} \ln\left(species\ occurence\ probability + 1\right) * SI$$

** Distribution lines considered maps from Collision and Electrocution, combining them and conserving the maximum value in each grid cell. That means if a grid cell has a value of 1 for electrocution but 0.5 for collision, the final grid cell value is 1.

Adding other important areas for bird conservation – STEP 4

Land Cover Land Use

To limit the impact of renewable energy, it is important to target development away from natural habitats and towards areas with low ecological value, such as those already highly modified by human activity (Kiesecker et al., 2019). For this purpose, we used land cover data to identify human-altered areas with lower ecological value. Specifically, we used the Copernicus global land-cover and the discrete land cover classification, which includes 23 classes at a ~100 m spatial resolution (Buchhorn et al., 2020). We chose to use this dataset for its high accuracy (average ~80%) and its suitability for conservation (Jung et al., 2020). First, we reclassified all land cover classes to have a value of 1 except for cropland and urban/built up areas which received a value of 0. We then calculated the percentage of natural areas present in each 5x5 km cell following a similar procedure as for distribution areas. In our scoring, cells with a higher percentage of natural areas will result in a higher sensitivity score. We combined the resulting land cover proxy map with the species cumulative map (step 3) using a Multicriteria Analysis (MCA) (Adem Esmail & Geneletti, 2018), weighting land cover proxy and species sensitivity according to bird expert opinion. So, land cover was weighted as 0.2 (contributing with 20% for the final layer) and priority species sensitivity (the maps merging collision and electrocution) as 0.8 (contributing with 80% for the final layer. This final outcome was then normalised between zero and 1.

Important Bird and Biodiversity Areas (IBAs)

Important Bird and Biodiversity Areas (IBAs) are a global dataset of areas of greatest significance for the conservation of the world's birds. This dataset is curated by BirdLife International and available through website (https://datazone.birdlife.org/country/factsheet/kenya). The most up-to-date version of this data was used (BirdLife International, 2024a). In some instances, proposed IBAs and areas not identified as IBAs but nonetheless known to be of global significance for at-risk bird species were also included. Cells overlapping with these areas received the maximum value of sensitivity.

Protected Areas

We used the World Database on Protected Areas (WDPA) from the Protected Planet website (www.protectedplanet.net). This database is updated by governments and curated by the UN Environment Programme World Conservation Monitoring Centre (UNEP-WCMC) and includes the most up-to-date information on protected areas. We used the latest version from 2024. All protected areas were included for Kenya, regardless of their IUCN management category. As with IBAs, cells overlapping with these areas automatically received the maximum level of sensitivity.

Identifying final sensitivity categories – STEP 5

We categorised geographical sensitivity by applying the Jenk's Natural Breaks algorithm (Natural breaks function, ArcGIS Pro (ESRI, 2023)) to identify four categories, which we interpret as Low, Medium, High, and Very High bird sensitivity. Natural Breaks minimize the squared deviations of a group's means and are a standard method for splitting spatial datasets. This produced a final bird sensitivity map in a format that provides meaningful visualization and is easier to interpret for a range of stakeholders in decision-making processes.

Solar Photovoltaic (PV)

Calculating Sensitivity for all species occurring in the country – STEP 1

The species-specific sensitivity based on different impacts created for the other types of energy developments does not apply to the context of solar photovoltaic energy. We have used a precautionary approach, considering that the presence of solar photovoltaics would result in habitat loss and/or degradation for all species that occur in the area, although some species can indeed coexist with solar PV installations.

We considered a list of all species occurring in the country, individually weighted by their respective Conservation Status (CnS - primary factor) and Endemicity (En - aggravating factor). For Kenya, we worked with 990 species in total.

Conservation Status (CnS): We used the IUCN Red List categories from 2021 as follows: 5 = Critically Endangered (CR); 4 = Endangered (EN); 3 = Vulnerable (VU); 2 = Near Threatened (NT); 1 = Least Concern (LC) or Data Deficient (DD).

Endemism (En): We calculated the percentage of the global distribution area inside each country's territory. To calculate this parameter, we used the distribution range maps (BirdLife International & The Handbook of the Birds of the World, 2019) and the global database of political boundaries GADM (Global Administrative Areas, 2021) in ArcGIS Pro (ESRI, 2023). To transform these values into categories from 1 to 5, we used the following conversion criteria: 1 = 0-20%, 2 = > 20-40%, 3 = > 40-60%, 4 = > 60-80%, 5 = > 80-100%. To standardise all metrics and make them comparable, we divided each by the maximum category value following recommendations from Certain et al. (2015).

$$Species\ sensitivity = (CnS)^{\left(1-(En)/((En)+0.5)\right)}$$

Mapping the species distribution according to the Sensitivity – STEP 2

We used the BirdLife range maps to create a raster layer for the 990 species with a 5x5 km grid cell resolution. The respective species sensitivity value weighted each raster surface.

Creating a species richness map – STEP 3

To create a surface representing the cumulative sensitivity (hereinafter bird richness). we summed all the raster in the same grid cell following the formula

$$Species\ sensitivity = \sum_{species}^{n} (CnS)^{\left(1-(En)/((En)+0.5)\right)}$$

Creating a layer with potential wilderness areas and adding important areas for bird conservation – STEP 4

To identify zones where the development of solar farms may negatively impact biodiversity, we combined the bird richness surface with a human footprint surface (used as a proxy to infer wilderness). Accordingly, areas far from the site with high value for the human footprint index (population density, built infrastructure such as roads, railways, factories, and night-time lights) would be less exposed to disturbance (Ascensão et al., 2023) and, therefore, consist of more relevant areas for bird conservation. We used HFI second generation of information with 300 m2 as resolution from https://wcshumanfootprint.org/ (data-access 31/10/2023).

The bird richness surface was combined with the human footprint surface, both calculated in 5x5 km using Multicriteria Analysis. The human footprint surface was weighted as 0.4 (contributing with 40% for the final layer) and the bird richness sensitivity as 0.6 (contributing with 60% for the final layer). This final outcome was then normalised between zero and 1.

The information for protected areas and IBAs was the same as previously used. To create the final sensitivity maps, we combined these datasets by retaining the maximum value from all overlapping cells. In this way, cells designated as IBAs and protected areas automatically received the maximum level of sensitivity (1), while all other cells will vary between 0 and 1 depending on their percentage on the trade-off between bird richness and human footprint layer.

Identifying final sensitivity categories – STEP 5

We categorized sensitivity by applying Jenk's Natural Breaks algorithm to identify four categories, which we interpret as Low, Moderate, High, and Very High bird sensitivity. This produced a final and continuous bird sensitivity map in a format that is easier to understand and could be used by a range of stakeholders in decision-making processes.

Offshore Wind

Delineate Area of Interest (AOI) – STEP 1

The first step in our offshore sensitivity analysis was delineating our Area of Interest (AOI). The offshore limits of the analysis (AOI) were set to the extent of the Exclusive Economic Zone (EEZ) in Kenya. This is done to facilitate incorporating the sensitivity map into future discussions about marine spatial planning and management of activities in the EEZ.

Identifying Species for Analysis – STEP 2

Collating the seabird species list for the AOI of a region is a process that we validate with local partners and experts where available. The flow chart below shows the range of sources we consider before a species is ultimately included or excluded.

For Kenya, all available range maps for species overlapping with the EEZ were considered. A literature review was carried out along with a review of available observation records (for example, eBird) to determine any additional species to be considered. Some birds listed as seabirds can exhibit both marine and onshore activity in their ranges (for example, species such as Cormorants, Terns and Grebes). For these groups, their distribution was checked within the AOI. In total, 38 species were identified for the offshore sensitivity analysis in Kenya.

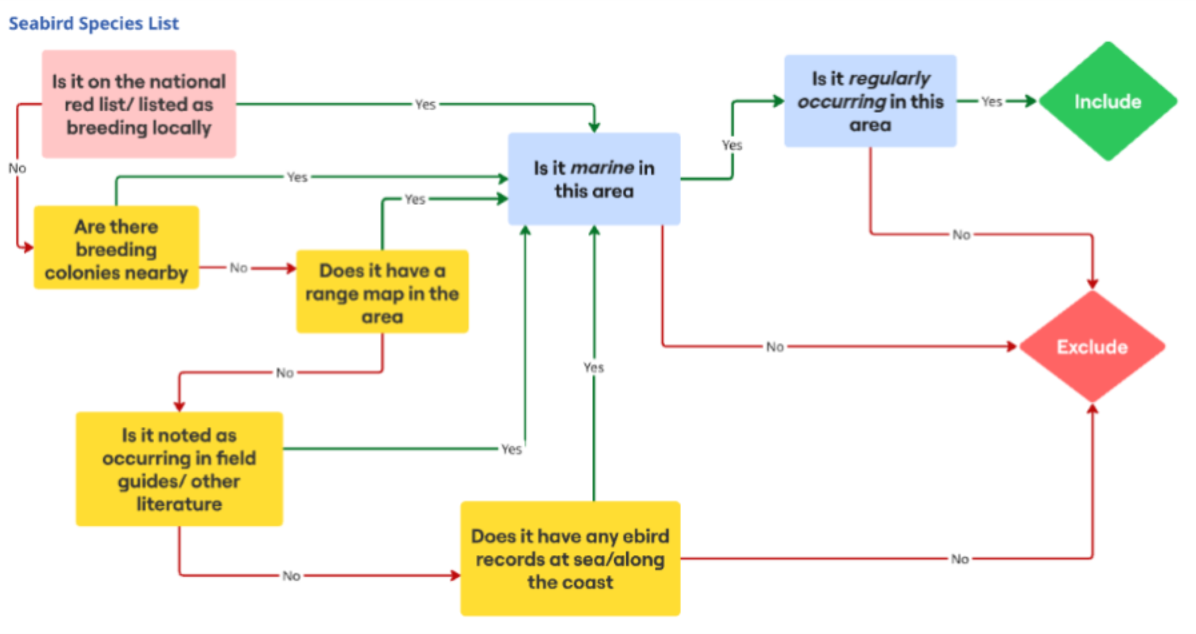

Figure 1: Flowchart of the decision-making process for seabird species selection in AVISTEP offshore analysis. The process starts with key sources (in red), additional corroborating sources are in yellow, country-specific distribution requirements are in blue. The process ends with a species being included or excluded from the species list.

Calculating Sensitivity for all Selected Species– STEP 3

Following the identification of species for analysis, sensitivity was calculated for all listed species. We estimated the individual risk factors collision (Co) and displacement (Di), along with the conservation status (CnS). Using a trait-based approach, estimated a level of sensitivity for individual species. As with previous projects, collision and displacement were calculated separately for offshore (Furness et al., 2013). These were combined with a conservation score (CnS) to create an overall sensitivity to both collision and displacement.

For each risk, all contributing factors were divided into primary and aggravating factors. Primary factors are inherently risky behaviour, traits, or demographic parameters that directly contribute to a species' sensitivity. Aggravating factors exacerbate an existing risk but have no inherent risk of their own (Certain et al., 2015).

We used a modified version of the sensitivity index developed by Certain et al. (2015) for sensitivity mapping in relation to offshore energy. This methodology has been used in similar exercises for Ireland (Critchley & Jessopp, 2019b) and Scotland (Searle et al., 2019). In turn, this index is a renewed version of one created by Garthe & Hüppop (2004) who pioneered this field of work. The main innovation of this methodology is the differentiation between primary and aggravation factors. Primary factors are species characteristics that directly control the vulnerability, while aggravation factors are those that can increase a vulnerability that already exists (Certain et al., 2015). These differences between factors are therefore incorporated in the mathematical formulation of the indices. Although we mostly based our work on this methodology, we incorporated concepts, information and methods from other works like Bradbury et al. (2014), Furness et al. (2013), and Kelsey et al. (2018). Moreover, most of the information for scoring the different parameters by species came from Bradbury et al. (2014), Certain et al. (2015), Critchley & Jessopp (2019), Furness et al. (2013), Kelsey et al. (2018) and, Robinson Willmott et al. (2013). When we could not find information from these sources, we conducted a literature review to extract the necessary information. If no information was available to estimate a metric value for a given species, we used data from similar species. Finally, when several sources disagreed, we used the most recent values. Information about parameter values and sources of information can be found in “AVISTEP_Kenya_Offshore.xlsx” in Supplementary Material.

Two different sensitivity indices were created:

$$Collision\ sensitivity\ index = (A1 \times A2)^{\left(1-\left(\frac{A3+A4}{2}\right)/\left(\frac{A3+A4}{2}\right)+0.5\right)} \times CnS^{\ (1-Su)/(Su+0.5)}$$

Percentage of time flying at blade height (A1). This parameter is directly related to the species flight height, and it is one of the main factors influencing collision. The height range selected to represent the blade height was 20-150 meters. We assigned values from 1 to 5 where:

- 1 = 0 – 5%
- 2 = > 5 – 10%
- 3 = > 10 – 15%
- 4 = > 15 – 20%
- 5 = > 20 – 100%

Percentage of time spent flying (A2). Percentage of time in flight during a complete day (24h; day and night). Robinson Willmott et al., 2013 and Kelsey et al., 2018 did not include this specific parameter, but instead they calculated diurnal flight activity and nocturnal flight activity separately. To use these sources, we calculated the average of the nocturnal and diurnal flying activity. We assigned values from 1 to 5 where:

- 1 = 0 – 20%
- 2 = > 20 – 40%
- 3 = > 40 – 60%
- 4 = > 60 – 80%
- 5 = > 80 – 100%

Flight Manoeuvrability (FM) & Nocturnal Activity (Noc): Once flying at a dangerous height, there are factors that may impact an individual’s ability to avoid possible collision. Based on previous work on collision sensitivity factors (Garthe & Hüppop, 2004; Furness et al. 2013; Bradbury et al. 2014; Certain et al. 2015), flight manoeuvrability and nocturnal activity were identified as aggravating factors to exposure. The application of aggravating factors assumes that, when all other factors are equal, a less manoeuvrable species or a species that is very active at night may be more vulnerable to collision than other species. When combining factors, how they interact determines how best to include them. As nocturnal activity and flight manoeuvrability are considered to aggravate the risk of flying near offshore turbines, we consider them as interactive with the exposure risk values for each species. Therefore, this factor is multiplied by the risk of exposure to rotor blades. Since we have no evidence that manoeuvrability and nocturnal activity interact dependently in relation to collision risk, we are using the average between the two to create an aggravated risk score to apply to exposure (Certain et al. 2015).

Nocturnal flight activity (A3). Percentage of time in flight during night. We assigned values from 1 to 5 where:

- 1 = 0 – 20%
- 2 = > 20 – 40%
- 3 = > 40 – 60%
- 4 = > 60 – 80%
- 5 = > 80 – 100%

Flight manoeuvrability (A4). Aerial agility of species and hence their potential to micro-avoid collision with wind turbines at sea. We assigned values from 1 to 5 where:

- 1 (very high manoeuvrability) to 5 (very low manoeuvrability)

Where there are three primary factors: B1 = disturbance by vessels & helicopters, B2 = disturbance by structures, and CnS = conservation status, and two aggravation factors: B3 = habitat flexibility, and Su = annual adult survival.

$$Displacement\ sensitivity\ index = \big((B1 + B2)/2\big)(1 - (B3)/(B3) + 0.5) \times CnS(1 - Su)/(Su + 0.5)$$

A detailed explanation of the different metrics employed is as follows:

Disturbance by vessels & helicopters (B1). This parameter measures the escape response produced by vessel and helicopter traffic.

- From 1 (low disturbance response) to 5 (high disturbance response)

Some authors do not distinguish between disturbance produced by fixed structures and marine traffic. However, since marine traffic (i.e., vessels and helicopters) is expected to increase during construction and operation of offshore wind farms, we included them separately. For some species we did not find information about both disturbance types, but only for fixed structures; on those occasions, we scored both parameters equally.

Disturbance by structures (B2). Macro-avoidance behaviour from fixed structures on the sea (i.e., offshore wind farms) and possible displacement from areas under the influence of these structures.

- From 1 (low disturbance response) to 5 (high disturbance response)

Habitat flexibility (B3). Ability of the species to feed on a variety of food sources and/or forage within multiple habitat types, or if, on the contrary, the species is restricted in their diet and/or forages in very particular habitats.

- From 1 (high habitat flexibility) to 5 (low habitat flexibility)

To standardise all metrics and make them comparable, we divided each on them by the maximum category value following recommendations from Certain et al. (2015).

Mapping distribution for all seabird species– STEP 4

Species distribution

For species geographical distributions, we used distribution range maps (BirdLife International and The Handbook of the Birds of the World, 2019). Some species did not have the marine part of their range included in the range map within the study area. For these species, we searched the literature for the offshore foraging range for the species and used this to buffer from the terrestrial part of the species range. Range maps for all species were rasterised at a 5x5km grid for breeding and non-breeding/passage ranges separately, included resident species in both the breeding and non-breeding maps.

Sensitivity map calculation

Following the same methodology we used for onshore wind energy, we first transferred the sensitivity indices values per species to their geographic distribution, making this value spatially explicit in a ~ 5x5 km grid cell. We then overlapped all the species geographic distributions by season and added the sensitivity values from all the species. Thus, the final score for each cell was the result of the summed values of all the species present in that cell. We did this separately for the breeding and non-breeding seasons for both collision and displacement sensitivity index; thus, four different maps were created, two for collision and two for displacement. To make these maps comparable with the rest of sources of information, we divided the values by the maximum so that the highest values from each map was 1. We then overlapped the four maps so that the final score of each cell was the maximum value. In this way, we ensured that the final sensitivity score for an area was calculated based on the most sensitive species present, regardless of the type of impact.

Additional Areas

Important Bird and Biodiversity Areas (IBAs)

Important Bird and Biodiversity Areas (IBAs) are a global dataset of areas of greatest significance for the conservation of the world's birds. They cover about 6.7% of terrestrial area, 1.6% of marine area and 3.1% of the total surface area of the Earth (Donald et al., 2019). This dataset is curated by BirdLife International and available through their website (http://datazone.birdlife.org/site). All countries included the most up-to-date version of this data from 2024 (Birdlife International, 2024b). We included all IBAs catalogued as marine by BirdLife International plus those coastal IBAs which had ≥5% overlap with the oceans following the classification applied in the Sustainable Development Goals (Goal 14.5 - Indicator 14.5.1) (United Nations Environment Programme, 2021). Cells overlapping with a marine or coastal IBA received the maximum level of sensitivity. A buffer of ~5 km was applied at value of 0.5 to all IBA polygons with breeding seabirds as trigger species to account for foraging movements out of the IBA boundaries. For Kenya, these sites were: Kisite island - Marine, Kiunga Marine National Reserve, Sabaki River Mouth, Mida Creek, and Whale Island and the Malindi - Watamu coast.

Categorising Sensitivity– STEP 6

Once the preliminary species sensitivity result layer was produced, we categorised the results our categories of low-high sensitivity. This was a classed raster with all cells values from 1 to 4 (green to red). This was done using Jenks natural breaks in the *ClassInt* package in R (Bivand et al., 2022).

Adding Other Important Areas for Birds and Conservation– STEP 7

As with onshore, areas that were determined to be key concern for bird conservation were included in our analysis for offshore wind. Shapefiles of selected areas were overlapped with the project fishnet and overlapping cells were rasterised to match the 5x5 km project grid. For Kenya these areas included oceanic habitats, Marine Protected Areas (MPAs) and Important Bird and Biodiversity Areas (IBAs) These areas were added at the highest sensitivity. As these were added after the classification of sensitivity using Jenks natural breaks, they did not impact on the relative sensitivity of nearby cells.

Ocean habitats

The analysis also contains information on the distribution of marine habitats that are of special importance for marine organisms and ecosystems. Overlapping cells with any of these habitats were given the maximum sensitivity value. For Egypt, three habitat types were considered.

- *Mangroves*. This dataset was created mostly from satellite imagery and shows the global distribution of mangroves. It was produced as a joint initiative of several international organizations (Spalding et al., 2010).

- *Coral reefs*. This dataset shows the global distribution of coral reefs in tropical and subtropical regions. It is the most comprehensive global dataset of warm-water coral reefs to date (UNEP-WCMC et al., 2021).

- *Seagrasses*. This global dataset of seagrass distribution was created from multiple sources (in 128 countries and territories), including maps (of varying scales), expert interpolation and point-based samples (UNEP-WCMC & FT Short, 2021).

This information is curated by UNEP-WCMC and available through the Ocean Data Viewer on their website (https://data.unep-wcmc.org/).

Overlapping cells with any of these three habitats were given the maximum sensitivity value.

Marine Protected Areas

Marine protected areas are sites designated for the conservation of marine habitats, species and ecosystems. Kenya has just over 5% of its marine environment designated as MPAs (www.protectedplanet.net). These were included in our offshore sensitivity analysis at the highest level of sensitivity. We used the World Database of Protected Areas (WDPA) from the Protected Planet website (www.protectedplanet.net). This database is updated regularly by governments and curated by UNEP-WCMC and includes the most up-to-date information on protected areas. The latest version from 2024 was used for Kenya. All protected areas classified as coastal or marine were included, regardless of their IUCN management category. Cells overlapping with these areas automatically received the maximum level of sensitivity.

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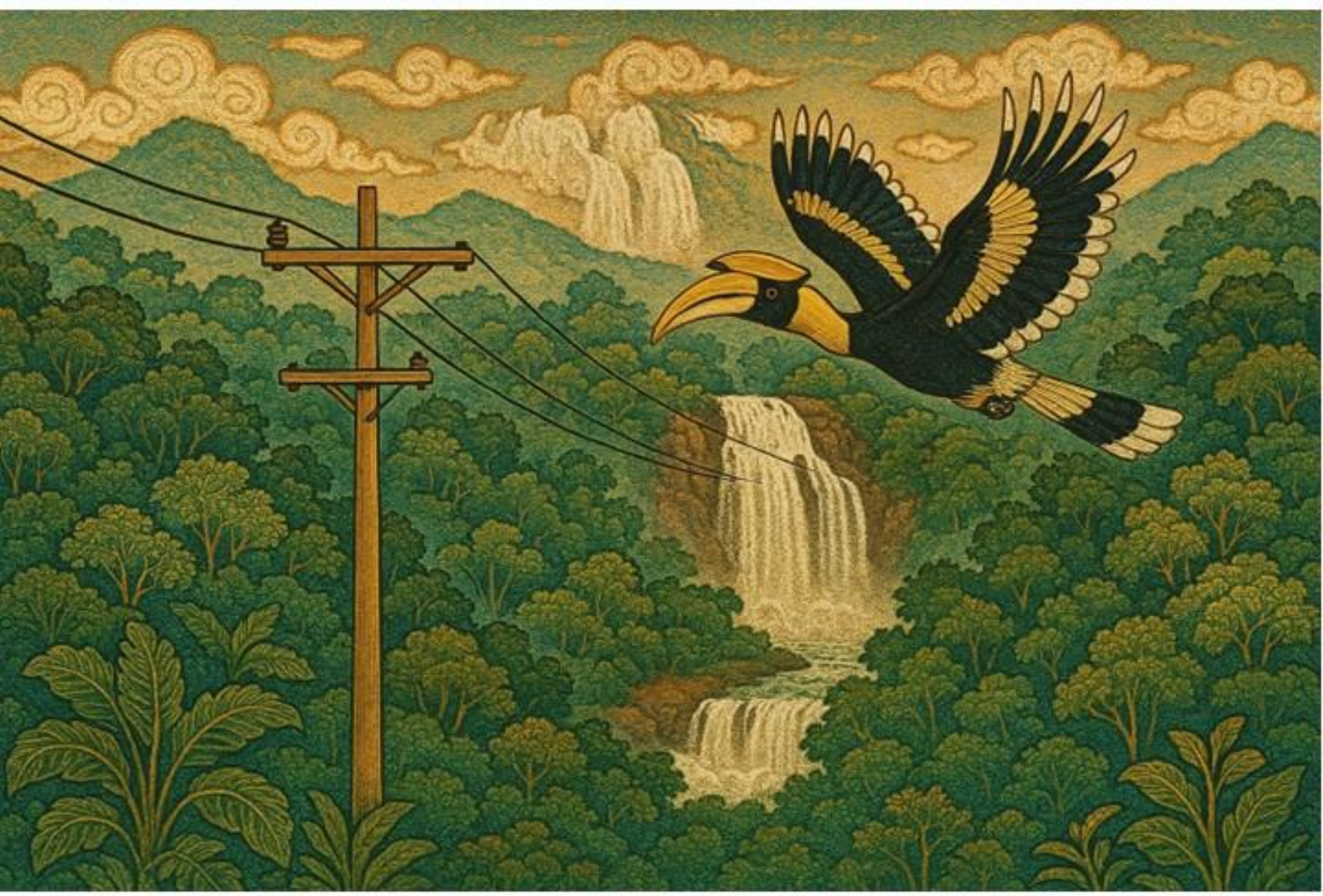
AVISTEP

The Avian Sensitivity Tool for Energy Planning

Appendix III – Lao PDR

November 2025



BirdLife INTERNATIONAL

KFW DEG Impulse

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Wind Farm Onshore

Calculating species sensitivity – STEP 1

The respective national species lists to be assessed were created in agreement with BirdLife International, and bird experts in Lao. The sensitivity index was calculated for each regularly occurring bird species, excluding flightless, vagrant, rare sightings, and restricted seabirds. For Lao, we calculated the sensitivity index for 724 bird species.

$$Sensitivity\ Index = \left(Co + \left(\frac{Di}{5}\right)\right) \times (CnS)^{\left(1-\left(\frac{(Su+En)}{2}\right)/\left(\left(\frac{(Su+En)}{2}\right)+0.5\right)\right)}$$

Collision (Co): To develop a metric that could identify the sensitivity of different taxonomic groups, we used a study by Thaxter et al. (2017). In this study, the authors analysed the ecological traits and phylogenetic characteristics that make different taxonomic groups more sensitive to collision. They assigned a collision probability to most land-bird species worldwide through a modelling approach. Based on the author's recommendations, we summarised this value at the family level based on global number of species (average value). After that, we categorised this value in four categories (ranging from 1 and 4). These categories were calculated following a natural break classification algorithm, the corresponding values for each category were: 1 ($x < 0.028$); 2 ($0.028 < x < 0.043$); 3 ($0.043 < x < 0.059$); 4 ($x > 0.059$).

Displacement (Di): To classify the displacement, we referred to Hötker (2017), who reviewed all the evidence from scientific sources and 148 grey literature reports on displacement in birds to produce a metric for European birds. The paper reported the number of times a negative effect (e.g. displacement reported to reduce species abundance) or a positive effect or no effect had been found per species and, for those groups with enough samples, the statistical significance of this difference (binomial test). To produce a relevant metric, we assigned the following values to each species: 1 = Displacement never reported; 2 = Displacement reported in at least one study; 3 = Displacement more often reported, but differences not statistically significant; 4 = Displacement more often reported and differences statistically significant. The whole family received the value of the highest-scoring species included in that family. This precautionary approach was taken to ensure that phylogenetically closer species, which are more similar and have not been directly studied, could also be evaluated. To complement the assessment regarding bird families different from Europe, a systematic review looking for articles published about bird displacement was conducted on Web of Science using the terms: ((TS=("wind*farm*" OR "onshore" OR "offshore" OR "wind*turbine*")) AND TS=("birds" OR "avian")) AND TS=("displacement" OR "avoidance" OR "space*use*") from 2000 to 2024. In total, 24 families had displacement evidence at different levels. Accipitridae, Muscicapidae, Scolopacidae, Anatidae, and Charadriidae were the families with the highest displacement category. The Supplementary Material contains bird families with their respective displacement assessments.

Conservation Status (CnS) was assigned at the species level using the IUCN Red List categories (2021) as follows: 5 = Critically Endangered (CR); 4 = Endangered (EN); 3 = Vulnerable (VU); 2 = Near Threatened (NT); 1 = Least Concern (LC) or Data Deficient (DD).

Annual adult survival (Su). We employed annual adult survival calculated for all bird species to include a metric that could capture life history factors (Bird et al., 2020). To transform these values into categories from 1 to 5, we used a natural breaks classification algorithm implemented in the RStudio package classes (Bivand et al., 2022). The corresponding values for each category were: 1 ($x < 0.466$); 2 ($0.466 \le x < 0.559$); 3 ($0.559 \le x < 0.655$); 4 ($0.655 \le x < 0.775$); 5 ($x > 0.911$).

Endemism (En): We consider the level of endemism for each species as the percentage of the global distribution area inside each country's territory. To calculate this parameter, we used the distribution range maps (BirdLife International & The Handbook of the Birds of the World, 2019) and the global database of

political boundaries GADM (Global Administrative Areas, 2021) in ArcGIS Pro (ESRI, 2023). To transform these values into categories from 1 to 5, we used the following conversion criteria: 1 = 0-20%, 2 = >20-40%, 3 = >40-60%, 4 = >60-80%, 5 = >80-100%.

To combine the five parameters above in the formula, balancing their contribution to the sensitivity index, we standardized all values from 0 to 1 by dividing each parameter by its maximum value, following recommendations from Certain et al. (2015).

To choose the final list of species to be included in the assessment, we ranked all species by country according to their sensitivity values. To avoid that considering several species with a lower index could add up to a greater sensitivity than a few species with high sensitivity, we decided to work with only those species with a sensitivity index of ≥ 0.286 (see "AVISTEP_LaoPDR_Onshore.xlsx" in Supplementary Material), corresponding to the top ~20% of all species per country. This threshold ensured that the most sensitive species were represented. Additionally, conducting workshop with bird experts, we assessed the list, uplisting or downlisting species, if necessary, according to their relevance to the national context for bird conservation. For Lao, we included 115 species as priority species regarding the wind farms onshore impacts. To produce the final sensitivity scores, we normalised the values to a 0.01 to 1 scale, emphasising the much greater sensitivity of species in the top part of the list compared to those at the bottom (Critchley & Jessopp, 2019).

The Supplementary Material contains 115 priority species with their respective information for different parameters.

Mapping the distribution area for priority species – STEP 2

We used the area of habitat (AOH) maps created for most bird species worldwide, with a resolution of 100x100 m grid cells. The AOH maps represent the utilised habitats within a species' range and can be considered an intermediate step between the Extent of Occurrence (EOO) and Area of Occupancy (AOO). These maps were created using a modelling approach based on remotely sensed land cover data, translated to species' habitat preferences according to the IUCN Red List Assessments (Lumbierres et al., 2022), and known maximum and minimum elevations. The AOH maps were created using binary information representing presence and absence, based solely on breeding, non-breeding, and resident distribution (for more details, see https://github.com/BirdLifeInternational/code_for_AOH). A raster layer for each species was created, representing the species occurrence probability described by the proportion of the area of suitable habitat in each grid cell. More specifically, since our assessment was conducted at a 5x5 km grid cell resolution, we transformed the original AOH maps to match our resolution, calculating the total percentage of AOH present in each cell. We also used occurrence points to refine the likelihood of occurring in each grid cell for each species from different sources: 1) Local bird experts compiled observational records for their respective countries from a range of sources (i.e., published and unpublished literature, survey and project data, and a range of other sources) and 2) eBIRD data (https://ebird.org). To ensure the accuracy of the data, we have only included recent observations (2012-2022) from eBIRD's protocol, whether made while stationary or in transit. The maximum distance travelled was set to 7 km to ensure that all records were contained within the final ~ 5x5 km cells.

Due to the scarcity of observational data for Lao, we assume the species has a very high probability of occurring in a grid cell if it has at least one occurrence of evidence that spatially overlaps with it. In these cases, we upgraded the cell value to the maximum value (=1), regardless of the amount of habitat available in the AOH surface.

For five species without AOH maps (species with just passage area inside the country) but still regularly occurring, we used the BirdLife range maps instead (BirdLife International 2021). We rasterised the polygons in a 5x5 km grid resolution. Due to the uncertainty about the occurrence of species in the ranges on a broad scale, we weighted all grid cells equally, representing a 50% chance of the species occurring there. We also upgraded the grid cell to a maximum value when a survey point overlaps the raster surface.

We adapted the formula by Bradbury et al. (2014) to weight the raster for each species by its respective sensitivity index and the amount of habitat in each grid cell. The final species sensitivity value (SI) was assigned for each grid cell following the formula below:

$$Species\ Sensitivity = ln(species\ occurence\ probability\ in\ the\ grid\ cell + 1) * SI$$

Species occurrence certainty

To provide information about the likelihood of the species' presence, we created a metric that combines the amount of AOH and the confirmed presence of the species in each grid cell. This categorical parameter has values ranging from 1 to 4 and reflects the evidence of the species' presence in that grid cell. The correspondence of the categories follows:

Low occurrence certainty. The percentage of AOH is < 50%, and the occurrence is not confirmed by on-the-ground surveys (1).

Medium occurrence certainty. The percentage of AOH is > 50%, and the occurrence is not confirmed by on-the-ground surveys (2).

High occurrence certainty. The percentage of AOH is < 50%, and the occurrence is confirmed by on-the-ground surveys (3).

Very high occurrence certainty. The percentage of AOH is> 50%, and the occurrence is confirmed by on-the-ground surveys (4).

For those distribution maps based just on the BirdLife range maps, we created a comparable classification based on the information available for those species. On these occasions, we gave the range area a generic value of 1 (low occurrence certainty) and a value of 3 (high occurrence certainty) to those grid cells where surveys confirmed the species' presence.

Creating multispecies combination map – STEP 3

We created a multispecies combination map by summing up all species-specific sensitivity maps. For Lao, we combined 115 priority species' rasters. Thus, the final score for each grid cell is the result of the summed values of all the species present in that cell. The bird sensitivity map captures the cumulative impact over the range of species present in each area. To make these maps comparable with the rest of the sources of information, we normalised the values from 0 to 1.

$$\sum_{species}^{n} ln(species\ occurence\ probability + 1) * SI$$

Adding other important areas for bird conservation – STEP 4

Land Cover Land Use

To limit the impact of renewable energy, it is important to target development away from natural habitats and towards areas with low ecological value, such as those already highly modified by human activity (Kiesecker et al., 2019). For this purpose, we used land cover data to identify human-altered areas with lower ecological value. Specifically, we utilised the Copernicus global land-cover dataset (https://lcviewer.vito.be/2019) and the discrete land cover classification, which comprises 23 classes at a spatial resolution of ~100 m (Buchhorn et al., 2020). We chose to use this dataset due to its high accuracy (average ~80%) and suitability for conservation (Jung et al., 2020). First, we reclassified all land cover classes to have a value of 1 except for cropland and urban/built-up areas, which received a value of 0. We then calculated the percentage of natural areas present in each 5x5 km cell following a similar procedure as for distribution areas. In our scoring, cells with a higher percentage of natural areas will result in a higher sensitivity score. We combined the resulting land cover proxy map with the species cumulative map (step 3) using a Multicriteria Analysis (MCA) (Adem Esmail & Geneletti, 2018), weighting land cover proxy and species sensitivity according to bird expert opinion. Therefore, land cover was weighted as 0.2 (contributing 20% to the final layer) and priority species sensitivity as 0.8 (contributing 80% to the final layer). This final outcome was then normalised between zero and 1.

Important Bird and Biodiversity Areas (IBAs)

Important Bird and Biodiversity Areas (IBAs) are a global dataset of areas of greatest significance for the conservation of the world's birds. This dataset is curated by BirdLife International and available through website (https://datazone.birdlife.org/country/factsheet/Lao). The most up-to-date version of this data was used (BirdLife International, 2024). In some instances, proposed IBAs and areas not identified as IBAs but known to be of global significance for at-risk bird species were also included. Cells overlapping with these areas received the maximum value of sensitivity.

Protected Areas

We used the World Database on Protected Areas (WDPA) from the Protected Planet website (www.protectedplanet.net). This database is updated by governments and curated by the UN Environment Programme World Conservation Monitoring Centre (UNEP-WCMC) and includes the most up-to-date information on protected areas. We used the latest version from 2024. All protected areas in Lao were included, regardless of their IUCN management category. As with IBAs, cells overlapping with these areas automatically received the maximum level of sensitivity.

Identifying final sensitivity categories – STEP 5

We categorised geographical sensitivity by applying Jenk's Natural Breaks algorithm (Natural breaks function, ArcGIS Pro; ESRI, 2023) to identify four categories, which we interpret as Low, Medium, High, and Very High bird sensitivity. Natural Breaks minimise the squared deviations of a group's means and are a standard method for splitting spatial datasets. This produced a final bird sensitivity map in a format that provides meaningful visualisation and is easier to interpret for a range of stakeholders in decision-making processes.

Power Line – High voltage

Calculating species sensitivity – STEP 1

The sensitivity index was calculated for each regularly occurring bird species, excluding flightless, vagrant, rare sightings, and restricted seabirds. For Lao, we calculated the sensitivity index for 724 bird species.

$$Sensitivity\ Index = (PwCo) \times (CnS)^{\left(1-\left(\frac{(Su+En)}{2}\right)/\left(\left(\frac{(Su+En)}{2}\right)+0.5\right)\right)}$$

Collision with energy cables (PwCo). Bird collisions occur during flight when birds fail to see the overhead wires. They represent a significant source of anthropogenic bird mortality (Loss et al., 2014) and are responsible for the decline of different populations (Biasotto & Kindel, 2018). Bird-related taxa typically show similar levels of sensitivity to collisions since they have a strong phylogenetic signal (Prinsen et al., 2011).

To assess the species' sensitivity to overhead collision, we used three main published reviews from Africa and Eurasia (Haas et al., 2003; Martín Martín et al., 2019; Prinsen et al., 2011). These reviews provide a classification at the family level of the main avifauna affected by collision. Four broad categories were used to measure sensitivity: **Category I** = casualties reported, but no apparent threat to the bird population. **Category II** = regionally or locally high casualties, but with no significant impact on the overall species population. **Category III** = Casualties are a significant mortality factor, threatening a species with extinction, either regionally or on a larger scale. To complement the assessment of global bird families, a systematic review was conducted on Web of Science to identify articles published on bird collisions with power lines. Slight differences were found in the classification for certain families, so we included each family in the following subcategories: **6** (III) = casualties constitute a significant mortality factor, threatening a species with extinction, regionally or at a larger scale. **5** (between category II and III). **4** (II) regionally or locally high casualties, but with no significant impact on the overall species population. **3** (between category II and I). **2** (I) casualties reported, but no apparent threat to the bird population. **1** No casualties reported or likely. The Supplementary Material contains bird families with their respective assessments.

Conservation status (CnS), Endemism (En), and Annual adult survival (Su) were calculated in the same way as for the onshore wind sensitivity index.

To combine the parameters in the formula and balance their contribution to the sensitivity index, we standardised all values from 0 to 1 by dividing each parameter by its maximum value, following recommendations from Certain et al. (2015).

To choose the final list of species to be included in the assessment, we ranked all species by country according to their sensitivity values. To avoid that considering several species with a lower index could add up to a greater sensitivity than a few species with high sensitivity, we decided to work with only those species with a sensitivity index of ≥ 0.2981 (Supplementary Material), corresponding to the top ~20% of all species per country. This threshold ensured that the most sensitive species were represented. Additionally, by conducting a workshop with local bird experts, we assessed the list, uplisting or downlisting species as necessary, according to their relevance to the national context for bird conservation. For Lao, we included 106 species as priority species due to their collision with power lines. To produce the final sensitivity scores, we normalised the values to a 0.01 to 1 scale, emphasising the much greater sensitivity of species in the top part of the list compared to those at the bottom (Critchley & Jessopp, 2019).

The Supplementary Material contains 106 priority species with their respective information for different parameters.

Mapping the distribution area for priority species – STEP 2

We used the area of habitat (AOH) maps created for most bird species worldwide in 100x100m grid cells as resolution. The AOH maps represent the utilized habitats within a species' range and can be considered an intermediate step between the Extent of Occurrence (EOO) and Area of Occupancy (AOO). These maps were created using a modelling approach based on remotely sensed land cover data translated to species' habitat preferences according to the IUCN Red List Assessments (Lumbierres et al., 2022) and known maximum and minimum elevation. The AOH maps were created using binary information representing presence and absence, and only based on breeding, non-breeding, and resident distribution (more details in https://github.com/BirdLifeInternational/code_for_AOH). A raster layer for each species was created, representing the species occurrence probability described by the proportion of area of suitable habitat in each grid cell. More specifically, since our assessment was in a 5x5 km grid cell resolution, we transformed the original AOH maps to our resolution, calculating the total percentage of AOH present in each cell. We also used occurrence points to refine the likelihood of occurring in each grid cell for each species from different sources: 1) Local bird experts compiled observational records for their respective countries from a range of sources (i.e., published, and unpublished literature, survey and project data, and a range of other sources) and 2) eBIRD data (https://ebird.org). To guarantee the accuracy of the data, we only included recent observations (2012 to 2022) that came from eBIRD's protocol, whether stationary or travelling. The maximum distance travelled was set to 7 km to ensure that all records were contained within the final ~ 5x5 km cells.

Due to the scarcity of observational data for Lao, we assume the species has a very high probability of occurring in a grid cell if it has at least one occurrence of evidence that spatially overlaps with it. In these cases, we upgraded the cell value to the maximum value (=1), regardless of the amount of habitat available in the AOH surface.

For five species without AOH maps (species with just passage area inside the country) but still regularly occurring, we used the BirdLife range maps instead. We rasterised the polygons in a 5x5 km grid resolution. Due to the uncertainty about the occurrence of species in the ranges on a broad scale, we weighted all grid cells equally, representing a 50% chance of the species occurring there. We also upgraded the grid cell to a maximum value when a survey point overlaps the raster surface.

We adapted the formula by Bradbury et al. (2014) to weight the raster for each species by its respective sensitivity index and the amount of habitat in each grid cell. The final species sensitivity value (SI) was assigned for each grid cell following the formula below:

$$Species\ Sensitivity = ln(species\ occurence\ probability\ in\ the\ grid\ cell + 1) * SI$$

Species occurrence certainty

To provide information about the likelihood of the species' presence, we created a metric that combines the amount of AOH and the confirmed presence of the species in each grid cell. This categorical parameter has values ranging from 1 to 4 and reflects the evidence of the species' presence in that grid cell. The correspondence of the categories follows:

Low occurrence certainty. The percentage of AOH is < 50%, and the occurrence is not confirmed by on-the-ground surveys (1).

Medium occurrence certainty. The percentage of AOH is > 50%, and the occurrence is not confirmed by on-the-ground surveys (2).

High occurrence certainty. The percentage of AOH is < 50%, and the occurrence is confirmed by on-the-ground surveys (3).

Very high occurrence certainty. The percentage of AOH is> 50%, and the occurrence is confirmed by on-the-ground surveys (4).

For those distribution maps based solely on the BirdLife range maps, we created a comparable classification using the available information for those species. On these occasions, we assigned a generic value of 1 (low occurrence certainty) to the range area and a value of 3 (high occurrence certainty) to those grid cells where surveys confirmed the species' presence.

Creating a multispecies combination map – STEP 3

We created a multispecies combination map by summing the sensitivity maps for all species. For Lao, we combined the rasters of 106 priority species. Thus, the final score for each grid cell is the result of the summed values of all the species present in that cell. The bird sensitivity map captures the cumulative impact over the range of species present in each area. To make these maps comparable with the rest of the sources of information, we normalised the values from 0 to 1.

$$\sum_{species}^{n} ln(species\ occurence\ probability + 1) * SI$$

Adding other important areas for bird conservation – STEP 4

Land Cover Land Use

To mitigate the impact of renewable energy, it is crucial to focus development away from natural habitats and towards areas with low ecological value, such as those already heavily modified by human activity (Kiesecker et al., 2019). For this purpose, we used land cover data to identify human-altered areas with lower ecological value. Specifically, we used the Copernicus global land-cover (https://lcviewer.vito.be/2019) and the discrete land cover classification, which includes 23 classes at a ~100 m spatial resolution (Buchhorn et al., 2020). We chose to use this dataset due to its high accuracy (average ~80%) and suitability for conservation (Jung et al., 2020). First, we reclassified all land cover classes to have a value of 1 except for cropland and urban/built-up areas, which received a value of 0. We then calculated the percentage of natural areas present in each 5x5 km cell following a similar procedure to that for distribution areas. In our scoring, cells with a higher percentage of natural areas will result in a higher sensitivity score. We combined the resulting land cover proxy map with the species cumulative map (step 3) using a Multicriteria Analysis (MCA) (Adem Esmail & Geneletti, 2018), weighting land cover proxy and species sensitivity according to bird expert opinion. Therefore, land cover was weighted as 0.2 (contributing 20% to the final layer) and priority species sensitivity as 0.8 (contributing 80% to the final layer). This final outcome was then normalised between zero and 1.

Important Bird and Biodiversity Areas (IBAs)

Important Bird and Biodiversity Areas (IBAs) are a global dataset of areas of greatest significance for the conservation of the world's birds. This dataset is curated by BirdLife International and available through website (https://datazone.birdlife.org/country/factsheet/Lao). The most up-to-date version of this data was used (BirdLife International, 2024). In some instances, proposed IBAs and areas not identified as IBAs but nonetheless known to be of global significance for at-risk bird species were also included. Cells overlapping with these areas received the maximum value of sensitivity.

Protected Areas

We used the World Database on Protected Areas (WDPA) from the Protected Planet website (www.protectedplanet.net). This database is updated by governments and curated by the UN Environment Programme's World Conservation Monitoring Centre (UNEP-WCMC), providing the most up-to-date information on protected areas. We used the latest version from 2024. All protected areas were included for Lao, regardless of their IUCN management category. As with IBAs, cells overlapping with these areas automatically received the maximum level of sensitivity.

Identifying final sensitivity categories – STEP 5

We categorised geographical sensitivity by applying Jenk's Natural Breaks algorithm (Natural breaks function, ArcGIS Pro; ESRI, 2023) to identify four categories, which we interpret as Low, Medium, High, and Very High bird sensitivity. Natural Breaks minimise the squared deviations of a group's means and are a standard method for splitting spatial datasets. This produced a final bird sensitivity map in a format that provides meaningful visualisation and is easier to interpret for a range of stakeholders in decision-making processes.

Power Line – Medium and Low voltage

Calculating species sensitivity – STEP 1

Distribution lines primarily impact birds through collisions with overhead cables and electrocution on energy pylons and cables. Therefore, in addition to considering the species most sensitive to collision using the formula mentioned for the High-voltage lines (PwCo), a specific formula for calculating and identifying species sensitive to electrocution was also applied separately:

$$Sensitivity\ Index = (PwElec) \times (CnS)^{\left(1-\left(\frac{(Su+En)}{2}\right)/\left(\left(\frac{(Su+En)}{2}\right)+0.5\right)\right)}$$

To assess the species' sensitivity to electrocution, we used three main published reviews from Africa and Eurasia (Haas et al., 2003; Martín Martín et al., 2019; Prinsen et al., 2011). These reviews provide a classification at the family level of the main avifauna affected by electrical shock. Four broad categories were used to measure sensitivity: **Category I** = casualties reported, but no apparent threat to the bird population. **Category II** = regionally or locally high casualties, but with no significant impact on the overall species population. **Category III** = Casualties are a major mortality factor, threatening a species with extinction, either regionally or on a larger scale. To complement the assessment of global bird families, a systematic review was conducted on Web of Science to identify articles published about bird electrocutions involving power lines. Slight differences were found in the classification for certain families, so we included each family in the following subcategories: **6** (III) = casualties are a major mortality factor, threatening a species with extinction, regionally or at a larger scale. **5** (between category II and III). **4** (II) regionally or locally high casualties, but with no significant impact on the overall species population. **3** (between category II and I). **2** (I) casualties reported, but no apparent threat to the bird population. **1** No casualties reported or likely. The Supplementary Material contains bird families with their respective assessments.

Conservation status (CnS), Endemism (En), and Annual adult survival (Su) were calculated in the same way as for the onshore wind sensitivity index.

To combine the parameters above in the formula and balance their contribution to the sensitivity index, we standardised all values from 0 to 1 by dividing each parameter by its maximum value, following recommendations from Certain et al. (2015).

To choose the final list of species to be included in the assessment, we ranked all species by country according to their sensitivity values. To avoid that, considering several species with a lower index could add up to a greater sensitivity than a few species with high sensitivity, we decided to work with only those species with a sensitivity index of ≥ 0.1829 (see "AVISTEP_LaoPDR_PW_Electrocution.xlsx" in Supplementary Material), corresponding to the top ~20% of all species per country. This threshold ensured that the most sensitive species were represented. Additionally, by conducting a workshop with local bird experts, we assessed the list, uplisting or downlisting species as necessary, according to their relevance to the national context for bird conservation. For Lao, we included 108 species as priority species due to their susceptibility to electrocution from power lines. To produce the final sensitivity scores, we normalised the values to a 0.01 to 1 scale, emphasising the much greater sensitivity of species in the top part of the list compared to those at the bottom (Critchley & Jessopp, 2019).

The Supplementary Material contains 108 priority species, along with their respective information for various parameters.

Mapping the distribution area for priority species – STEP 2

We used the area of habitat (AOH) maps created for most bird species worldwide, with a resolution of 100x100m grid cells. The AOH maps represent the utilised habitats within a species' range and can be considered an intermediate step between the Extent of Occurrence (EOO) and Area of Occupancy (AOO). These maps were created using a modelling approach based on remotely sensed land cover data, translated to species' habitat preferences according to the IUCN Red List Assessments (Lumbierres et al., 2022), and known maximum and minimum elevations. The AOH maps were created using binary information representing presence and absence, based solely on breeding, non-breeding, and resident distribution (for more details, see https://github.com/BirdLifeInternational/code_for_AOH). A raster layer for each species was created, representing the species occurrence probability described by the proportion of area of suitable habitat in each grid cell. More specifically, since our assessment was conducted at a 5x5 km grid cell resolution, we transformed the original AOH maps to match our resolution, calculating the total percentage of AOH present in each cell. We also used occurrence points to refine the likelihood of occurring in each grid cell for each species from different sources: 1) Local bird experts compiled observational records for their respective countries from a range of sources (i.e., published and unpublished literature, survey and project data, and a range of other sources) and 2) eBIRD data (https://ebird.org). To ensure the accuracy of the data, we have only included recent observations (2012-2022) from eBIRD's protocol, whether made while stationary or in transit. The maximum distance travelled was set to 7 km to ensure that all records were contained within the final ~ 5x5 km cells.

Due to the scarcity of observational data for Lao, we assume the species has a very high probability of occurring in a grid cell if it has at least one occurrence of evidence that spatially overlaps with it. In these cases, we upgraded the cell value to the maximum value (=1), regardless of the amount of habitat available in the AOH surface.

For five species without AOH maps (species with just passage area inside the country) but still regularly occurring, we used the BirdLife range maps instead. We rasterised the polygons in a 5x5 km grid resolution. Due to the uncertainty about the occurrence of species in the ranges on a broad scale, we weighted all grid cells equally, representing a 50% chance of the species occurring there. We also upgraded the grid cell to a maximum value when a survey point overlaps the raster surface.

We adapted the formula by Bradbury et al. (2014) to weight the raster for each species by its respective sensitivity index and the amount of habitat in each grid cell. The final species sensitivity value (SI) was assigned for each grid cell following the formula below:

$$Species\ Sensitivity = ln(species\ occurence\ probability\ in\ the\ grid\ cell + 1) * SI$$

Species occurrence certainty

To provide information about the likelihood of the species' presence, we created a metric that combines the amount of AOH and the confirmed presence of the species in each grid cell. This categorical parameter has values ranging from 1 to 4 and reflects the evidence of the species' presence in that grid cell. The correspondence of the categories follows:

Low occurrence certainty. The percentage of AOH is < 50%, and the occurrence is not confirmed by on-the-ground surveys (1).

Medium occurrence certainty. The percentage of AOH is > 50%, and the occurrence is not confirmed by on-the-ground surveys (2).

High occurrence certainty. The percentage of AOH is < 50%, and the occurrence is confirmed by on-the-ground surveys (3).

Very high occurrence certainty. The percentage of AOH is> 50%, and the occurrence is confirmed by on-the-ground surveys (4).

For those distribution maps based solely on the BirdLife range maps, we created a comparable classification using the available information for those species. On these occasions, we assigned a generic value of 1 (low occurrence certainty) to the range area and a value of 3 (high occurrence certainty) to those grid cells where surveys confirmed the species' presence.

Creating a multispecies combination map – STEP 3

We created a multispecies combination map by summing the sensitivity maps for all species. We create one map specific to collision (combining 106 species) and another for electrocution (combining 108 species). Thus, the final score for each grid cell is the result of the summed values of all the species present in that cell. The bird sensitivity map captures the cumulative impact over the range of species present in each area. To make these maps comparable with the rest of the sources of information, we normalised the values from 0 to 1.

$$\sum_{species}^{n} ln(species\ occurence\ probability + 1) * SI$$

** Distribution lines considered maps from Collision and Electrocution, combining them and conserving the maximum value in each grid cell. That means if a grid cell has a value of 1 for electrocution but 0.5 for collision, the final grid cell value is 1.

Adding other important areas for bird conservation – STEP 4

Land Cover Land Use

To mitigate the impact of renewable energy, it is crucial to focus development away from natural habitats and towards areas with low ecological value, such as those already heavily modified by human activity (Kiesecker et al., 2019). For this purpose, we used land cover data to identify human-altered areas with lower ecological value. Specifically, we utilised the Copernicus global land-cover dataset (https://lcviewer.vito.be/2019) and the discrete land cover classification, which comprises 23 classes at a spatial resolution of ~100 m (Buchhorn et al., 2020). We chose to use this dataset due to its high accuracy (average ~80%) and suitability for conservation (Jung et al., 2020). First, we reclassified all land cover classes to have a value of 1 except for cropland and urban/built-up areas, which received a value of 0. We then calculated the percentage of natural areas present in each 5x5 km cell following a similar procedure as for distribution areas. In our scoring, cells with a higher percentage of natural areas will result in a higher sensitivity score. We combined the resulting land cover proxy map with the species cumulative map (step 3) using a Multicriteria Analysis (MCA) (Adem Esmail & Geneletti, 2018), weighting land cover proxy and species sensitivity according to bird expert opinion. So, land cover was weighted as 0.2 (contributing with 20% for the final layer) and priority species sensitivity (the maps merging collision and electrocution) as 0.8 (contributing with 80% for the final layer. This outcome was then normalised between zero and 1.

Important Bird and Biodiversity Areas (IBAs)

Important Bird and Biodiversity Areas (IBAs) are a global dataset of areas of greatest significance for the conservation of the world's birds. This dataset is curated by BirdLife International and available through website (https://datazone.birdlife.org/country/factsheet/Lao). The most up-to-date version of this data was used (BirdLife International, 2024). In some instances, proposed IBAs and areas not identified as IBAs but nonetheless known to be of global significance for at-risk bird species were also included. Cells overlapping with these areas received the maximum value of sensitivity.

Protected Areas

We used the World Database on Protected Areas (WDPA) from the Protected Planet website (www.protectedplanet.net). This database is updated by governments and curated by the UN Environment Programme's World Conservation Monitoring Centre (UNEP-WCMC), providing the most up-to-date information on protected areas. We used the latest version from 2024. All protected areas in Lao were included, regardless of their IUCN management category. As with IBAs, cells overlapping with these areas automatically received the maximum level of sensitivity.

Identifying final sensitivity categories – STEP 5

We categorised geographical sensitivity by applying Jenk's Natural Breaks algorithm (Natural breaks function, ArcGIS Pro; ESRI, 2023) to identify four categories, which we interpret as Low, Medium, High, and Very High bird sensitivity. Natural Breaks minimise the squared deviations of a group's means and are a standard method for splitting spatial datasets. This produced a final bird sensitivity map in a format that provides meaningful visualisation and is easier to interpret for a range of stakeholders in decision-making processes.

Solar Photovoltaic (PV)

Calculating Sensitivity for all species occurring in the country – STEP 1

The species-specific sensitivity based on different impacts created for the other types of energy developments does not apply to the context of solar photovoltaic energy. We have used a precautionary approach, considering that the presence of solar photovoltaics would result in habitat loss and/or degradation for all species that occur in the area, although some species can indeed coexist with solar PV installations.

We considered a list of all species occurring in the country, individually weighted by their respective Conservation Status (CnS, the primary factor) and Endemicity (En, an aggravating factor). For Lao, we worked with a total of 724 species.

Conservation Status (CnS): We used the IUCN Red List categories from 2021 as follows: 5 = Critically Endangered (CR); 4 = Endangered (EN); 3 = Vulnerable (VU); 2 = Near Threatened (NT); 1 = Least Concern (LC) or Data Deficient (DD).

Endemism (En): We calculated the percentage of the global distribution area inside each country's territory. To calculate this parameter, we utilised the distribution range maps (BirdLife International & The Handbook of the Birds of the World, 2019) and the global database of political boundaries, GADM (Global Administrative Areas, 2024), in ArcGIS Pro (ESRI, 2023). To transform these values into categories from 1 to 5, we used the following conversion criteria: 1 = 0-20%, 2 = >20-40%, 3 = >40-60%, 4 = >60-80%, 5 = >80-100%. To standardise all metrics and make them comparable, we divided each by the maximum category value following recommendations from Certain et al., 2015.

$$Species\ sensitivity = (CnS)^{\left(1-(En)/((En)+0.5)\right)}$$

Mapping the species distribution according to the Sensitivity – STEP 2

We used the BirdLife range maps to create a raster layer for the 724 species with a 5x5 km grid cell resolution. The respective species sensitivity value was weighted for each raster surface.

Creating a species richness map – STEP 3

To create a surface representing the cumulative sensitivity (hereinafter bird richness). we summed all the raster in the same grid cell following the formula

$$\sum_{species}^{n} (CnS)^{\left(1-(En)/((En)+0.5)\right)}$$

Creating a layer with potential wilderness areas and adding important areas for bird conservation – STEP 4

To identify zones where the development of solar farms may negatively impact biodiversity, we combined the bird richness surface with a human footprint surface (used as a proxy to infer wilderness). Accordingly, areas far from the site with high value for the human footprint index (population density, built infrastructure such as roads, railways, factories, and night-time lights) would be less exposed to disturbance (Ascensão et al. 2023) and, therefore, consist of more relevant areas for bird conservation. We used HFI second generation of information with 300 m^2 as resolution from https://wcshumanfootprint.org/ (data-access 31/10/2023).

The bird richness surface was combined with the human footprint surface, both calculated at a 5x5km resolution and combined using Multicriteria Analysis. The human footprint surface was weighted as 0.4 (contributing 40% to the final layer), and the bird richness sensitivity was weighted as 0.6 (contributing 60% to the final layer). This outcome was then normalised between zero and 1.

The information for protected areas and IBAs was the same as previously used. To create the final sensitivity maps, we combined these datasets by retaining the maximum value from all overlapping cells. In this way, cells designated as IBAs and protected areas automatically received the maximum level of sensitivity (1), while all other cells will vary between 0 and 1 depending on their percentage on the trade-off between bird richness and human footprint layer.

Identifying final sensitivity categories – STEP 5

We categorised sensitivity by applying Jenks' Natural Breaks algorithm to identify four categories, which we interpret as Low, Moderate, High, and Very High bird sensitivity. This produced a final and continuous bird sensitivity map in a format that is easier to understand and could be used by a range of stakeholders in decision-making processes.

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AVISTEP

The Avian Sensitivity Tool for Energy Planning

Appendix IV – Uzbekistan

November 2025

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Wind Farm Onshore

Calculating species sensitivity – STEP 1

The respective national species lists to be assessed were created in agreement with BirdLife International, and bird experts in Uzbekistan. The sensitivity index was calculated for each regularly occurring bird species, excluding flightless, vagrant, and rare sightings, as well as restricted seabirds. For Uzbekistan, we calculated the sensitivity index for 321 bird species following the formula.

$$Sensitivity\ Index = \left(Co + \left(\frac{Di}{5}\right)\right) \times (CnS)^{\left(1-\left(\frac{(Su+En)}{2}\right)/\left(\left(\frac{(Su+En)}{2}\right)+0.5\right)\right)}$$

Collision (Co): To develop a metric that could identify the sensitivity of different taxonomic groups, we used a study by Thaxter et al. (2017). In this study, the authors analysed the ecological traits and phylogenetic characteristics that make different taxonomic groups more sensitive to collision. They assigned a collision probability to most land-bird species worldwide through a modelling approach. Based on the author's recommendations, we summarised this value at the family level based on the global number of species (average value). After that, we categorised this value into four categories (ranging from 1 to 4). These categories were calculated following a natural break classification algorithm; the corresponding values for each category were: 1 ($x < 0.028$); 2 ($0.028 < x < 0.043$); 3 ($0.043 < x < 0.059$); 4 ($x > 0.059$).

Displacement (Di): To classify the displacement, we referred to Hötker (2017), who reviewed all the evidence from scientific sources and 148 grey literature reports on displacement in birds to produce a metric for European birds. The paper reported the number of times a negative effect (e.g., displacement reported to reduce species abundance) or a positive effect or no effect had been found per species, and, for those groups with sufficient samples, the statistical significance of this difference (using a binomial test). To produce a relevant metric, we assigned the following values to each species: 1 = Displacement never reported; 2 = Displacement reported in at least one study; 3 = Displacement more often reported, but with differences not statistically significant; 4 = Displacement more often reported and with statistically significant differences. The entire family received the value of the highest-scoring species within that family. This precautionary approach was taken to ensure that phylogenetically closer species, which are more similar and have not been directly studied, could also be evaluated. To complement the assessment regarding bird families different from Europe, a systematic review looking for articles published about bird displacement was conducted on Web of Science using the terms: ((TS=("wind*farm*" OR "onshore" OR "offshore" OR "wind*turbine*")) AND TS=("birds" OR "avian")) AND TS=("displacement" OR "avoidance" OR "space*use*") from 2000 to 2024. In total, 24 families had evidence of displacement at various levels. Accipitridae, Muscicapidae, Scolopacidae, Anatidae, and Charadriidae were the families with the highest displacement category. The Supplementary Material contains bird families with their respective displacement assessments.

Conservation Status (CnS) was assigned at the species level using the IUCN Red List categories (2021) as follows: 5 = Critically Endangered (CR); 4 = Endangered (EN); 3 = Vulnerable (VU); 2 = Near Threatened (NT); 1 = Least Concern (LC) or Data Deficient (DD).

Annual adult survival (Su). We employed annual adult survival calculated for all bird species to include a metric that could capture life history factors (Bird et al., 2020). To transform these values into categories from 1 to 5, we used a natural breaks classification algorithm implemented in the RStudio package classes (Bivand et al., 2022). The corresponding values for each category were: 1 ($x < 0.49$); 2 ($0.49 \le x < 0.59$); 3 ($0.59 \le x < 0.69$); 4 ($0.69 \le x < 0.80$); 5 ($x > 0.80$).

Endemism (En): We consider the level of endemism for each species as the percentage of the global distribution area inside each country's territory. To calculate this parameter, we utilized the distribution range maps (BirdLife International & The Handbook of the Birds of the World, 2021) and the global database of political boundaries, GADM (Global Administrative Areas, 2021), in ArcGIS Pro (ESRI, 2023). To transform these values into categories from 1 to 5, we used the following conversion criteria: 1 = 0-20%; 2 = >20-40%; 3 = >40-60%; 4 = >60-80%; 5 = > 80-100%.

To combine the five parameters above in the formula, balancing their contribution to the sensitivity index, we standardized all values from 0 to 1 by dividing each parameter by its maximum value, following recommendations from Certain et al. (2015).

To choose the final list of species to be included in the assessment, we ranked all species by country according to their sensitivity values. To avoid that considering several species with a lower index could add up to a greater sensitivity than a few species with high sensitivity, we decided to work with only those species with a sensitivity index of ≥ 0.313 (see "AVISTEP_Uzbekistan_Onshore.xlsx" in Supplementary Material), corresponding to the top ~20% of all species per country. This threshold ensured that the most sensitive species were represented. Additionally, we assessed the list with local bird experts, uplisting or downlisting species, if necessary, according to their relevance to the national context for bird conservation. For Uzbekistan, we included 55 species as priority species regarding the wind farms onshore impacts. To produce the final sensitivity scores, we normalised the values to a 0.01 to 1 scale, emphasizing the much greater sensitivity of species in the top part of the list compared to those at the bottom (Critchley & Jessopp, 2019).

The Supplementary Material contains 55 priority species, along with their respective information for the different parameters.

Mapping the distribution area for priority species – STEP 2

We used the area of habitat (AOH) maps created for most bird species worldwide, with a resolution of 100x100m grid cells. The AOH maps represent the utilized habitats within a species' range and can be considered an intermediate step between the Extent of Occurrence (EOO) and Area of Occupancy (AOO). These maps were created using a modelling approach based on remotely sensed land cover data, translated to species' habitat preferences according to the IUCN Red List Assessments (Lumbierres et al., 2022) and known maximum and minimum elevations. The AOH maps were created using binary information representing presence and absence, based solely on breeding, non-breeding, and resident distribution (for more details, see https://github.com/BirdLifeInternational/code_for_AOH). A raster layer was created for each species, representing the species' occurrence probability as the proportion of suitable habitat area in each grid cell. More specifically, since our assessment was conducted at a 5x5 km grid cell resolution, we transformed the original AOH maps to match our resolution, calculating the total percentage of AOH present in each cell. We also used occurrence points to refine the likelihood of occurring in each grid cell for each species from different sources: 1) Local bird experts compiled observational records for their respective countries from a range of sources (i.e., published, and unpublished literature, survey and project data, and a range of other sources) and 2) eBIRD data (https://ebird.org). To download and curate the datasets, we used the RStudio package *auk* (Strimas-Mackey et al., 2018). To ensure the accuracy of the data, we have only included recent observations (2012-2022) from eBIRD's protocol, whether made while stationary or travelling. The maximum distance travelled was set to 7 km to ensure that all records were contained within the final ~ 5x5 km cells.

Due to the scarcity of observational data for Uzbekistan, we assume the species has a very high probability of occurring in a grid cell if it has at least one occurrence of evidence that spatially overlaps with it. In these cases, we upgraded the cell value to the maximum value (1), regardless of the amount of habitat available in the AOH surface.

For a few species without AoH maps (species with just passage area inside the country) but still regularly occurring, we used the BirdLife range maps instead (BirdLife International 2021). We rasterised the polygons in a 5x5 km grid resolution. Due to the uncertainty about the occurrence of species in the ranges on a broad scale, we weighted all grid cells equally = at 0.5, representing a 50% chance of the species occurring there. We also upgraded the grid cell to a maximum value when a survey point overlaps the raster surface.

We adapted the formula by Bradbury et al. (2014) to weight the raster for each species by its respective sensitivity index and the amount of habitat in each grid cell. The final species sensitivity value (SI) was assigned for each grid cell following the formula below:

$$Species\ Sensitivity = ln(species\ occurence\ probability\ in\ the\ grid\ cell + 1) * SI$$

Species occurrence certainty

To provide information about the likelihood of the species' presence, we created a metric that combines the amount of AOH and the confirmed presence of the species in each grid cell. This categorical parameter has values ranging from 1 to 4 and reflects the evidence of the species' presence in that grid cell. The correspondence of the categories follows:

Low occurrence certainty. The percentage of AOH is < 50%, and the occurrence is not confirmed by on-the-ground surveys (1).

Medium occurrence certainty. The percentage of AOH is > 50%, and the occurrence is not confirmed by on-the-ground surveys (2).

High occurrence certainty. The percentage of AOH is < 50%, and the occurrence is confirmed by on-the-ground surveys (3).

Very high occurrence certainty. The percentage of AOH is> 50%, and the occurrence is confirmed by on-the-ground surveys (4).

For those distribution maps based solely on the BirdLife range maps, we created a comparable classification using the available information for those species. On these occasions, we assigned a generic value of 1 (low occurrence certainty) to the range area and a value of 3 (high occurrence certainty) to those grid cells where surveys confirmed the species' presence.

Creating multispecies combination map – STEP 3

We created a multispecies combination map by summing the sensitivity maps for all species. For Uzbekistan, we combined 55 priority species' rasters. Thus, the final score for each grid cell is the result of the summed values of all the species present in that cell. The bird sensitivity map captures the cumulative impact over the range of species present in each area. To make these maps comparable with the rest of the sources of information, we normalised the values from 0 to 1.

$$\sum_{species}^{n} ln(species\ occurence\ probability + 1) * SI$$

Adding other important areas for bird conservation – STEP 4

Land Cover Land Use

To mitigate the impact of renewable energy, it is crucial to focus development away from natural habitats and towards areas with low ecological value, such as those already heavily modified by human activity (Kiesecker et al., 2019). For this purpose, we used land cover data to identify human-altered areas with lower ecological value. Specifically, we utilized the Copernicus global land-cover dataset (https://lcviewer.vito.be/2019) and the discrete land cover classification, which comprises 23 classes at a spatial resolution of ~100 m (Buchhorn et al., 2020). We chose to use this dataset due to its high accuracy (average ~80%) and suitability for conservation (Jung et al., 2020).

Uzbekistan has a unique biodiversity resulting from a combination of geographic, climatic, and ecological factors that make it distinct within Central Asia and globally. Based on this, we created a different hierarchy of weights to work with the various land cover classes, assigning greater relevance to classes that are more relevant to biodiversity and have undergone less human-induced change. Thus, we applied the Analytic Hierarchy Process (AHP) to contrast different land cover, and we set the following hierarchy of weights: all types of forests – open and closed, permanent water bodies, herbaceous wetland, moss and lichen had the maximum weight (grid cell received value of 100); following by Shrubs, Herbaceous vegetation (grid cell received value of 52); Bare, desert and sparse vegetation (grid cell received value of 27); Cultivated and managed vegetation/agriculture (cropland) (grid cell received value of 14); and Urban / built up - Land covered by buildings and other man-made structures (grid cell received value of 7). We then calculated the median value for each 5x5 cell to create an index to represent a proxy to infer value for biodiversity. In our scoring, cells with a higher percentage of natural areas will result in a higher sensitivity score. We combined the resulting land cover proxy map with the species cumulative map (step 3) using a Multicriteria Analysis (MCA) (Adem Esmail & Geneletti, 2018), weighting land cover proxy and species sensitivity according to bird expert opinion. Therefore, land cover was weighted as 0.4 (contributing 40% to the final layer) and priority species sensitivity as 0.6 (contributing 60% to the final layer). This final outcome was then normalized to a value between 0 and 1.

Important Bird and Biodiversity Areas (IBAs)

Important Bird and Biodiversity Areas (IBAs) are a global dataset of areas of greatest significance for the conservation of the world's birds. This dataset is curated by BirdLife International and available through website (https://datazone.birdlife.org/country/factsheet/uzbekistan). The most up-to-date version of this data was used (BirdLife International, 2024). Cells overlapping with these areas received the maximum value of sensitivity.

Protected Areas

We used the World Database on Protected Areas (WDPA) from the Protected Planet website (www.protectedplanet.net). This database is updated by governments and curated by the UN Environment Programme's World Conservation Monitoring Centre (UNEP-WCMC), providing the most up-to-date information on protected areas. We used the latest version from 2024. All protected areas in Uzbekistan were included, regardless of their IUCN management category. As with IBAs, cells overlapping with these areas automatically received the maximum level of sensitivity.

Special areas for birds

Some areas in Uzbekistan are critically important for migratory species, such as bustards, as they provide ideal habitat conditions, migration stopover points, and breeding or wintering grounds that birds depend on (Roy et al., 2025; Kesller and Collar, 2022). Steppe and semi-desert habitats were mapped as well as specific sites important for Bustards (stopover points, wintering grounds, and main migratory flightways). As with IBAs, cells overlapping with these areas automatically received the maximum level of sensitivity.

Identifying final sensitivity categories – STEP 5

We categorised geographical sensitivity by applying the Jenk's Natural Breaks algorithm (Natural breaks function, ArcGIS Pro; ESRI, 2023) to identify four categories, which we interpret as Low, Medium, High, and Very High bird sensitivity. Natural Breaks minimize the squared deviations of a group's means and are a standard method for splitting spatial datasets. This produced a final bird sensitivity map in a format that provides meaningful visualization and is easier to interpret for a range of stakeholders in decision-making processes.

Power Line – High voltage

Calculating species sensitivity – STEP 1

The sensitivity index was calculated for each regularly occurring bird species, excluding flightless, vagrant, rare sightings, and restricted seabirds. For Uzbekistan, we calculated the sensitivity index for 321 bird species.

$$Sensitivity\ Index = (PwCo) \times (CnS)^{\left(1-\left(\frac{(Su+En)}{2}\right)/\left(\left(\frac{(Su+En)}{2}\right)+0.5\right)\right)}$$

Collision with energy cables (PwCo). Bird collisions with overhead wires occur during flight when birds fail to see the cable or don't have enough time to avoid them. They represent a significant source of anthropogenic bird mortality (Loss et al., 2014) and are responsible for the decline of different populations (Biasotto & Kindel, 2018; Uddin et al 2021). Bird-related taxa typically show similar levels of sensitivity to collisions since they have a strong phylogenetic signal (Prinsen et al., 2011).

To assess the species' sensitivity to overhead collision, we used three main published reviews from Africa and Eurasia (Haas et al., 2003; Martín Martín et al., 2019; Prinsen et al., 2011). These reviews provide a classification at the family level of the main avifauna affected by collision. Four broad categories were used to measure sensitivity: **Category I** = casualties reported, but no apparent threat to the bird population. **Category II** = regionally or locally high casualties, but with no significant impact on the overall species population. **Category III** = Casualties are a major mortality factor, threatening a species with extinction, either regionally or on a larger scale. To complement the assessment regarding global bird families, a systematic review looking for articles published about bird collisions with power lines was conducted on Web of Science. Slight differences were found in the classification for certain families, so we included each family in the following subcategories: **6** (III) = casualties are a major mortality factor, threatening a species with extinction, regionally or at a larger scale. **5** (between category II and III). **4** (II) regionally or locally high casualties, but with no significant impact on the overall species population. **3** (between category II and I). **2** (I) casualties reported, but no apparent threat to the bird population. **1** No casualties reported or likely. The Supplementary Material "AVISTEP_Uzbekistan_PW_Collision.xlsx" contains bird families with their respective assessments.

Conservation status (CnS), endemism (En), and annual adult survival (Su) were calculated in the same way as for the onshore wind sensitivity index.

To combine the parameters in the formula and balance their contribution to the sensitivity index, we standardized all values from 0 to 1 by dividing each parameter by its maximum value, following recommendations from Certain et al. (2015).

To choose the final list of species to be included in the assessment, we ranked all species by country according to their sensitivity values. To avoid that considering several species with a lower index could add up to a greater sensitivity than a few species with high sensitivity, we decided to work with only those species with a sensitivity index of ≥ 0.2981 (see "AVISTEP_Uzbekistan_PW_Collision.xlsx" in Supplementary Material), corresponding to the top ~20% of all species per country. This threshold ensured that the most sensitive species were represented. Additionally, conducting workshop with local bird experts, we assessed the list, uplisting or downlisting species, if necessary, according to their relevance to the national context for bird conservation. For Uzbekistan, we included 59 species as priority species regarding the collision with power lines. To produce the final sensitivity scores, we normalised the values to a 0.01 to 1 scale, emphasizing the much greater sensitivity of species in the top part of the list compared to those at the bottom (Critchley & Jessopp, 2019).

The Supplementary Material contains 59 priority species along with their respective information for different parameters.

Mapping the distribution area for priority species – STEP 2

We used the area of habitat (AOH) maps created for most bird species worldwide, with a resolution of 100x100m grid cells. The AOH maps represent the utilized habitats within a species' range and can be considered an intermediate step between the Extent of Occurrence (EOO) and Area of Occupancy (AOO). These maps were created using a modelling approach based on remotely sensed land cover data, translated to species' habitat preferences according to the IUCN Red List Assessments (Lumbierres et al., 2022) and known maximum and minimum elevations. The AOH maps were created using binary information representing presence and absence, based solely on breeding, non-breeding, and resident distribution (for more details, see https://github.com/BirdLifeInternational/code_for_AOH). A raster layer was created for each species, representing the species' occurrence probability as the proportion of suitable habitat area in each grid cell. More specifically, since our assessment was conducted at a 5x5 km grid cell resolution, we transformed the original AOH maps to match our resolution, calculating the total percentage of AOH present in each cell. We also used occurrence points to refine the likelihood of occurring in each grid cell for each species from different sources: 1) Local bird experts compiled observational records for their respective countries from a range of sources (i.e., published, and unpublished literature, survey and project data, and a range of other sources) and 2) eBIRD data (https://ebird.org). To download and curate the datasets, we used the RStudio package auk (Strimas-Mackey et al., 2018). To ensure the accuracy of the data, we have only included recent observations (2012-2022) from eBIRD's protocol, whether made while stationary or travelling. The maximum distance travelled was set to 7 km to ensure that all records were contained within the final ~ 5x5 km cells.

Due to the scarcity of observational data for Uzbekistan, we assume the species has a very high probability of occurring in a grid cell if it has at least one occurrence of evidence that spatially overlaps with it. In these cases, we upgraded the cell value to the maximum value (1), regardless of the amount of habitat available in the AOH surface.

For a few species without AoH maps (species with just passage area inside the country) but still regularly occurring, we used the BirdLife range maps instead (BirdLife International 2021). We rasterised the polygons in a 5x5 km grid resolution. Due to the uncertainty about the occurrence of species in the ranges on a broad scale, we weighted all grid cells equally = at 0.5, representing a 50% chance of the species occurring there. We also upgraded the grid cell to a maximum value when a survey point overlaps the raster surface.

We adapted the formula by Bradbury et al. (2014) to weight the raster for each species by its respective sensitivity index and the amount of habitat in each grid cell. The final species sensitivity value (SI) was assigned for each grid cell following the formula below:

$$Species\ Sensitivity = ln(species\ occurence\ probability\ in\ the\ grid\ cell + 1) * SI$$

Species occurrence certainty

To provide information about the likelihood of the species' presence, we created a metric that combines the amount of AOH and the confirmed presence of the species in each grid cell. This categorical parameter has values ranging from 1 to 4 and reflects the evidence of the species' presence in that grid cell. The correspondence of the categories follows:

Low occurrence certainty. The percentage of AOH is < 50%, and the occurrence is not confirmed by on-the-ground surveys (1).

Medium occurrence certainty. The percentage of AOH is > 50%, and the occurrence is not confirmed by on-the-ground surveys (2).

High occurrence certainty. The percentage of AOH is < 50%, and the occurrence is confirmed by on-the-ground surveys (3).

Very high occurrence certainty. The percentage of AOH is> 50%, and the occurrence is confirmed by on-the-ground surveys (4).

For those distribution maps based solely on the BirdLife range maps, we created a comparable classification using the available information for those species. On these occasions, we assigned a generic value of 1 (low occurrence certainty) to the range area and a value of 3 (high occurrence certainty) to those grid cells where surveys confirmed the species' presence.

Creating multispecies combination map – STEP 3

We created a multispecies combination map by summing the sensitivity maps for all species. For Uzbekistan, we combined the rasters of 59 priority species. Thus, the final score for each grid cell is the result of the summed values of all the species present in that cell. The bird sensitivity map captures the cumulative impact over the range of species present in each area. To make these maps comparable with the rest of the sources of information, we normalised the values from 0 to 1.

$$\sum_{species}^{n} ln(species\ occurence\ probability + 1) * SI$$

Adding other important areas for bird conservation – STEP 4

Land Cover Land Use

To mitigate the impact of renewable energy, it is crucial to focus development away from natural habitats and towards areas with low ecological value, such as those already heavily modified by human activity (Kiesecker et al., 2019). For this purpose, we used land cover data to identify human-altered areas with lower ecological value. Specifically, we utilized the Copernicus global land-cover dataset (https://lcviewer.vito.be/2019) and the discrete land cover classification, which comprises 23 classes at a spatial resolution of ~100 m (Buchhorn et al., 2020). We chose to use this dataset due to its high accuracy (average ~80%) and suitability for conservation (Jung et al., 2020).

Uzbekistan has a unique biodiversity resulting from a combination of geographic, climatic, and ecological factors that make it distinct within Central Asia and globally. Based on this, we created a different hierarchy of weights to work with the various land cover classes, assigning greater relevance to classes that are more relevant for biodiversity and have undergone less human-induced change. Thus, we applied the Analytic Hierarchy Process (AHP) to contrast different land cover, and we set the following hierarchy of weights: all types of forests – open and closed, permanent water bodies, herbaceous wetland, moss and lichen had the maximum weight (grid cell received value of 100); following by Shrubs, Herbaceous vegetation, Bare, desert and sparse vegetation (grid cell received value of 32); Cultivated and managed vegetation/agriculture (cropland) (grid cell received value of 16); and Urban / built up - Land covered by buildings and other man-made structures (grid cell received value of 7). We then calculated the median value for each 5x5 cell to create an index that represents a proxy for inferring the value of biodiversity. In our scoring, cells with a higher percentage of natural areas will result in a higher sensitivity score. We combined the resulting land cover proxy map with the species cumulative map (step 3) using a Multicriteria Analysis (MCA) (Adem Esmail & Geneletti, 2018), weighting land cover proxy and species sensitivity according to bird expert opinion. Therefore, land cover was weighted as 0.4 (contributing 40% to the final layer), and priority species sensitivity was weighted as 0.6 (contributing 60% to the final layer). This final outcome was then normalized to a value between 0 and 1.

Important Bird and Biodiversity Areas (IBAs)

Important Bird and Biodiversity Areas (IBAs) are a global dataset of areas of greatest significance for the conservation of the world's birds. This dataset is curated by BirdLife International and available through website (https://datazone.birdlife.org/country/factsheet/uzbekistan). The most up-to-date version of this data was used (BirdLife International, 2024). Cells overlapping with these areas received the maximum value of sensitivity.

Protected Areas

We used the World Database on Protected Areas (WDPA) from the Protected Planet website (www.protectedplanet.net). This database is updated by governments and curated by the UN Environment Programme's World Conservation Monitoring Centre (UNEP-WCMC), providing the most up-to-date information on protected areas. We used the latest version from 2024. All protected areas in Uzbekistan were included, regardless of their IUCN management category. As with IBAs, cells overlapping with these areas automatically received the maximum level of sensitivity.

Special areas for birds

Some areas in Uzbekistan are critically important for migratory species, such as bustards, as they provide ideal habitat conditions, migration stopover points, and breeding or wintering grounds that birds depend on (Burnside et al., 2016; Silva et al., 2022). Steppe and semi-desert habitats were mapped as well as specific sites important for Bustards (stopover points, wintering grounds, and main migratory flightways). As with IBAs, cells overlapping with these areas automatically received the maximum level of sensitivity.

Identifying final sensitivity categories – STEP 5

We categorised geographical sensitivity by applying the Jenk's Natural Breaks algorithm (Natural breaks function, ArcGIS Pro; ESRI, 2023) to identify four categories, which we interpret as Low, Medium, High, and Very High bird sensitivity. Natural Breaks minimize the squared deviations of a group's means and are a standard method for splitting spatial datasets. This produced a final bird sensitivity map in a format that provides meaningful visualization and is easier to interpret for a range of stakeholders in decision-making processes.

Power Line – Medium and Low voltage

Calculating species sensitivity – STEP 1

Distribution lines primarily impact birds through collisions with overhead cables and electrocution on energy pylons and cables. Therefore, in addition to considering the species most sensitive to collision using the formula mentioned for the High-voltage lines (PwCo), a specific formula for calculating and identifying species sensitive to electrocution was also applied separately:

$$Sensitivity\ Index = (PwElec) \times (CnS)^{\left(1-\left(\frac{(Su+En)}{2}\right)/\left(\left(\frac{(Su+En)}{2}\right)+0.5\right)\right)}$$

To assess the species' sensitivity to electrocution, we used three main published reviews from Africa and Eurasia (Haas et al., 2003; Martín Martín et al., 2019; Prinsen et al., 2011). These reviews provide a classification at the family level of the main avifauna affected by electrical shock. Four broad categories were used to measure sensitivity: **Category I** = casualties reported, but no apparent threat to the bird population. **Category II** = regionally or locally high casualties, but with no significant impact on the overall species population. **Category III** = Casualties are a major mortality factor, threatening a species with extinction, either regionally or on a larger scale. To complement the assessment regarding global bird families, a systematic review looking for articles published about bird electrocutions with power lines was conducted on Web of Science. Slight differences were found in the classification for certain families, so we included each family in the following subcategories: **6** (III) = casualties are a major mortality factor, threatening a species with extinction, regionally or at a larger scale. **5** (between category II and III). **4** (II) regionally or locally high casualties, but with no significant impact on the overall species population. **3** (between category II and I). **2** (I) casualties reported, but no apparent threat to the bird population. **1** No casualties reported or likely. The Supplementary Material contains bird families with their respective assessments.

Conservation status (CnS), endemism (En), and annual adult survival (Su) were calculated in the same way as for the onshore wind sensitivity index.

To combine the parameters above in the formula and balance their contribution to the sensitivity index, we standardized all values from 0 to 1 by dividing each parameter by its maximum value, following recommendations from Certain et al. (2015).

To choose the final list of species to be included in the assessment, we ranked all species by country according to their sensitivity values. To avoid that considering several species with a lower index could add up to a greater sensitivity than a few species with high sensitivity, we decided to work with only those species with a sensitivity index of ≥ 0.2045 (see "AVISTEP_Uzbekistan_PW_Electrocution.xlsx" in Supplementary Material), corresponding to the top ~20% of all species per country. This threshold ensured that the most sensitive species were represented. Additionally, we assessed the list in collaboration with local bird experts, uplisting or downlisting species as necessary, based on their relevance to the national context for bird conservation. For Uzbekistan, we included 51 species as priority species due to their susceptibility to electrocution. To produce the final sensitivity scores, we normalized the values to a 0.01 to 1 scale, emphasizing the much greater sensitivity of species in the top part of the list compared to those at the bottom (Critchley & Jessopp, 2019).

The Supplementary Material contains 51 priority species with their respective information for different parameters.

Mapping the distribution area for priority species – STEP 2

We used the area of habitat (AOH) maps created for most bird species worldwide, with a resolution of 100x100m grid cells. The AOH maps represent the utilized habitats within a species' range and can be considered an intermediate step between the Extent of Occurrence (EOO) and Area of Occupancy (AOO). These maps were created using a modelling approach based on remotely sensed land cover data, translated to species' habitat preferences according to the IUCN Red List Assessments (Lumbierres et al., 2022), and known maximum and minimum elevations. The AOH maps were created using binary information representing presence and absence, based solely on breeding, non-breeding, and resident distribution (for more details, see https://github.com/BirdLifeInternational/code_for_AOH). A raster layer was created for each species, representing the species' occurrence probability as the proportion of suitable habitat area in each grid cell. More specifically, since our assessment was conducted at a 5x5 km grid cell resolution, we transformed the original AOH maps to match our resolution, calculating the total percentage of AOH present in each cell. We also used occurrence points to refine the likelihood of occurring in each grid cell for each species from different sources: 1) Local bird experts compiled observational records for their respective countries from a range of sources (i.e., published, and unpublished literature, survey and project data, and a range of other sources) and 2) eBIRD data (https://ebird.org). To download and curate the datasets, we used the RStudio package *auk* (Strimas-Mackey et al., 2018). To ensure the accuracy of the data, we have only included recent observations (2012-2022) from eBIRD's protocol, whether made while stationary or in transit. The maximum distance travelled was set to 7 km to ensure that all records were contained within the final ~ 5x5 km cells.

Due to the scarcity of observational data for Uzbekistan, we assume the species has a very high probability of occurring in a grid cell if it has at least one occurrence of evidence that spatially overlaps with it. In these cases, we upgraded the cell value to the maximum value (=1), regardless of the amount of habitat available in the AOH surface.

For a few species without AoH maps (species with just passage area inside the country) but still regularly occurring, we used the BirdLife range maps instead (BirdLife International 2021). We rasterised the polygons in a 5x5 km grid resolution. Due to the uncertainty about the occurrence of species in the ranges on a broad scale, we weighted all grid cells equally = 0.5, representing the 50% chance of the species occurring there. We also upgraded the grid cell to a maximum value when a survey point overlaps the raster surface.

We adapted the formula by Bradbury et al. (2014) to weight the raster for each species by its respective sensitivity index and the amount of habitat in each grid cell. The final species sensitivity value (SI) was assigned for each grid cell following the formula below:

$$Species\ Sensitivity = ln(species\ occurence\ probability\ in\ the\ grid\ cell + 1) * SI$$

Species occurrence certainty

To provide information about the likelihood of the species' presence, we created a metric that combines the amount of AOH and the confirmed presence of the species in each grid cell. This categorical parameter has values ranging from 1 to 4 and reflects the evidence of the species' presence in that grid cell. The correspondence of the categories follows:

Low occurrence certainty. The percentage of AOH is < 50%, and the occurrence is not confirmed by on-the-ground surveys (1).

Medium occurrence certainty. The percentage of AOH is > 50%, and the occurrence is not confirmed by on-the-ground surveys (2).

High occurrence certainty. The percentage of AOH is < 50%, and the occurrence is confirmed by on-the-ground surveys (3).

Very high occurrence certainty. The percentage of AOH is> 50%, and the occurrence is confirmed by on-the-ground surveys (4).

For those distribution maps based solely on the BirdLife range maps, we created a comparable classification using the available information for those species. On these occasions, we assigned a generic value of 1 (low occurrence certainty) to the range area and a value of 3 (high occurrence certainty) to those grid cells where surveys confirmed the species' presence.

Creating multispecies combination map – STEP 3

We created a multispecies combination map by summing the sensitivity maps for all species. We create one map specific for collision (combining 59 species) and another for electrocution (combining 51 species). For each map individually, the final score for each grid cell is the sum of the values of all species present in that cell. The bird sensitivity map captures the cumulative impact over the range of species present in each area. To make these maps comparable with the rest of the information sources, we normalized the values from 0 to 1.

$$\sum_{species}^{n} ln(species\ occurence\ probability + 1) * SI$$

** Distribution lines considered maps from Collision and Electrocution, combining them and conserving the maximum value in each grid cell. As a precautionary approach, that means if a grid cell has a value of 1 for electrocution but 0.5 for collision, the final grid cell value is 1.

Adding other important areas for bird conservation – STEP 4

Land Cover Land Use

To mitigate the impact of renewable energy, it is crucial to focus development away from natural habitats and towards areas with low ecological value, such as those already heavily modified by human activity (Kiesecker et al., 2019). For this purpose, we used land cover data to identify human-altered areas with lower ecological value. Specifically, we utilized the Copernicus global land-cover dataset (https://lcviewer.vito.be/2019) and the discrete land cover classification, which comprises 23 classes at a spatial resolution of ~100 m (Buchhorn et al., 2020). We chose to use this dataset due to its high accuracy (average ~80%) and suitability for conservation (Jung et al., 2020).

Uzbekistan has a unique biodiversity resulting from a combination of geographic, climatic, and ecological factors that make it distinct within Central Asia and globally. Based on this, we created a different hierarchy of weights to work with the various land cover classes, assigning greater relevance to classes that are more relevant for biodiversity and have undergone less human-induced change. Thus, we applied the Analytic Hierarchy Process (AHP) to contrast different land cover, and we set the following hierarchy of weights: all types of forests – open and closed, permanent water bodies, herbaceous wetland, moss and lichen had the maximum weight (grid cell received value of 100); following by Shrubs, Herbaceous vegetation, Bare, desert and sparse vegetation (grid cell received value of 32); Cultivated and managed vegetation/agriculture (cropland) (grid cell received value of 16); and Urban / built up - Land covered by buildings and other man-made structures (grid cell received value of 7). We then calculated the median value for each 5x5 cell to create an index that represents a proxy for inferring the value of biodiversity. In our scoring, cells with a higher percentage of natural areas will result in a higher sensitivity score. We combined the resulting land cover proxy map with the species cumulative map (step 3) using a Multicriteria Analysis (MCA) (Adem Esmail & Geneletti, 2018), weighting land cover proxy and species sensitivity according to bird expert opinion. Therefore, land cover was weighted as 0.4 (contributing 40% to the final layer), and priority species sensitivity was weighted as 0.6 (contributing 60% to the final layer). This final outcome was then normalized to a value between 0 and 1.

Important Bird and Biodiversity Areas (IBAs)

Important Bird and Biodiversity Areas (IBAs) are a global dataset of areas of greatest significance for the conservation of the world's birds. This dataset is curated by BirdLife International and available through website (https://datazone.birdlife.org/country/factsheet/uzbekistan). The most up-to-date version of this data was used (BirdLife International, 2024). Cells overlapping with these areas received the maximum value of sensitivity.

Protected Areas

We used the World Database on Protected Areas (WDPA) from the Protected Planet website (www.protectedplanet.net). This database is updated by governments and curated by the UN Environment Programme's World Conservation Monitoring Centre (UNEP-WCMC), providing the most up-to-date information on protected areas. We used the latest version from 2024. All protected areas in Uzbekistan were included, regardless of their IUCN management category. As with IBAs, cells overlapping with these areas automatically received the maximum level of sensitivity.

Special areas for birds

Some areas in Uzbekistan are critically important for migratory species, such as bustards, as they provide ideal habitat conditions, migration stopover points, and breeding or wintering grounds that birds depend on (Burnside et al., 2015; Silva et al 2023). Steppe and semi-desert habitats were mapped as well as specific sites important for Bustards (stopover points, wintering grounds, and main migratory flightways). As with IBAs, cells overlapping with these areas automatically received the maximum level of sensitivity.

Identifying final sensitivity categories – STEP 5

We categorised geographical sensitivity by applying the Jenk's Natural Breaks algorithm (Natural breaks function, ArcGIS Pro; ESRI, 2023) to identify four categories, which we interpret as Low, Medium, High, and Very High bird sensitivity. Natural Breaks minimize the squared deviations of a group's means and are a standard method for splitting spatial datasets. This produced a final bird sensitivity map in a format that provides meaningful visualization and is easier to interpret for a range of stakeholders in decision-making processes.

Solar Photovoltaic (PV)

Calculating Sensitivity for all species occurring in the country – STEP 1

The species-specific sensitivity based on different impacts created for the other types of energy developments does not apply to the context of solar photovoltaic energy. Although some species can indeed coexist with solar PV installations, we have used a precautionary approach, considering that the presence of solar photovoltaics would result in habitat loss and/or degradation for all species that occur in the area.

We considered a list of all species occurring in the country, individually weighted by their respective Conservation Status (CnS - primary factor) and Endemicity (En - aggravating factor). For Uzbekistan, we worked with a total of 321 species.

Conservation Status (CnS): We used the IUCN Red List categories from 2021 as follows: 5 = Critically Endangered (CR); 4 = Endangered (EN); 3 = Vulnerable (VU); 2 = Near Threatened (NT); 1 = Least Concern (LC) or Data Deficient (DD).

Endemism (En): We calculated the percentage of the global distribution area inside each country's territory. To calculate this parameter, we used the distribution range maps (BirdLife International and The Handbook of the Birds of the World, 2021) and the global database of political boundaries GADM (Global Administrative Areas, 2021) in ArcGIS Pro (ESRI, 2023). To transform these values into categories from 1 to 5, we used the following conversion criteria: 1 = 0-20%, 2 = >20-40%, 3 = >40-60%, 4 = >60-80%, 5 = >80-100%. To standardise all metrics and make them comparable, we divided each by the maximum category value following recommendations from Certain et al. (2015).

$$Species\ sensitivity = (CnS)^{\left(1-(En)/((En)+0.5)\right)}$$

Mapping the species distribution according to the Sensitivity – STEP 2

We used the BirdLife range maps (BirdLife International 2021) to create a raster layer for the 321 species with a 5x5 km grid cell resolution. The respective species sensitivity value was weighted for each raster surface.

Creating a species richness map – STEP 3

To create a surface representing the cumulative sensitivity (hereinafter, bird richness). we summed all the rasters in the same grid cell following the formula

$$\sum_{species}^{n} (CnS)^{\left(1-(En)/((En)+0.5)\right)}$$

Creating a layer with potential wilderness areas and adding important areas for bird conservation – STEP 4

To identify zones where the development of solar farms may negatively impact biodiversity, we combined the bird richness surface with a human footprint surface (used as a proxy to infer wilderness). Accordingly, areas far from the site with high value for the human footprint index – HFI - (population density, built infrastructure such as roads, railways, factories, and night-time lights) would be less exposed to disturbance (Ascensão et al., 2023) and, therefore, consist of more relevant areas for bird conservation. We used HFI second generation of information with 300 m^2 as resolution from https://wcshumanfootprint.org/ (data-access 31/10/2023).

The bird richness surface was combined with the human footprint surface, both calculated in 5x5 km using Multicriteria Analysis. The human footprint surface was weighted as 0.4 (contributing with 40% for the final layer) and the bird richness sensitivity as 0.6 (contributing with 60% for the final layer). This final outcome was then normalized between zero and 1.

The information for IBAs, protected areas, and Special areas for birds was the same as previously used for Wind farms and powerlines. To create the final sensitivity maps, we combined these datasets by retaining the maximum value from all overlapping cells. In this way, cells designated as IBAs, protected areas AND Important Areas for Birds, automatically received the maximum level of sensitivity (1), while all other cells will vary between 0 and 1 depending on their percentage on the trade-off between bird richness and human footprint layer.

Identifying final sensitivity categories – STEP 5

We categorized sensitivity by applying Jenk's Natural Breaks algorithm to identify four categories, which we interpret as Low, Moderate, High, and Very High bird sensitivity. This produced a final and continuous bird sensitivity map in a format that is easier to understand and could be used by a range of stakeholders in decision-making processes.

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AVISTEP

The Avian Sensitivity Tool for Energy Planning

Appendix V – Egypt

November 2025

Nature Conservation Egypt
الجمعية المصرية لحماية الطبيعة

BirdLife INTERNATIONAL

KFW DEG Impulse

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Wind Farm Onshore

Calculating species sensitivity – STEP 1

The respective national species lists to be assessed were created in agreement with BirdLife International, and bird experts from Nature Conservation Egypt (NCE), a BirdLife International partner. The sensitivity index was calculated for each regularly occurring bird species, excluding flightless, vagrant, rare sightings, and restricted seabirds. For Egypt, we calculated the sensitivity index for 330 bird species.

$$Sensitivity\ Index = \left(Co + \left(\frac{Di}{5}\right)\right) \times (CnS)^{\left(1-\left(\frac{Su+En}{2}\right)/\left(\left(\frac{Su+En}{2}\right)+0.5\right)\right)}$$

Collision (Co): To develop a metric that could identify the sensitivity of different taxonomic groups, we used a study by Thaxter et al. (2017). In this study, the authors analysed the ecological traits and phylogenetic characteristics that make different taxonomic groups more sensitive to collision. They assigned a collision probability to most land-bird species worldwide through a modelling approach. Based on the author's recommendations, we summarised this value at the family level based on global number of species (average value). After that, we categorised this value in four categories (ranging from 1 and 4). These categories were calculated following a natural break classification algorithm, the corresponding values for each category were: 1($x < 0.028$); 2 ($0.028 < x < 0.043$); 3 ($0.043 < x < 0.059$); 4 ($x > 0.059$).

Displacement (Di): To classify the displacement, we referred to Hötker (2017), who reviewed all the evidence from scientific sources and 148 grey literature reports on displacement in birds to produce a metric for European birds. The paper reported the number of times a negative effect (e.g. displacement reported to reduce species abundance) or a positive effect or no effect had been found per species and, for those groups with enough samples, the statistical significance of this difference (binomial test). To produce a relevant metric, we assigned the following values to each species: 1 = Displacement never reported; 2 = Displacement reported in at least one study; 3 = Displacement more often reported, but differences not statistically significant; 4 = Displacement more often reported and differences statistically significant. The whole family received the value of the highest-scoring species included in that family. This precautionary approach was taken to ensure that phylogenetically closer species, which are more similar and have not been directly studied, could also be evaluated. To complement the assessment regarding bird families different from Europe, a systematic review looking for articles published about bird displacement was conducted on Web of Science using the terms: ((TS=("wind*farm*" OR "onshore" OR "offshore" OR "wind*turbine*")) AND TS=("birds" OR "avian")) AND TS=("displacement" OR "avoidance" OR "space*use*") from 2000 to 2024. In total, 24 families had displacement evidence at different levels. Accipitridae, Muscicapidae, Scolopacidae, Anatidae, and Charadriidae were the families with the highest displacement category. The Supplementary Material contains bird families with their respective displacement assessments.

Conservation Status (CnS) was assigned at the species level using the IUCN Red List categories (2023) as follows: 5 = Critically Endangered (CR); 4 = Endangered (EN); 3 = Vulnerable (VU); 2 = Near Threatened (NT); 1 = Least Concern (LC) or Data Deficient (DD).

Annual adult survival (Su). We employed annual adult survival calculated for all bird species to include a metric that could capture life history factors (Bird et al., 2020). To transform these values into categories from 1 to 5, we used a natural breaks classification algorithm implemented in the RStudio package classes (Bivand, 2022). The corresponding values for each category were: 1 ($x < 0.466$); 2 ($0.466 \leq x < 0.559$); 3 ($0.559 \leq x < 0.655$); 4 ($0.655 \leq x < 0.775$); 5 ($x > 0.911$).

Endemism (En): We consider the level of endemism for each species as the percentage of the global distribution area inside each country's territory. To calculate this parameter, we used the distribution range maps (BirdLife International & The Handbook of the Birds of the World, 2019) and the global database of

political boundaries GADM (Global Administrative Areas, 2021) in ArcGIS Pro (ESRI, 2023). To transform these values into categories from 1 to 5, we used the following conversion criteria: 1 = 0-20%, 2 = >20-40%, 3 = >40-60%, 4 = >60-80%, 5 = >80-100%.

To combine the five parameters above in the formula, balancing their contribution to the sensitivity index, we standardised all values from 0 to 1 by dividing each parameter by its maximum value, following recommendations from Certain et al. (2015).

To choose the final list of species to be included in the assessment, we ranked all species by country according to their sensitivity values. To avoid that considering several species with a lower index could add up to a greater sensitivity than a few species with high sensitivity, we decided to work with only those species with a sensitivity index of ≥ 0.339 (see "AVISTEP_Egypt_Onshore.xlsx" in Supplementary Material), corresponding to the top ~20% of all species per country. This threshold ensured that the most sensitive species were represented. Additionally, conducting workshop with bird experts, we assessed the list, uplisting or downlisting species, if necessary, according to their relevance to the national context for bird conservation. For Egypt, we included 64 species as priority species regarding the wind farms onshore impacts. To produce the final sensitivity scores, we normalised the values to a 0.01 to 1 scale in order to emphasise the much greater sensitivity of species in the top part of the list compared to the species at the bottom (Critchley & Jessopp, 2019).

The Supplementary Material contains 64 priority species with their respective information for different parameters.

Mapping the distribution area for priority species – STEP 2

We used the area of habitat (AOH) maps created for most bird species worldwide in 100x100m grid cells as resolution. The AOH maps represent the utilised habitats within a species' range and can be considered an intermediate step between the Extent of Occurrence (EOO) and Area of Occupancy (AOO). These maps were created using a modelling approach based on remotely sensed land cover data translated to species' habitat preferences according to the IUCN Red List Assessments (Lumbierres et al., 2022) and known maximum and minimum elevation. The AOH maps were created using binary information representing presence and absence, and only based on breeding, non-breeding, and resident distribution (more details in https://github.com/BirdLifeInternational/code_for_AOH). A raster layer for each species was created, representing the species occurrence probability described by the proportion of area of suitable habitat in each grid cell. More specifically, since our assessment was in a 5x5 km grid cell resolution, we transformed the original AOH maps to our resolution, calculating the total percentage of AOH present in each cell. We also used occurrence points to refine the likelihood of occurring in each grid cell for each species from different sources: 1) Local bird experts compiled observational records for their respective countries from a range of sources (i.e., published, and unpublished literature, survey and project data, and a range of other sources) and 2) eBIRD data. To guarantee the accuracy of the data, we only included recent observations (2013 to 2024) that came from eBIRD's protocol, whether stationary or travelling. The maximum distance travelled was set to 7 km to ensure that all records were contained within the final ~ 5x5 km cells.

Due to the scarcity of observational data for Egypt, we assume the species has a very high probability of occurring in a grid cell if it has at least one occurrence of evidence spatially overlapping it. In these cases, we upgraded the cell value to the maximum value (=1), regardless of the amount of habitat available in the AOH surface.

For 16 species without AOH maps (species with just passage area inside the country) but still regularly occurring, we used the BirdLife range maps instead (BirdLife International 2021). We rasterised the polygons into a 5x5 km grid resolution. Due to the uncertainty about the occurrence of species in the ranges in their broad scale, we weighted all grid cells equally = 0.5, representing the 50% change to have or not the species occurring there. We also upgraded the grid cell to a maximum value when a survey point overlaps the raster surface.

We adapted the Bradbury et al. (2014) formula to weight the raster for each species by its respective sensitivity index and amount of habitat in each grid cell. The final species sensitivity value (SI) was assigned for each grid cell following the formula below:

$$Species\ Sensitivity = \ln(species\ occurence\ probability\ in\ the\ grid\ cell + 1) * SI$$

Species occurrence certainty

To provide information about the species' presence likelihood, we created a metric combining the amount of AOH and the confirmed presence of the species in each grid cell. This categorical parameter has values ranging from 1 to 4 and reflects the evidence of the presence of the species in that grid cell. The correspondence of the categories follows:

Low occurrence certainty. The percentage of AOH is < 50%, and the occurrence is not confirmed by on-the-ground surveys (1).

Medium occurrence certainty. The percentage of AOH is > 50%, and the occurrence is not confirmed by on-the-ground surveys (2).

High occurrence certainty. The percentage of AOH is < 50%, and the occurrence is confirmed by on-the-ground surveys (3).

Very high occurrence certainty. The percentage of AOH is> 50%, and the occurrence is confirmed by on-the-ground surveys (4).

For those distribution maps based just on the BirdLife range maps, we created a comparable classification based on the information available for those species. On these occasions, we gave the range area a generic value of 1 (low occurrence certainty) and a value of 3 (high occurrence certainty) to those grid cells where surveys confirmed the species' presence.

Creating multispecies combination map – STEP 3

We created a multispecies combination map by summing up all species-specific sensitivity maps. For Egypt, we combined 64 priority species' rasters. Thus, the final score for each grid cell is the result of the summed values of all the species present in that cell. The bird sensitivity map captures the cumulative impact over the range of species present in each area. To make these maps comparable with the rest of the sources of information, we normalised the values from 0 to 1.

$$\sum_{species}^{n} ln(species\ occurence\ probability\ in\ the\ grid\ cell + 1) * SI$$

** Distribution lines considered maps from Collision and Electrocution, combining them and conserving the maximum value in each grid cell. That means if a grid cell has a value of 1 for electrocution but 0.5 for collision, the final grid cell value is 1.

Adding other important areas for bird conservation – STEP 4

Understanding Egyptian landbird movement is critically essential to ensure that sensitivity maps accurately represent crucial stopover wetlands and do not misrepresent aerial connectivity between breeding and feeding grounds. For onshore, we developed a layer to represent the movement of landbirds over Egyptian, combining two main approaches:

Approximate migration corridor based on range maps - based on Bird Tracking Data

Raw animal tracking data for migratory birds were collected from published studies, author-provided datasets, and Movebank (www.movebank.org). After assessing the Movebank data, we included only GPS fixes with timestamps for 14 species (Caspian Tern - *Hydroprogne caspia*, Eastern Imperial Eagle - *Aquila heliaca*, Egyptian Vulture - *Neophron percnopterus*, Eleonora's Falcon - *Falco eleonorae*, European Honey-buzzard - *Pernis apivorus*, Great White Pelican - *Pelecanus onocrotalus*, Greater Spotted Eagle - *Clanga clanga*, Griffon Vulture - *Gyps fulvus*, Lesser Black-backed Gull - *Larus fuscus*, Lesser Spotted Eagle - *Clanga pomarina*, Osprey - *Pandion haliaetus*, Short-toed Snake-eagle - *Circaetus gallicus*, Steppe Eagle - *Aquila nipalensis*, White Stork - *Ciconia ciconia*). We followed steps according to the *Track2KBA* R package as follows. To clean the data, we removed duplicate records and ran a McConnel speed filter. To obtain locations at regular intervals required for kernel density analysis, we interpolated each track to a regular time interval specific to each species using linear interpolation in time. Trips with fewer than five valid fixes were excluded. Data from stationary periods associated with capture, breeding or local roosting were also removed to focus on migratory or passage movements. Following interpolation, each individual's track was segmented into discrete movement trips using buffers of 3 km (departure) and 10 km (return) around a location outside of the study area. This delineation enabled the identification of outbound and inbound flights within the broader context of migratory movements. We cropped the tracks to the study area for land and sea plus a buffer larger than the smoothing parameter. All pre-processed data were visually inspected for trajectory continuity, geographic plausibility, and temporal regularity before being included in species-level modelling. For each species, we then used kernel density estimation (KDE) in the *adehabitatHR* R package to convert point locations into a 5x5km grid representing the density of time spent by tracked birds. The smoothing parameters used for kernel densities were determined according to bird behaviour (larger smoothing parameters were used for species that travel further and faster than others) and the accuracy of the data available. We then cropped the rasters to the study area and rescaled the values to have a maximum value of 1. The resulting dataset represented standardised, quality-controlled movement records suitable for estimating species flyways and composite sensitivity indices across Egypt.

The 14 individual species rasters were combined, weighted according to their respective species sensitivity index.

Approximate migration corridor based on range maps - passage area

Given the number of species for which telemetry data are available, species distribution polygons were compiled from the IUCN Red List database, with a focus on passage range classifications. Polygons were dissolved into a single multipart geometry per species. In total, only 109 species had a passage area delineated over Egypt. To match the extent of movement analyses, all polygons were clipped to the Egyptian region of interest (ROI). Each species' polygon was rasterised to the 5 km grid, producing binary presence rasters that represented passage areas. Each resultant raster was weighted according to the previous set of conservation status values. The range rasters were combined into a multi-species stack (summed). The final output was normalised presence rasters (score 0 - 1), representing a range-based proxy for migratory flyway use across the Egyptian region.

Both the Passage Areas and Migratory Corridor maps were rescaled into 0 and 1 and combined by maximum value, resulting in a final 'migratory' layer. Then, to compose a unique Bird Sensitivity map, we combined the Final Species Sensitivity map with the Final Migratory layer, giving both the same weight – 50% of the contribution each, according to the formula:

$$Final\ Bird\ Movement = (Species\ Cumulative\ map \times 0.5) + (Final\ Migratory\ layer \times 0.5)$$

Land Cover/Land Use

To mitigate the impact of renewable energy, it is crucial to focus development away from natural habitats and towards areas with low ecological value, such as those already heavily modified by human activity (Kiesecker et al., 2019). For this purpose, we used land cover data to identify human-altered areas with lower ecological value. Specifically, we utilised the Copernicus global land-cover dataset and the discrete land cover classification, which comprises 23 classes at a spatial resolution of ~100 m (Buchhorn et al., 2020). We chose to use this dataset due to its high accuracy (average ~80%) and suitability for conservation (Jung et al., 2020).

Egypt has a unique biodiversity resulting from a combination of geographic, climatic, and ecological factors, with a considerable part of his territory being desert or bare sand. Based on this, we created a different hierarchy of weights to work with the various land cover classes, assigning greater relevance to classes that are more relevant to biodiversity and have undergone less human-induced change. We also added a water incidence layer summarising annual precipitation (Fick & Hijmans, 2017) and months when water is present (Pekel et al., 2016).

We applied the Analytic Hierarchy Process (AHP) to contrast different land cover, and we set the following hierarchy of weights: all types of forests – open and closed, permanent water bodies, herbaceous wetland, Shrubs, Herbaceous vegetation, moss and lichen had the maximum weight (grid cell received value of 100) cultivated and managed vegetation was also included as maximum value due to its relevance for birds in the Egyptian context; following by Bare, desert and sparse vegetation (grid cell received value of 45); and Urban / built up - Land covered by buildings and other man-made structures (grid cell received value of 8). We then calculated the median value for each 5x5 cell to create an index that represents a proxy for inferring the value of biodiversity. In our scoring, cells with a higher percentage of natural areas will result in a higher sensitivity score. We combined the resulting land cover proxy map with the final water incidence layer to create a final landcover map giving both the same weight. This map was then combined with the species cumulative map (step 3) conserving the maximum value between the two layers. This final outcome was then normalised to a value between 0 and 1.

Identifying final sensitivity categories – STEP 5

Classifying the sensitivity value into categories

We categorised geographical sensitivity by applying the Jenk's Natural Breaks algorithm (Natural Breaks algorithm (Natural breaks function, ArcGIS Pro; ESRI, 2023) to classify sensitivity values across grid cells into four classes, which we interpret as Low (1), Medium (2), High (3), and Very High (4) bird sensitivity. Natural Breaks minimise the squared deviations of a group's means and are a standard method for splitting spatial datasets. The map shows the four final bird sensitivities in a format that provides meaningful visualisation and is easier to interpret for a range of stakeholders in decision-making processes.

Including Additional key areas

Additional key areas are considered as those already designated for bird conservation purposes or for conservation of their habitats, regardless of whether they focus on a priority species concerning the impacts of energy infrastructure. Examples include Protected Areas (PAs) and Important Bird and Biodiversity Areas (IBAs).

Important Bird and Biodiveristy Areas (IBAs)

Important Bird and Biodiversity Areas (IBAs) are a global dataset of areas of greatest significance for the conservation of the world's birds. This dataset is curated by BirdLife International and available through website (https://datazone.birdlife.org/country/factsheet/egypt). The most up-to-date version of this data was used (BirdLife International, 2024). In some instances, proposed IBAs and areas not identified as IBAs but nonetheless known to be of global significance for at-risk bird species were also included. Cells overlapping with these areas received the maximum value of sensitivity.

Protected Areas

We used the World Database on Protected Areas (WDPA) from the Protected Planet website (www.protectedplanet.net). This database is updated by governments and curated by the UN Environment Programme World Conservation Monitoring Centre (UNEP-WCMC) and includes the most up-to-date information on protected areas. We used the latest version from 2024. All protected areas were included for Egypt, regardless of their IUCN management category. As with IBAs, cells overlapping with these areas automatically received the maximum level of sensitivity.

All the above information was rasterised in a resolution of 5km^2. We combined additional key areas with very high sensitivity value (assigned the maximum value of 4) into the final sensitivity layer, which already contained four categories. For each grid cell, the highest sensitivity value was retained. As a result, cells with lower initial sensitivity that overlapped spatially with these additional key areas were upgraded to the maximum sensitivity value. This approach ensures that areas already recognised as important for bird conservation receive the highest sensitivity rating and are avoided from energy planning. Likewise, areas previously classified as highly sensitive remain so when overlapping with additional key areas.

Power Line – High voltage

Calculating species sensitivity – STEP 1

The sensitivity index was calculated for each regularly occurring bird species, excluding flightless, vagrant, rare sightings, and restricted seabirds. For Egypt, we calculated the sensitivity index for 330 bird species.

$$Sensitivity\ Index = (PwCo) \times (CnS)^{\left(1-\left(\frac{(Su+En)}{2}\right)/\left(\left(\frac{(Su+En)}{2}\right)+0.5\right)\right)}$$

Collision with energy cables (PwCo). Bird collisions occur during flight when birds fail to see the overhead wires. They represent a significant source of anthropogenic bird mortality (Loss et al., 2014) and are responsible for the decline of different populations (Biasotto & Kindel, 2018). Bird-related taxa typically show similar levels of sensitivity to collisions since they have a strong phylogenetic signal (Prinsen et al., 2011).

To assess the species' sensitivity to overhead collision, we used three main published reviews from Africa and Eurasia (Haas et al., 2003; Martín Martín et al., 2019; Prinsen et al., 2011). These reviews provide a classification at the family level of the main avifauna affected by collision. Four broad categories were used to measure sensitivity: **Category I** = casualties reported, but no apparent threat to the bird population. **Category II** = regionally or locally high casualties, but with no significant impact on the overall species population. **Category III** = casualties are a major mortality factor, threatening a species with extinction, regionally or at a larger scale. To complement the assessment regarding global bird families, a systematic review looking for articles published about bird collisions with power lines was conducted on Web of Science. Slight differences were found in the classification for certain families, so we included each family in the following subcategories: **6** (III) = casualties are a major mortality factor, threatening a species with extinction, regionally or at a larger scale. **5** (between category II and III). **4** (II) regionally or locally high casualties, but with no significant impact on the overall species population. **3** (between category II and I). **2** (I) casualties reported, but no apparent threat to the bird population. **1** No casualties reported or likely. The Supplementary Material contains bird families with their respective assessments.

Conservation status (CnS), endemism (En), and annual adult survival (Su) were calculated in the same way as for the onshore wind sensitivity index.

To combine the parameters in the formula and balance their contribution to the sensitivity index, we standardised all values from 0 to 1 by dividing each parameter by its maximum value, following recommendations from Certain et al. (2015).

To choose the final list of species to be included in the assessment, we ranked all species by country according to their sensitivity values. To avoid that considering several species with a lower index could add up to a greater sensitivity than a few species with high sensitivity, we decided to work with only those species with a sensitivity index of ≥ 0.321 (see "AVISTEP_Egypt_PW_Collision.xlsx" in Supplementary

Material), corresponding to the top ~20% of all species per country. This threshold ensured that the most sensitive species were represented. Additionally, conducting workshop with local bird experts, we assessed the list, uplisting or downlisting species, if necessary, according to their relevance to the national context for bird conservation. For Egypt, we included 54 species as priority species regarding the collision with power lines. To produce the final sensitivity scores, we normalised the values to a 0.01 to 1 scale in order to emphasise the much greater sensitivity of species in the top part of the list compared to the species at the bottom (Critchley & Jessopp, 2019).

The Supplementary Material contains 54 priority species with their respective information for different parameters.

Mapping the distribution area for priority species – STEP 2

We used the area of habitat (AOH) maps created for most bird species worldwide in 100x100 m grid cells as resolution. The AOH maps represent the utilised habitats within a species' range and can be considered an intermediate step between the Extent of Occurrence (EOO) and Area of Occupancy (AOO). These maps were created using a modelling approach based on remotely sensed land cover data translated to species' habitat preferences according to the IUCN Red List Assessments (Lumbierres et al., 2022) and known maximum and minimum elevation. The AOH maps were created using binary information representing presence and absence, and only based on breeding, non-breeding, and resident distribution (more details in https://github.com/BirdLifeInternational/code_for_AOH). A raster layer for each species was created, representing the species occurrence probability described by the proportion of area of suitable habitat in each grid cell. More specifically, since our assessment was in a 5x5 km grid cell resolution, we transformed the original AOH maps to our resolution, calculating the total percentage of AOH present in each cell. We also used occurrence points to refine the likelihood of occurring in each grid cell for each species from different sources: 1) Local bird experts compiled observational records for their respective countries from a range of sources (i.e., published, and unpublished literature, survey and project data, and a range of other sources) and 2) eBIRD data. To guarantee the accuracy of the data, we only included recent observations (2013 to 2024) that came from eBIRD's protocol, whether stationary or travelling. The maximum distance travelled was set to 7 km to ensure that all records were contained within the final ~ 5x5 km cells.

Due to the scarcity of observational data for Egypt, we assume the species has a very high probability of occurring in a grid cell if it has at least one occurrence of evidence spatially overlapping it. In these cases, we upgraded the cell value to the maximum value (=1), regardless of the amount of habitat available in the AOH surface.

For 12 species without AOH maps (species with just passage area inside the country) but still regularly occurring, we used the BirdLife range maps instead (BirdLife International 2021). We rasterised the polygons in a 5x5 km grid resolution. Due to the uncertainty about the occurrence of species in the ranges in their broad scale, we weighted all grid cells equally = 0.5, representing the 50% change to have or not the species occurring there. We also upgraded the grid cell to a maximum value when a survey point overlaps the raster surface.

We adapted the Bradbury et al. (2014) formula to weight the raster for each species by its respective sensitivity index and amount of habitat in each grid cell. The final species sensitivity value (SI) was assigned for each grid cell following the formula below:

$$Species\ Sensitivity = \ln(species\ occurence\ probability\ in\ the\ grid\ cell + 1) * SI$$

Species occurrence certainty

To provide information about the species' presence likelihood, we created a metric combining the amount of AOH and the confirmed presence of the species in each grid cell. This categorical parameter has values ranging from 1 to 4 and reflects the evidence of the presence of the species in that grid cell. The correspondence of the categories follows:

Low occurrence certainty. The percentage of AOH is < 50%, and the occurrence is not confirmed by on-the-ground surveys (1).

Medium occurrence certainty. The percentage of AOH is > 50%, and the occurrence is not confirmed by on-the-ground surveys (2).

High occurrence certainty. The percentage of AOH is < 50%, and the occurrence is confirmed by on-the-ground surveys (3).

Very high occurrence certainty. The percentage of AOH is> 50%, and the occurrence is confirmed by on-the-ground surveys (4).

For those distribution maps based just on the BirdLife range maps, we created a comparable classification based on the information available for those species. On these occasions, we gave the range area a generic value of 1 (low occurrence certainty) and a value of 3 (high occurrence certainty) to those grid cells where surveys confirmed the species' presence.

Creating multispecies combination map – STEP 3

We created a multispecies combination map by summing up all species-specific sensitivity maps. For Egypt, we combined 54 priority species' rasters. Thus, the final score for each grid cell is the result of the summed values of all the species present in that cell. The bird sensitivity map captures the cumulative impact over the range of species present in each area. To make these maps comparable with the rest of the sources of information, we normalised the values from 0 to 1.

$$\sum_{species}^{n} \ln\left(species\ occurence\ probability + 1\right) * SI$$

Adding other important areas for bird conservation – STEP 4

Land Cover Land Use

To limit the impact of renewable energy, it is important to target development away from natural habitats and towards areas with low ecological value, such as those already highly modified by human activity (Kiesecker et al., 2019). For this purpose, we used land cover data to identify human-altered areas with lower ecological value. Specifically, we used the Copernicus global land-cover and the discrete land cover classification, which includes 23 classes at a ~100 m spatial resolution (Buchhorn et al., 2020). We chose to use this dataset for its high accuracy (average ~80%) and its suitability for conservation (Jung et al., 2020). First, we reclassified all land cover classes to have a value of 1 except for cropland and urban/built up areas which received a value of 0. We then calculated the percentage of natural areas present in each 5x5 km cell following a similar procedure as for distribution areas. In our scoring, cells with a higher percentage of natural areas will result in a higher sensitivity score. We combined the resulting land cover proxy map with the species cumulative map (step 3) using a Multicriteria Analysis (MCA) (Adem Esmail & Geneletti, 2018), weighting land cover proxy and species sensitivity according to bird expert opinion. So, land cover was weighted as 0.2 (contributing with 20% for the final layer) and priority species sensitivity as 0.8 (contributing with 80% for the final layer). This final outcome was then normalised between zero and 1.

Identifying final sensitivity categories – STEP 5

We followed the same approach as for onshore wind farms. Go to STEP 5 to read more.

Power Line – Medium and Low voltage

Calculating species sensitivity – STEP 1

Distribution lines impact birds mainly through collision with overhead cables and electrocution on energy pylons. Therefore, in addition to considering the species most sensitive to collision using the formula mentioned for the High-voltage lines (PwCo), a specific formula for calculating and identifying species sensitive to electrocution was also applied separately:

$$Sensitivity\ Index = (PwElec) \times (CnS)^{\left(1-\left(\frac{(Su+En)}{2}\right)/\left(\left(\frac{(Su+En)}{2}\right)+0.5\right)\right)}$$

To assess the species' sensitivity to electrocution, we used three main published reviews from Africa and Eurasia (Haas et al., 2003; Martín Martín et al., 2019; Prinsen et al., 2011). These reviews provide a classification at the family level of the main avifauna affected by electrical shock. Four broad categories were used to measure sensitivity: **Category I** = casualties reported, but no apparent threat to the bird population. **Category II** = regionally or locally high casualties, but with no significant impact on the overall species population. **Category III** = casualties are a major mortality factor, threatening a species with extinction, regionally or at a larger scale. To complement the assessment regarding global bird families, a systematic review looking for articles published about bird electrocutions with power lines was conducted on Web of Science. Slight differences were found in the classification for certain families, so we included each family in the following subcategories: **6** (III) = casualties are a major mortality factor, threatening a species with extinction, regionally or at a larger scale. **5** (between category II and III). **4** (II) regionally or locally high casualties, but with no significant impact on the overall species population. **3** (between category II and I). **2** (I) casualties reported, but no apparent threat to the bird population. **1** No casualties reported or likely. The Supplementary Material contains bird families with their respective assessments.

Conservation status (CnS), endemism (En), and annual adult survival (Su) were calculated in the same way as for the onshore wind sensitivity index.

To combine the parameters above in the formula and balance their contribution to the sensitivity index, we standardised all values from 0 to 1 by dividing each parameter by its maximum value, following recommendations from Certain et al. (2015).

To choose the final list of species to be included in the assessment, we ranked all species by country according to their sensitivity values. To avoid that considering several species with a lower index could add up to a greater sensitivity than a few species with high sensitivity, we decided to work with only those species with a sensitivity index of ≥ 0.204 (see "AVISTEP_Egypt_PW_Electrocution.xlsx" in Supplementary Material), corresponding to the top ~20% of all species per country. This threshold ensured that the most sensitive species were represented. Additionally, conducting workshop with local bird experts, we assessed the list, uplisting or downlisting species, if necessary, according to their relevance to the national context for bird conservation. For Egypt, we included 58 species as priority species regarding the electrocution with power lines. To produce the final sensitivity scores, we normalised the values to a 0.01 to 1 scale in order to emphasise the much greater sensitivity of species in the top part of the list compared to the species at the bottom (Critchley & Jessopp, 2019).

The Supplementary Material contains 58 priority species with their respective information for different parameters.

Mapping the distribution area for priority species – STEP 2

We used the area of habitat (AOH) maps created for most bird species worldwide in 100x100 m grid cells as resolution. The AOH maps represent the utilised habitats within a species' range and can be considered an intermediate step between the Extent of Occurrence (EOO) and Area of Occupancy (AOO). These maps were created using a modelling approach based on remotely sensed land cover data translated to species' habitat preferences according to the IUCN Red List Assessments (Lumbierres et al., 2022) and known maximum and minimum elevation. The AOH maps were created using binary information representing presence and absence, and only based on breeding, non-breeding, and resident distribution (more details in https://github.com/BirdLifeInternational/code_for_AOH). A raster layer for each species was created, representing the species occurrence probability described by the proportion of area of suitable habitat in each grid cell. More specifically, since our assessment was in a 5x5 km grid cell resolution, we transformed the original AOH maps to our resolution, calculating the total percentage of AOH present in each cell. We also used occurrence points to refine the likelihood of occurring in each grid cell for each species from different sources: 1) Local bird experts compiled observational records for their respective countries from a range of sources (i.e., published, and unpublished literature, survey and project data, and a range of other sources) and 2) eBIRD data. To guarantee the accuracy of the data, we only included recent observations (2013 to 2024) that came from eBIRD's protocol, whether stationary or travelling. The maximum distance travelled was set to 7 km to ensure that all records were contained within the final ~ 5x5 km cells.

Due to the scarcity of observational data for Egypt, we assume the species has a very high probability of occurring in a grid cell if it has at least one occurrence of evidence spatially overlapping it. In these cases, we upgraded the cell value to the maximum value (=1), regardless of the amount of habitat available in the AOH surface.

For 12 species without AOH maps (species with just passage area inside the country) but still regularly occurring, we used the BirdLife range maps instead (BirdLife International 2021). We rasterised the polygons in a 5x5 km grid resolution. Due to the uncertainty about the occurrence of species in the ranges in their broad scale, we weighted all grid cells equally = 0.5, representing the 50% change to have or not the species occurring there. We also upgraded the grid cell to a maximum value when a survey point overlaps the raster surface.

We adapted the Bradbury et al. (2014) formula to weight the raster for each species by its respective sensitivity index and amount of habitat in each grid cell. The final species sensitivity value (SI) was assigned for each grid cell following the formula below:

$$Species\ Sensitivity = \ln(species\ occurence\ probability\ in\ the\ grid\ cell + 1) * SI$$

Species occurrence certainty

To provide information about the species' presence likelihood, we created a metric combining the amount of AOH and the confirmed presence of the species in each grid cell. This categorical parameter has values ranging from 1 to 4 and reflects the evidence of the presence of the species in that grid cell. The correspondence of the categories follows:

Low occurrence certainty. The percentage of AOH is < 50%, and the occurrence is not confirmed by on-the-ground surveys (1).

Medium occurrence certainty. The percentage of AOH is > 50%, and the occurrence is not confirmed by on-the-ground surveys (2).

High occurrence certainty. The percentage of AOH is < 50%, and the occurrence is confirmed by on-the-ground surveys (3).

Very high occurrence certainty. The percentage of AOH is> 50%, and the occurrence is confirmed by on-the-ground surveys (4).

For those distribution maps based just on the BirdLife range maps, we created a comparable classification based on the information available for those species. On these occasions, we gave the range area a generic value of 1 (low occurrence certainty) and a value of 3 (high occurrence certainty) to those grid cells where surveys confirmed the species' presence.

Creating multispecies combination map – STEP 3

We created a multispecies combination map by summing up all species-specific sensitivity maps. We create one map specific for collision (combining 54 species) and another for electrocution (combining 58 species). Thus, the final score for each grid cell is the result of the summed values of all the species present in that cell. The bird sensitivity map captures the cumulative impact over the range of species present in each area. To make these maps comparable with the rest of the sources of information, we normalised the values from 0 to 1.

$$\sum_{species}^{n} \ln\left(species\ occurence\ probability + 1\right) * SI$$

** Distribution lines considered maps from Collision and Electrocution, combining them and conserving the maximum value in each grid cell. That means if a grid cell has a value of 1 for electrocution but 0.5 for collision, the final grid cell value is 1.

Adding other important areas for bird conservation – STEP 4

Land Cover Land Use

To limit the impact of renewable energy, it is important to target development away from natural habitats and towards areas with low ecological value, such as those already highly modified by human activity (Kiesecker et al., 2019). For this purpose, we used land cover data to identify human-altered areas with lower ecological value. Specifically, we used the Copernicus global land-cover and the discrete land cover classification, which includes 23 classes at a ~100 m spatial resolution (Buchhorn et al., 2020). We chose to use this dataset for its high accuracy (average ~80%) and its suitability for conservation (Jung et al., 2020). First, we reclassified all land cover classes to have a value of 1 except for cropland and urban/built up areas which received a value of 0. We then calculated the percentage of natural areas present in each 5x5 km cell following a similar procedure as for distribution areas. In our scoring, cells with a higher percentage of natural areas will result in a higher sensitivity score. We combined the resulting land cover proxy map with the species cumulative map (step 3) using a Multicriteria Analysis (MCA) (Adem Esmail & Geneletti, 2018), weighting land cover proxy and species sensitivity according to bird expert opinion. So, land cover was weighted as 0.2 (contributing with 20% for the final layer) and priority species sensitivity (the maps merging collision and electrocution) as 0.8 (contributing with 80% for the final layer. This final outcome was then normalised between zero and 1.

Identifying final sensitivity categories – STEP 5

We followed the same approach as for onshore wind farms. Go to STEP 5 to read more.

Solar Photovoltaic (PV)

Calculating Sensitivity for all species occurring in the country – STEP 1

The species-specific sensitivity based on different impacts created for the other types of energy developments does not apply to the context of solar photovoltaic energy. We have used a precautionary approach, considering that the presence of solar photovoltaics would result in habitat loss and/or degradation for all species that occur in the area, although some species can indeed coexist with solar PV installations.

We considered a list of all species occurring in the country, individually weighted by their respective Conservation Status (CnS - primary factor) and Endemicity (En - aggravating factor). For Egypt, we worked with 330 species in total.

Conservation Status (CnS): We used the IUCN Red List categories from 2021 as follows: 5 = Critically Endangered (CR); 4 = Endangered (EN); 3 = Vulnerable (VU); 2 = Near Threatened (NT); 1 = Least Concern (LC) or Data Deficient (DD).

Endemism (En): We calculated the percentage of the global distribution area inside each country's territory. To calculate this parameter, we used the distribution range maps (BirdLife International & The Handbook of the Birds of the World, 2019) and the national boundaries (Global Administrative Areas, 2021) in ArcGIS Pro (ESRI, 2023). To transform these values into categories from 1 to 5, we used the following conversion criteria: 1 = 0-20%, 2 = > 20-40%, 3 = > 40-60%, 4 = > 60-80%, 5 = > 80-100%. To standardise all metrics and make them comparable, we divided each by the maximum category value following recommendations from Certain et al. (2015).

$$Species\ sensitivity = (CnS)^{\left(1-(En)/((En)+0.5)\right)}$$

Mapping the species distribution according to the Sensitivity – STEP 2

We used the BirdLife range maps (BirdLife International 2021) to create a raster layer for the 330 species with a 5x5 km grid cell resolution. The respective species sensitivity value weighted each raster surface.

Creating a species richness map – STEP 3

To create a surface representing the cumulative sensitivity, we summed all the raster in the same grid cell following the formula

$$Species\ sensitivity = \sum_{species}^{n} (CnS)^{\left(1-(En)/((En)+0.5)\right)}$$

Creating a layer with potential wilderness areas and adding important areas for bird conservation – STEP 4

To identify zones where the development of solar farms may negatively impact biodiversity, we first combined the bird richness surface with land cover information, using the same set of criteria as in previous infrastructures, while conserving the maximum value between the two layers. This final Bird Conservation layer was then combined with a human footprint surface (used as a proxy to infer wilderness). Accordingly, areas far from the site with high value for the human footprint index (population density, built infrastructure such as roads, railways, factories, and night-time lights) would be less exposed to disturbance (Ascensão et al., 2023) and, therefore, consist of more relevant areas for bird conservation. We used HFI second generation of information with 300 m2 as resolution from https://wcshumanfootprint.org/ (data-access 31/10/2023).

The final bird conservation layer was combined with the human footprint surface, both calculated in 5x5km using Multicriteria Analysis. The human footprint surface was weighted as 0.2 (contributing with 20% for the final layer) and the bird richness sensitivity as 0.8 (contributing with 80% for the final layer). This final outcome was then normalised between zero and 1.

Identifying final sensitivity categories – STEP 5

We followed the same approach as for onshore wind farms. Go to STEP 5 to read more.

Offshore Wind

Delineate Area of Interest (AOI) – STEP 1

The first step in our offshore sensitivity analysis was delineating our Area of Interest (AOI). The offshore limits of the analysis (AOI) were set to the extent of the Exclusive Economic Zone (EEZ) in Egypt. This is done to facilitate incorporating the sensitivity map into future discussions about marine spatial planning and management of activities in the EEZ.

Identifying Species for Analysis – STEP 2

Collating the seabird species list for the AOI of a region is a process that we validate with local partners and experts where available. The flow chart below shows the range of sources we consider before a species is ultimately included or excluded (Figure 1).

For Egypt, all available range maps for species overlapping with the EEZ were considered. A literature review was carried out along with a review of available observation records (for example, eBird) to determine any additional species to be considered. Some birds listed as seabirds can exhibit both marine and onshore activity in their ranges (for example, species such as Cormorants, Terns and Grebes). For these groups, their distribution was checked within the AOI. In total, 31 species were identified for the offshore sensitivity analysis in Egypt.

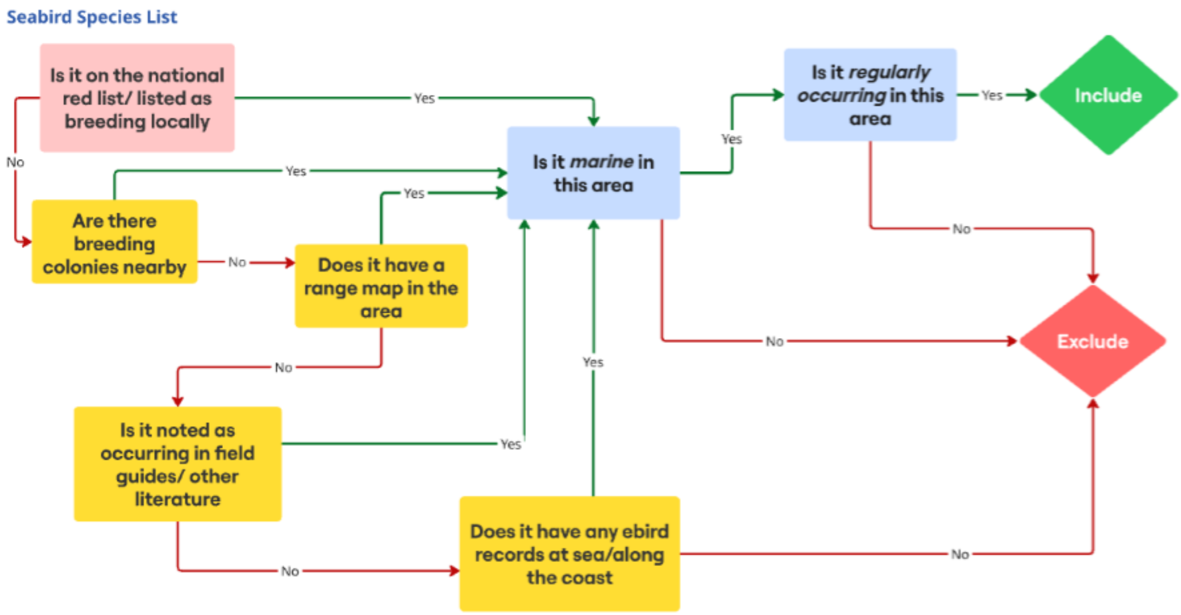

Figure 1: Flowchart of the decision-making process for seabird species selection in AVISTEP offshore analysis. The process starts with key sources (in red), additional corroborating sources are in yellow, country-specific distribution requirements are in blue. The process ends with a species being included or excluded from the species list.

Calculating Sensitivity for all Selected Species– STEP 3

Following the identification of species for analysis, sensitivity was calculated for all listed species. We estimated the individual risk factors collision (Co) and displacement (Di), along with the population level risk conservation status (CnS). Using a trait-based approach, estimated a level of sensitivity for individual species. As with previous projects, collision and displacement were calculated separately for offshore (Furness et al., 2013). These were combined with a conservation score (CnS) to create an overall sensitivity to both collision and displacement.

For each risk, all contributing factors were divided into primary and aggravating factors. Primary factors are inherently risky behaviour, traits, or demographic parameters that directly contribute to a species' sensitivity. Aggravating factors exacerbate an existing risk but have no inherent risk of their own (Certain et al., 2015).

We used a modified version of the sensitivity index developed by Certain et al. (2015) for sensitivity mapping in relation to offshore energy. This methodology has been used in similar exercises for Ireland (Critchley & Jessopp, 2019) and Scotland (Searle et al., 2019). In turn, this index is a renewed version of one created by Garthe & Hüppop (2004) who pioneered this field of work. The main innovation of this methodology is the differentiation between primary and aggravation factors. Primary factors are species characteristics that directly control the vulnerability, while aggravation factors are those that can increase a vulnerability that already exists (Certain et al., 2015). These differences between factors are therefore incorporated in the mathematical formulation of the indices. Although we mostly based our work on this methodology, we incorporated concepts, information and methods from other works like Bradbury et al. (2014), Furness et al. (2013), and Kelsey et al. (2018). Moreover, most of the information for scoring the different parameters by species came from Bradbury et al. (2014), Certain et al. (2015), Critchley & Jessopp (2019), Furness et al. (2013), Kelsey et al. (2018) and, Robinson Willmott et al. (2013). When we could not find information from these sources, we conducted a literature review to extract the necessary information. If no information was available to estimate a metric value for a given species, we used data from similar species.

Finally, when several sources disagreed, we used the most recent values. Information about parameter values and sources of information can be found in "AVISTEP_Egypt_Offshore.xlsx" in the of the Supplementary Material.

Two different sensitivity indices were created:

Where there are three primary factors: A1 = % of time flying at blade height, A2 = % of time spent flying, and CnS = conservation status, and three aggravation factors: A3 = nocturnal flight activity, A4 = flight manoeuvrability, and Su = annual adult survival.

$$Collision\ sensitivity\ index = (A1 \times A2)^{\left(1-\left(\frac{A3+A4}{2}\right)/\left(\frac{A3+A4}{2}\right)+0.5\right)} \times CnS^{\ (1-Su)/(Su+0.5)}$$

A detailed explanation of the different metrics employed is as follows:

Conservation status (CnS) was the same parameter used in the onshore sensitivity assessment. Most previous studies have included information about population and conservation status at the national or regional level (e.g., Bradbury et al., 2014, Kelsey et al., 2018). The lack of this information for our study area, obliged us to employ a simplified version of this score of 1-5 for least concern to critically endangered.

- 1 = Least Concern (LC)
- 2= Near threatened (NT)
- 3= Vulnerable (VU)
- 4= Endangered (EN)
- 5 = Critically Endangered (CR)

Annual Adult Survival (Su): There are various life-history factors than can affect a population's ability to recover from additional moralities or poor breeding success, we use annual adult survival as a metric to capture these traits. These values, which have been recently calculated for all bird species (Bird et al., 2020) are used as an aggravating factor to red list status. As with onshore, annual adult survival is treated as an exponential factor to red list status. For offshore, we followed the classification proposed by Critchley & Jessopp (2019), specifically for seabirds.

- 1 = < 0.75
- 2 = > 0.75 – 0.8
- 3 = > 0.8 – 0.85
- 4 = > 0.85 – 0.9
- 5 = > 0.9

Collision (Co): Offshore structures are novel obstructions that do not form part of the natural environment and pose a threat of collision to seabirds. Collision can occur with the mobile rotor blades of the turbine or with the static structure below. Collision risk modelling has been the focus of windfarm sensitivity analysis in areas with established offshore wind industries (Furness et al., 2013; Garthe & Hüppop, 2004). Despite ongoing research into collision, there is still uncertainty surrounding the drivers and the frequency of collision of seabirds. As a result, risk of collision is estimated by scoring various behavioural and morphological traits of individual species.

Percentage of time flying at blade height (A1). This parameter is directly related to the species flight height, and it is one of the main factors influencing collision. The height range selected to represent the blade height was between 20-150 meters.

We assigned values from 1 to 5 where:

- 1 = 0 – 5%
- 2 = > 5 – 10%
- 3 = > 10 – 15%
- 4 = > 15 – 20%
- 5 = > 20 – 100%

Percentage of time spent flying (A2). Percentage of time in flight during a complete day (24h; day and night). Robinson Willmott et al. (2013) and Kelsey et al. (2018) did not include this specific parameter, but instead they calculated diurnal flight activity and nocturnal flight activity separately. To use these sources, we calculated the average of the nocturnal and diurnal flying activity. We assigned values from 1 to 5 where:

- 1 = 0 – 20%
- 2 = > 20 – 40%
- 3 = > 40 – 60%
- 4 = > 60 – 80%
- 5 = > 80 – 100%

Flight Manoeuvrability (FM) & Nocturnal Activity (Noc): Once flying at a dangerous height, there are factors that may impact an individual's ability to avoid possible collision. Based on previous work on collision sensitivity factors (Garthe & Hüppop, 2004; Furness et al., 2013; Bradbury et al., 2014; Certain et al., 2015), flight manoeuvrability and nocturnal activity were identified as aggravating factors to exposure. The application of aggravating factors assumes that, when all other factors are equal, a less manoeuvrable species or a species that is very active at night may be more vulnerable to collision than other species. When combining factors, how they interact determines how best to include them. As nocturnal activity and flight manoeuvrability are considered to aggravate the risk of flying near offshore turbines, we consider them as interactive with the exposure risk values for each species. Therefore, this factor is multiplied by the risk of exposure to rotor blades. Since we have no evidence that manoeuvrability and nocturnal activity interact dependently in relation to collision risk, we are using the average between the two to create an aggravated risk score to apply to exposure (Certain et al., 2015).

Nocturnal flight activity (A3). Percentage of time in flight during night. We assigned values from 1 to 5 where:

- 1 = 0 – 20%
- 2 = > 20 – 40%
- 3 = > 40 – 60%
- 4 = > 60 – 80%
- 5 = > 80 – 100%

Flight manoeuvrability (A4). Aerial agility of species and hence their potential to micro-avoid collision with wind turbines at sea. We assigned values from 1 to 5 where:

- 1 (very high manoeuvrability) to 5 (very low manoeuvrability)

Where there are three primary factors: B1 = disturbance by vessels & helicopters, B2 = disturbance by structures, and CnS = conservation status, and two aggravation factors: B3 = habitat flexibility, and Su = annual adult survival.

$$Displacement\ sensitivity\ index = \left((B1 + B2)/2\right)(1 - (B3)/(B3) + 0.5) \times CnS(1 - Su)/(Su + 0.5)$$

Disturbance by vessels & helicopters (B1). This parameter measures the escape response produced by vessel and helicopter traffic.

A detailed explanation of the different metrics employed is as follows:

- From 1 (low disturbance response) to 5 (high disturbance response)

Some authors do not distinguish between disturbance produced by fixed structures and marine traffic. However, since marine traffic (i.e., vessels and helicopters) is expected to increase during construction and operation of offshore wind farms, we included them separately. For some species we did not find information about both disturbance types, but only for fixed structures; on those occasions, we scored both parameters equally.

Disturbance by structures (B2). Macro-avoidance behaviour from fixed structures on the sea (i.e., offshore wind farms) and possible displacement from areas under the influence of these structures.

- From 1 (low disturbance response) to 5 (high disturbance response)

Habitat flexibility (B3). Ability of the species to feed on a variety of food sources and/or forage within multiple habitat types, or if, on the contrary, the species is restricted in their diet and/or forages in very particular habitats.

- From 1 (high habitat flexibility) to 5 (low habitat flexibility)

To standardise all metrics and make them comparable, we divided each on them by the maximum category value following recommendations from Certain et al. (2015).

Mapping distribution for all seabird species– STEP 4

Species distribution

For species geographical distributions, we used distribution range maps (BirdLife International & The Handbook of the Birds of the World, 2019). Some species did not have the marine part of their range included in the range map within the study area. For these species, we searched the literature for the offshore foraging range for the species and used this to buffer from the terrestrial part of the species range. Range maps for all species were rasterised at a 5x5 km grid for breeding and non-breeding/passage ranges separately, included resident species in both the breeding and non-breeding maps.

Sensitivity map calculation

Following the same methodology we used for onshore wind energy, we first transferred the sensitivity indices values per species to their geographic distribution, making this value spatially explicit in a ~ 5x5 km grid cell. We then overlapped all the species geographic distributions by season and added the sensitivity values from all the species. Thus, the final score for each cell was the result of the summed values of all the species present in that cell. We did this separately for the breeding and non-breeding seasons for both collision and displacement sensitivity index; thus, four different maps were created, two for collision and two for displacement. To make these maps comparable with the rest of sources of information, we divided the values by the maximum so that the highest values from each map was 1. We then overlapped the four maps so that the final score of each cell was the maximum value. In this way, we ensured that the final sensitivity score for an area was calculated based on the most sensitive species present, regardless of the type of impact.

Mapping distribution for non-marine species– STEP 5

Terrestrial Bird Migration

Egypt supports a crucial bottle neck for terrestrial bird species migrating within the African-Eurasian flyway, many of which make sea crossings to reduce their distance travels over their long migrations. To account for this, we used the marine part of the terrestrial bird migration layer created using kernel density analysis to map satellite tracking data for 14 species as described in the previous section on onshore wind.

This layer was then combined with the species sensitivity layer by overlapping the rasters and selecting the maximum value from any given cell. The output map contained either the highest sensitivity from the seabird sensitivity map or migratory map in any given cell

Additional Areas

Important Bird and Biodiversity Areas (IBAs)

Important Bird and Biodiversity Areas (IBAs) are a global dataset of areas of greatest significance for the conservation of the world's birds. They cover about 6.7% of terrestrial area, 1.6% of marine area and 3.1% of the total surface area of the Earth (Donald et al., 2019). This dataset is curated by BirdLife International and available through their website (http://datazone.birdlife.org/site). All countries included the most up-to-date version of this data from 2024 (Birdlife International, 2024). We included all IBAs catalogued as marine by BirdLife International plus those coastal IBAs which had ≥5% overlap with the oceans following the classification applied in the Sustainable Development Goals (Goal 14.5 - Indicator 14.5.1) (United Nations Environment Programme, 2021). Cells overlapping with a marine or coastal IBA received the maximum level of sensitivity. A buffer of ~5 km was applied at value of 0.5 to all IBA polygons with breeding seabirds as trigger species to account for foraging movements out of the IBA boundaries. For Egypt, these sites were: Lake Burullus, Lake Manzala, Lake Bardawil, Zaranik Protected Area, Hurghada archipelago, Tiran island, Qulan islands, Zabargad island, Siyal islands, Rawabel islands and Wadi Gimal island.

Categorising Sensitivity– STEP 6

Once the preliminary species sensitivity result layer was produced, we categorised the results our categories of low-high sensitivity. This was a classed raster with all cells values from 1 to 4 (green to red). This was done using Jenks natural breaks in the *ClassInt* package in R (Bivand et al., 2022).

Adding Other Important Areas for Birds and Conservation– STEP 7

As with onshore, areas that were determined to be key concern for bird conservation were included in our analysis for offshore wind. Shapefiles of selected areas were overlapped with the project fishnet and overlapping cells were rasterised to match the 5x5 km project grid. For Egypt these areas included oceanic habitats, Marine Protected Areas (MPAs) and Important Bird and Biodiversity Areas (IBAs) These areas were added at the highest sensitivity. As these were added after the classification of sensitivity using Jenks natural breaks, they did not impact on the relative sensitivity of nearby cells.

Ocean habitats

The analysis also contains information on the distribution of marine habitats that are of special importance for marine organisms and ecosystems. Overlapping cells with any of these habitats were given the maximum sensitivity value. For Egypt, three habitat types were considered.

- *Mangroves*. This dataset was created mostly from satellite imagery and shows the global distribution of mangroves. It was produced as a joint initiative of several international organizations (Spalding et al., 2010).

- *Coral reefs*. This dataset shows the global distribution of coral reefs in tropical and subtropical regions. It is the most comprehensive global dataset of warm-water coral reefs to date UNEP-WCMC, WorldFish Centre, WRI, & TNC (2021).

- *Seagrasses*. This global dataset of seagrass distribution was created from multiple sources (in 128 countries and territories), including maps (of varying scales), expert interpolation and point-based samples (UNEP-WCMC and FT Short, 2021).

This information is curated by UNEP-WCMC and available through the Ocean Data Viewer on their website (https://data.unep-wcmc.org/).

Overlapping cells with any of these three habitats were given the maximum sensitivity value.

Marine Protected Areas

Marine protected areas are sites designated for the conservation of marine habitats, species and ecosystems. Egypt has just over 5% of its marine environment designated as MPAs (www.protectedplanet.net). These were included in our offshore sensitivity analysis at the highest level of sensitivity. We used the World Database of Protected Areas (WDPA) from the Protected Planet website (www.protectedplanet.net). This database is updated regularly by governments and curated by UNEP-WCMC and includes the most up-to-date information on protected areas. The latest version from 2024 was used for Egypt. All protected areas classified as coastal or marine were included, regardless of their IUCN management category. Cells overlapping with these areas automatically received the maximum level of sensitivity.

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AVISTEP

The Avian Sensitivity Tool for Energy Planning

Appendix VI – Australia

November 2025

BirdLife INTERNATIONAL

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Onshore Wind Energy

Calculating species sensitivity – STEP 1

In creating a species sensitivity index, we adapted the sensitivity index developed by Certain et al. (2015) which main innovation has been to differentiate between primary and aggravation factors. Read Certain et al. (2015) and Garthe & Hüppop (2004) for more details on parameter combinations. For the taxonomy we followed the HBW-BirdLife v.9 (https://datazone.birdlife.org/about-our-science/taxonomy).

The respective national species lists to be assessed were created in agreement with BirdLife Australia, and other bird experts. The sensitivity index was calculated for each regularly occurring bird species, excluding flightless, vagrant, and rare sightings, as well as restricted seabirds. For Australia, we calculated the sensitivity index for 607 bird species following the formula:

$$Sensitivity\ Index = \left(Co + \left(\frac{Di}{5}\right)\right) \times (CnS)^{\left(1-(Su)/((Su)+0.5)\right)}$$

Collision (Co): We employed a trait-based approach to infer the potential collision risk at the species level, thereby developing a metric that identifies a species' sensitivity to collisions with turbines. Factors influencing a species' collision vulnerability to onshore wind farms are related to intrinsic factors, such as ecological, behavioural, morphological, and life-history aspects, as well as the bird's level of exposure to turbines when in flight. Therefore, we primarily focused on two concepts: bird exposure and bird susceptibility, which, when combined, lead to the risk of collision. We also considered adding an extra risk factor to account for aspects that increase the risk of collision but are unique to some species and, therefore, not applicable to all species.

$$\boldsymbol{C}ollision = (Exp \times Suscep) + Ext.risk$$

Bird exposure (Exp) refers to the probability of a bird encountering a turbine, based on the time they fly at heights compatible with the rotor sweep zone. We classified each species in four different exposure categories:

- **No exposure**: Species that are never or very rarely active at a vulnerable height, representing flightless, terrestrial, and ground-dwelling birds. Birds that rarely fly at height, in open landscapes away from forest vegetation, such as forest dwellers and species that stay close to the ground, were also classified in this category.
- **Low exposure**: Species that are not active daily at a vulnerable height but spend some time at the RSZ during their annual cycle are often represented by migratory and dispersive species, such as migratory honeyeaters and altitudinal migrants.
- **Moderate exposure**: Species that spend less than 50% of their daily active time at a vulnerable height, represented by species that make daily movements across open air space as they commute between roosting and foraging sites. This category typically includes many members of the following families: corvids, parrots, pigeons and doves, waterfowl, gulls and terns, shorebirds, pelicans, cormorants, bustards, cranes, herons, ibis, magpies, and birds of prey that hunt from a perch or within forests.
- **High exposure**: Species that spend more than 50% of their daily active time at a vulnerable height, represented by aerial insectivores such as swifts and swallows, and birds of prey that hunt on the wing, often from a high soar.

Since a bird can collide only when it is exposed to the turbines, we work with this set of weights: No exposure (zero); Low (0.333); Moderate (0.666); High (1).

Bird susceptibility (Suscep) refers to the species' intrinsic characters, which are mainly related to the morpho-behavioural and life-history traits linked with flight behaviour. Theoretically, large, heavy, relatively small-winged birds with poor vision are most susceptible to collision, while small, light, relatively large-winged birds with acute vision are least susceptible. All volant, terrestrial species are potentially susceptible, and most fall between these extremes.

$$\boldsymbol{Bird\ Suceptibility} = (\boldsymbol{Forag.behav} \times \boldsymbol{Mnvr})$$

Foraging behaviour (Forag.behav): Variations in visual field topography among birds have been interpreted as adaptations to the specific perceptual challenges posed by the species' foraging ecology. At the same time, visual perception, when combined with specific foraging behaviours during flight, can affect the likelihood of bird collision with different human infrastructures.

Visual topography differs between species, particularly in the extent and position of the binocular field relative to the bill, as well as the extent of blind areas above and behind the head. These differences are primarily correlated with differences in foraging ecology, even among closely related species (Martin & Portugal 2011). Birds differ in the vertical extent of their binocular fields, resulting in differences in the extent of the blind areas in front of the head, a key region for detecting obstacles in flight. These differences must arise primarily due to differences in the positioning of the eyes in the skull. Overall, bird species with more comprehensive coverage of the frontal hemisphere gain full visual coverage of the airspace ahead of them, regardless of the head position adopted in flight. This is likely to contribute to lower vulnerability to collisions. We are interested in the phylogenetic signal for the maximum vertical height of the binocular field and foraging ecology based on the family level. Therefore, we classified birds into four different types of risk of collision according to eye position in the skull, vertical extension of the binocular visual field, foraging behaviour, head position during flying, and diet:

- **Low risk:** Birds with frontal eye position, excellent binocular view, and large vertical extension of the binocular field. They have forward-facing vision, which means that during flight, they forage looking forward, not looking down, catching prey in mid-air (e.g., some insectivorous birds).
- **Medium risk**: Inside medium risk, we can identify two groups: a) Birds with lateral eye position and those with limited forward vision. Full celestial/hemisphere view is in monocular, with almost no blind areas (associated with anti-predator vigilance). Looking for foraging spots when flying. Foraging looking forward, not looking down while flying, represented mainly by tactile/filter foragers. b) Lateral eye position, forward vision limited. Benefit from monocular vision. But have a large vertical extension of the binocular field (small blind area). Looking for foraging spots when flying. Foraging looking forward, not looking down, represented mainly by Pecking foragers, using the bill like pincers (catching seeds or evasive prey).
- **High risk:** More frontal eye position, Excellent binocular vision, but limited vertical extension of the binocular field resulting in extensive blind areas. Forward-facing vision, but forages looking down. Overall, carrion eaters and birds of prey.
- **Very high**: They also benefit from lateral vision. Very limited vertical extension of the binocular field (even a slight 30-degree head turn can send them flying forward blindly), forward-facing vision often looking down. Overall, a diet based on a range of stationary sources such as seeds, berries, bulbs, and non-evasive animals.

Manoeuvrability (Mnvr). The scientific literature highlights that wing loading (resulting from body mass divided by wing area) is one of the most relevant morphological traits that predicts species' probability of colliding and is associated with high manoeuvrability in flight (Bevanger, 1998; Janss, 2000). However, measures such as wing area or specific measurements necessary to calculate wing area, such as wingspan, are not always available. We demonstrated that wing length is highly correlated with wingspan. When bird weight is divided by the wing length, it produces a proxy valid to infer manoeuvrability (D'Amico et al., 2019; Reid et al., 2023) that could conserve the same relative difference between species as using wing area. Both weight and wing length are commonly recorded measurements and are available for all birds worldwide in Tobias et al. (2022). Therefore, we have:

$$Mnvr\_proxy = \left(\frac{weight\ (g)}{wing\ \ length\ (cm)}\right)$$

Extra risk factor (Ext.risk): Some species possess additional or aggravating risk factors for collisions that cannot be generalised across all species. For example, even a bird with great manoeuvrability and adequate vision can be frequently involved in collisions. In those cases, other intrinsic traits, such as very high flight speeds, or flock-oriented flight patterns, may play a role, especially when combined with low-light conditions typical of crepuscular or nocturnal activity. However, these traits alone do not universally predict collision risk: not all fast-flying, flocking, or nocturnal species are equally affected. For example, some nocturnal birds have specialised night vision and can evade manoeuvres even in the dark. Therefore, when we could identify a special trait, we gave some species with at least one of these potential special traits an additional weight = 0,2 as an extra risk factor. Additionally, we assigned an extra weight of 1 to species frequently recorded as victims of turbine and/or overhead cable collisions worldwide. An extra weight of 1 was also given to a few Australian species that faced threats from energy infrastructure in their National Recovery Plan (See "AVISTEP_Australia_Onshore.xlsx" in Sup. Material to check species that received the Extra risk factor).

*It's important to recognise that any flying species may eventually collide. In addition to intrinsic species characteristics, collisions can occur due to other external environmental and technical factors, and the frequency of recordings may be attributed to population abundance. Therefore, a species that is not prone to collisions, flying in extreme weather conditions such as wind and low light availability, combined with a lack of mitigation, may also collide. Our approach aims to capture collision risk based only on intrinsic aspects of the species.

Displacement (Di): Displacement refers to the reduction in habitat use within areas influenced by wind energy facilities, which can result in decreased bird densities and, consequently, functional habitat loss over the medium and long term (May, 2015). Although research on displacement is relatively recent compared to studies addressing collision risk, the concept was first applied and explored in marine environments. These habitats are physically more homogeneous than terrestrial ones, which allows for clearer and more conclusive findings in offshore contexts. In contrast, for onshore bird species, demonstrating that observed alterations in habitat use are directly attributable to the presence of wind farms is considerably more complex. While reduced habitat use is also relevant in terrestrial contexts, the available evidence is limited and less conclusive. Consequently, within our analytical framework, displacement was assigned a lower relative importance, weighted at one-fifth of the value of other parameters.

A literature review was conducted using the Web of Science database to identify studies addressing bird displacement in the context of wind energy. The search query employed was as follows: (TS = ("wind*farm" OR "onshore" OR "offshore" OR "wind*turbine") AND TS = ("birds" OR "avian")) AND TS = ("displacement" OR "avoidance" OR "space*use"). TS means title, abstract, and author keywords.

The displacement parameter was incorporated only for bird families with studies presenting consistent evidence of displacement effects. For these families in Australia—Accipitridae, Anatidae, Falconidae, Gruidae, and Podicipedidae—the maximum displacement value of 1 was assigned. For families exhibiting contradictory findings—Strigidae, Laridae, Scolopacidae, and Charadriidae—an intermediate value of 0.5 was used. The parameter was not included in the analytical formula for most bird families, where displacement has not been explicitly investigated.

Conservation Status (CnS) was assigned to each species by integrating information from both the Global Red List (GRL) and the National Red List (NRL). Species were then classified according to their Conservation Status and Population Trend (if population are increasing, stable or decreasing in numbers). To determine the relative importance among different categories, we used the Analytic Hierarchy Process (AHP), applying a Saaty pairwise comparison matrix across categories to evaluate and contrast their relevance to extinction risk. The assessment was conducted in collaboration with colleagues from the

IUCN Red List. The weights assigned increased exponentially according to the highest threat category as follows:

- Critically Endangered (CR) + any species with number of mature individuals < 1,000 = **1.00**
- Endangered (EN) + any species with number of mature individuals < 2,500 = **0.59**
- Vulnerable (VU) + any species with number of mature individuals < 10,000 = **0.41**
- Near Threatened (NT) = **0.12**
- Least Concerned (LC) and population trend decreasing = **0.08**
- LC and population trend increasing or stable = **0.06**

We did not have data-deficient (DD) species. The same values were considered for the Global and National Red List categories. Then, the mean value was used as the final CnS, since the categories may differ between global and national assessments.

$$\boldsymbol{CnS} = \left(\frac{\boldsymbol{GRL} + \boldsymbol{NRL}}{\boldsymbol{2}}\right)$$

Annual adult survival (Su). The population-level impact of a single individual fatality event depends primarily on the species' life history traits. Specific life history traits, such as fecundity, age of maturity, and adult survival, are particularly relevant. K-selected species are characterised by low fecundity, late ages of maturity and high survival; thus, adult mortality impacts these populations (Niel & Lebreton, 2005; Sæther & Bakke, 2000). The species groups with the highest rates of impact from wind development tend to be K-selected species, such as Accipitridae, Ciconiidae, or Bucerotidae (Thaxter et al., 2017); thus, this factor must be carefully considered when evaluating impacts on bird conservation. We employed annual adult survival estimated for all bird species to include a metric that could capture these life history factors (Bird et al., 2020). For Australian birds, the adult annual survival ranged from 0.41 to 0.93.

To combine the five parameters above in the formula and balance their contributions to the sensitivity index, we rescaled all values from 0.01 to 1, following the recommendations of Certain et al. (2015).

We ranked all species according to their sensitivity values to identify the priority species for spatial assessment. To identify the subset most affected, we split the ranking into different classes using a cluster method proposed by Jiang (2013) for data with heavy-tailed distributions. The method partitions the class intervals and establishes the number of groups through an iterative approach. This approach resulted in five groups, which we interpreted as extremely high, very high, high, medium, and low sensitivity. To be more conservative, we considered the species in all categories different from low sensitivity as priority species, totalling 145 Australian birds (See “AVISTEP_Australia_Onshore.xlsx” in Sup. Material).

Mapping the distribution area for priority species – STEP 2

We used a version of the area of habitat (AOH) maps that were explicitly created for Australian terrestrial birds (the data are currently under review and are available upon request). The AOH maps represent the utilised habitats within a species’ range and can be considered an intermediate step between the Extent of Occurrence (EOO) and Area of Occupancy (AOO). These maps were created with a 100x100m grid cell resolution using a modelling approach based on the Australian National Vegetation Information System (NVIS v.6). The NVIS classes were translated to species’ habitat preferences according to Garnet et al. (2015) inside species distribution maps combining BirdLife International & Australian Bird Guide ranges. The AOH maps were created using binary information representing presence and absence, and were based only on breeding, non-breeding, and resident distribution.

A raster layer for each species was produced, representing the species occurrence probability described by the proportion of area of suitable habitat in each grid cell. More specifically, since our assessment was in a 5x5 km grid cell resolution, we transformed the original AOH maps to our resolution, calculating the total percentage of AOH present in each cell. We also used occurrence points from the last 15 years (2010 to 2025) from different sources to refine the likelihood of occurring in each grid cell for each species: 1) eBIRD data (https://ebird.org). To guarantee the accuracy of the data, we only included observations that came from eBIRD's protocol, whether stationary or travelling. The maximum distance travelled was set to 7 km to ensure that all records were contained within the final ~ 5x5 km cells. To curate the datasets, we used the RStudio package *auk* (Strimas-Mackey et al., 2025); 2) Birdata is BirdLife Australia's online national bird monitoring platform, which compiles data from professional researchers' projects and citizen scientists. It also incorporates BirdLife Australia's nationwide surveys and targeted threatened species surveys; we included all data except eBird to avoid duplicate data. To guarantee the accuracy of the data, we only included observations that came from eBIRD's protocol, whether stationary or travelling. The maximum distance travelled was set to 7 km to ensure that all records were contained within the final ~ 5x5 km cells. To curate the datasets, we used the RStudio package auk (Strimas-Mackey et al., 2025), and 3) Tasmania Data - Bird occurrences from Natural Values Atlas, which provides comprehensive information on Tasmania's birds. Since the occurrence data are not evenly observed and distributed over the Australian territory, we assume the species has a very high probability of occurring in a grid cell if it has at least one occurrence of evidence spatially overlapping it. In these cases, we upgraded the cell value to the maximum value (=1), regardless of the amount of habitat available in the AOH surface.

The bird ranges provided by the BLA contained separate polygons for the species' core area - primary habitats that are essential for a bird species' survival, reproduction, and long-term persistence - and non-core areas - secondary or peripheral habitats that birds use less frequently, seasonally, or opportunistically. Thus, the amount of habitat for non-core areas was evaluated as less (divided by 2) than in the species' core areas.

We adapted the formula by Bradbury et al. (2014) to weight the raster for each species by its respective sensitivity index and the amount of habitat in each grid cell. The final species sensitivity value (SI) was assigned for each grid cell following the formula below:

$$Species\ Sensitivity\ core = ln(species\ occurence\ probability\ per\ pixel + 1) * SI$$

$$Species\ Sensitivity\ non\_core = ln((species\ occurence\ probability\ per\ pixel + 1)/2) * SI$$

Species occurrence certainty

- **Very-high occurrence certainty (4):** Inside core areas, the percentage of habitat suitable for the species (%AOH) and the occurrence confirmed by on-the-ground surveys.
- **High occurrence certainty (3)**: Inside core areas, the percentage of habitat suitable to find the species is > 50% (AOH) without occurrence confirmed by on-the-ground surveys; and outside core areas, the percentage of habitat suitable for the species (%AOH) and the occurrence confirmed by on-the-ground surveys.
- **Medium occurrence certainty (2)**: Inside core areas, the percentage of habitat suitable to find the species is < 50% (AOH) without occurrence confirmed by on-the-ground surveys; and outside core areas, the percentage of habitat suitable to find the species is > 50% (AOH) without occurrence confirmed by on-the-ground surveys.
- **Low occurrence certainty (1)**: Outside core areas, the percentage of habitat suitable to find the species is < 50% (AOH), and there is no occurrence confirmed by on-the-ground surveys.

This information is available on the AVISTEP maps, which show all priority species in each grid cell with their respective SI and Occurrence Certainty. Some species in Australia are being considered sensitive. Therefore, publication or information on species distribution patterns could put those sites at risk and is not recommended. Nine species in Australia (Australasian Bittern, Red Goshawk, Grey Falcon, Orange-bellied Parrot, Plains-wanderer, Night Parrot, Princess Parrot, Golden-shouldered Parrot, and Letterwinged Kite) had their sensitivity index and sites considered in the analysis; however, the display showing occurrence certainty was omitted.

Creating a multispecies combination map – STEP 3

We created a multispecies combination map by summing the sensitivity maps for all species. For onshore wind in Australia, we combined rasters for 145 priority species. Thus, the final score for each grid cell results from the summed values of all the species present in that cell. The bird sensitivity map captures the cumulative impact over the range of species present in each area. The final cumulative sensitivity map was rescaled in values between 0 and 1(Figure 1).

$$\sum_{species}^{n} ln(species\ occurence\ probability + 1) * SI$$

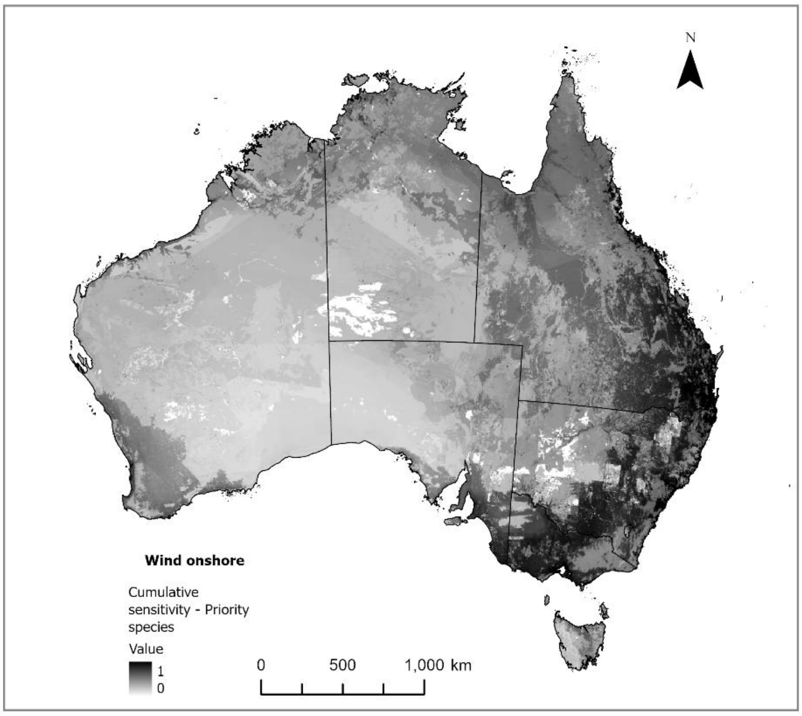

Figure 1. The cumulative sensitivity raster combining the sensitivity layers for 145 priority species facing impacts from the wind farm onshore. Values rescaled between zero and 1.

Adding other important areas for birds and conservation – STEP 4

To mitigate the impact of renewable energy, it is crucial to focus development away from natural habitats and important areas for biodiversity and towards areas with low ecological value, such as those already heavily modified by human activity (Kiesecker et al., 2019). For this purpose, in addition to the priority species cumulative surface, we also integrated various spatial information regarding areas relevant to bird and biodiversity conservation, which were integrated using Multicriteria Analysis – MCA (Esmail & Geneletti, 2018). First, for Australia, we worked on different levels to map bird sensitivity, where each letter **A, B, C, D** and **E** refers to a specific step in Figure 4.

A) Due to a combination of geological, climatic, and evolutionary factors, Australia hosts high rates of endemism at species and higher taxonomic levels up to that of families, especially among the passerines (Garnett et al., 2015). Although many of these subspecies may not be directly affected by impacts from energy infrastructures, they are very rare and have a restricted distribution. Therefore, they warrant priority in conservation efforts and spatial planning to avoid their distribution areas. To account for these subspecies, we developed a spatial layer representing the "Richness of Threatened Subspecies", based on polygons delineating the distribution areas of 84 subspecies classified under the threat categories Near Threatened (NT), Vulnerable (VU), Endangered (EN), and Critically Endangered (CR). To produce a Final Species Sensitivity (A), this layer was combined with the priority species cumulative map, but with less weight (contributing with only 20%) since the polygons are less accurate regarding the probability of finding the species when compared to the information used to prepare the cumulative map of priority species (contributing with 80%). All the maps were rescaled into 0 and 1.

$$Final\ Species\ Sensitivity = (Cumulative\ Sensi.of\ PS\ \times 0.8) + (Richness\ of\ Threatned\ subsp\ \times 0.2)$$

B) Although less studied and predictable than some migratory routes in other continents (e.g La Sorte et al., 2016; Gauld et al., 2022), understanding Australian landbird movement is critically essential to ensure that sensitivity maps accurately represent crucial stopover wetlands and do not misrepresent aerial connectivity between breeding and feeding grounds.

For onshore, we developed a layer to represent the movement of landbirds over Australian lands (Australia mainland and Tasmania), combining two main approaches:

Delineating Waterbird Polygons based on Bird Tracking Data

Raw animal tracking data for migratory birds were collected from published studies, author-provided datasets, and Movebank (www.movebank.org). After assessing the Movebank data, we included only GPS and PTT fixes with timestamps for three species (Bar-tailed Godwit, Grey Teal, and Bar-tailed Godwit), covering 21 individuals. To reduce temporal autocorrelation and ensure uniform temporal sampling among individuals, we interpolated each track to a regular time interval specific to each species (typically 10 – 30 minutes) using linear interpolation in time. Short-duration tracks (< 1 hour) or trips with fewer than five valid fixes were excluded. Data from stationary periods associated with capture, breeding or local roosting were also removed to focus on migratory or passage movements.

Following interpolation, each individual's track was segmented into discrete movement trips using buffers of 3 km (departure) and 10 km (return) around a pseudo-colony centroid. This delineation enabled the identification of outbound and inbound flights within the broader context of migratory movements. Trips were projected onto a national 5 km equal-area grid, which formed the basis for subsequent kernel density estimation (KDE) and synthesis analyses.

All pre-processed data were visually inspected for trajectory continuity, geographic plausibility, and temporal regularity before being included in species-level modelling. The resulting dataset represented standardised, quality-controlled movement records suitable for estimating species flyways and composite sensitivity indices across Australia.

We also included the final polygons produced by McGiness et al. (2024a) and McGiness et al. (2024b), which cover the Royal Spoonbill and Straw-necked Ibis, delineated using tracking data. For more details, please refer to McGiness et al. (2024a) and McGiness et al. (2024b).

The five individual species rasters were weighted according to the previous set of conservation status values.

Approximate migration corridor based on range maps - passage area

Given the limited number of species telemetry data available, species distribution polygons were compiled from the IUCN Red List database, with a focus on passage range classifications (BirdLife International &

Handbook of the Birds of the World, 2024). Polygons were dissolved into a single multipart geometry per species. In total, only nine species had a passage area delineated over Australia (*Calidris ferruginea, Calidris pugnax, Chalcites lucidus, Coracina novaehollandiae, Egretta picata, Gallinago hardwickii, Hirundapus caudacutus, Neophema chrysogaster, Sterna paradisaea*). To match the extent of movement analyses, all polygons were clipped to the Australian region of interest (ROI). Each species' polygon was rasterised to the 5 km grid, producing binary presence rasters that represented passage areas. The nine individual species rasters were weighted according to the previous set of conservation status values. The range rasters were combined into a multi-species stack (summed). The final output was normalised presence rasters (score 0 - 1), representing a range-based proxy for migratory flyway use across the Australian region.

Both the Waterbird Polygons and Migratory Corridor maps were rescaled into 0 and 1 and combined with the same weight – 50% of the contribution each, since a similar number of species were represented in each map, according to the formula:

$$Final\ Bird\ Movement = (Waterbird\ Polygons\ \times 0.5)\ +\ (Migratory\ Corridor\ \times 0.5)$$

C) To compose a unique Bird Sensitivity map, we combined the Final Species Sensitivity map with the Final Bird Movement map. The Final Species Sensitivity contribution more (90%) over the Final Bird Movement because the first map considers many more species and subspecies:

$$Bird\ Sensitivity = (Final\ Species\ Sensitivity\ \times 0.9) + \ (Final\ Bird\ Movement\ \times 0.1)$$

D) To identify habitats most relevant for bird conservation, we used data from the National Vegetation Information System (NVIS) Version 7.0, which provides delineations of 32 major Vegetation Groups representing native vegetation classes across Australia at a 100 m resolution. We developed a bird richness map based on 607 Australian bird species, weighting each species according to its global Conservation Status as follows: Critically Endangered (CR) + any species with number of mature individuals < 1,000 = 1.00; Endangered (EN) + any species with number of mature individuals < 2,500 = 0.59; Vulnerable (VU) + any species with number of mature individuals < 10,000 = 0.41; Near Threatened (NT) = 0.12; Least Concerned (LC) and population trend decreasing = 0.08; LC and population trend increasing/stable = 0.06. For each grid cell, the cumulative value of bird richness & conservation status was calculated, and the final values were rescaled to a range of zero to one.

Vegetation classes were ordinated using Principal Component Analysis (PCA), considering the proportion of each vegetation class in Australia, the median bird richness and conservation status, and the maximum richness value within each class. Bartlett's test of sphericity (Bartlett, 1951) was applied to evaluate the suitability of the data for factor analysis. Composite scores were obtained by multiplying the factors derived from the first ordination axis by that axis's shared variance. Based on these results, eleven vegetation classes were identified as being important for bird conservation: 1)Eucalypt Open Forests, 2)Eucalypt Tall Open Forests, 3)Eucalypt Woodlands, 4)Rainforests and Vine Thickets, 5)Casuarina Forests and Woodlands, 6)Mangroves, 7)Tussock Grasslands, 8)Callitris Forests and Woodlands, 9)Eucalypt Low Open Forests, 10)Heathlands, and 11)Inland Aquatic - freshwater, salt lakes, lagoons (Figure 2). To support this assessment, we also referred to the EPBC Act List of Threatened Ecological Communities and the Australian National Botanic Gardens – Centre for Australian National Biodiversity Research.

The NVIS map was subsequently reclassified by assigning a value of 1 to the 11 vegetation classes selected and a value of 0 to all others. The percentage of important vegetation within each 5x5 km cell was then calculated following the same procedure as in STEP 2. Consequently, cells with a higher proportion of important vegetation received higher sensitivity scores.

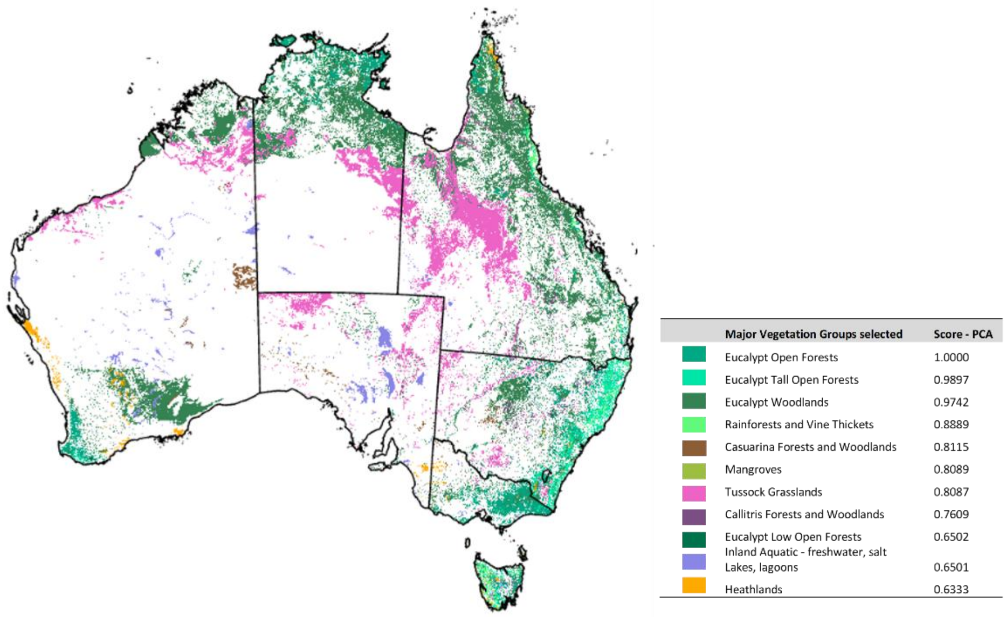

Figure 2. Eleven classes selected to represent the rarest vegetation in Australia in accordance with PCA rank analysis, EPBC Act List of Threatened Ecological Communities and the Australian National Botanic Gardens – Centre for Australian National Biodiversity Research.

To complement the habitat assessment, in addition to creating the Rare vegetation & high bird conservation map, we also included the Protected Areas database from Collaborative Australian Protected Areas Database (CAPAD 2024). This database provides spatial information on Australia's protected areas at national, state, and territory levels, including IUCN categories (i.e., categories Ia to VI), which classify protected areas according to their management objectives (Dudley, 2008).

First, all protected areas (PAs) that were designated specifically for bird conservation or that represent essential habitats for particular bird species were identified. This resulted in a set of 5,605 PAs, which were extracted and carried forward to the next step (see STEP 5). From the remaining PAs, different weights were assigned according to the IUCN management categories. PAs classified as Ia (Strict Nature Reserve), Ib (Wilderness Area), II (National Park), III (Natural Monument or Feature), and IV (Habitat/Species Management Area) were given the highest weight of 1.0. In contrast, PAs under categories V (Protected Landscape or Seascape) and VI (Protected Area with Sustainable Use of Natural Resources) were considered lower priorities for bird conservation, as they allow a broader range of human activities. These were assigned a weight of 0.4. The set of weights was determined using the Analytic Hierarchy Process (AHP).

D)All the above information was rasterised at a resolution of 5 km^2. The final habitat sensitivity map was created by combining the Rare Vegetation & High Bird Conservation Value map with the IUCN-triggered PA map (Figure 3), both given the same weight in the MCA combination according to the equation:

$$Final\ Habitat\ Sensitivity = (Rare\ veg.\&high\ bird\ cons.value\ \times 0.5) + (PAs_{IUCN}triggered\ \times 0.5)$$

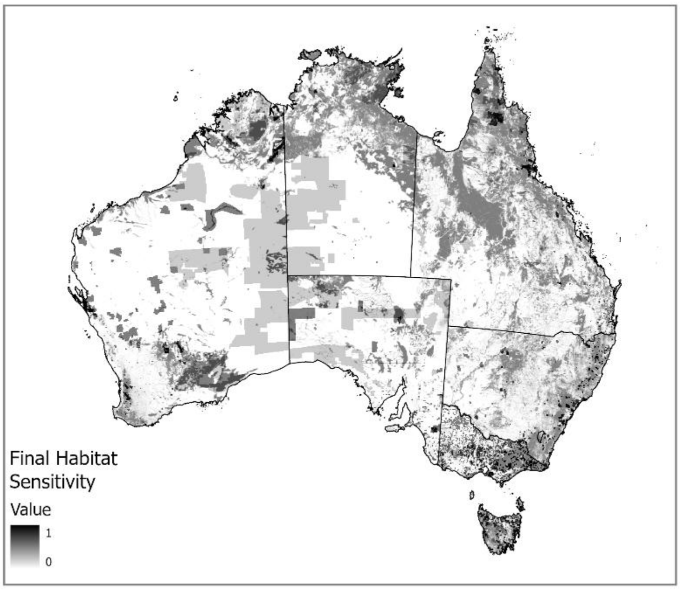

Figure 3. Final Habitat Sensitivity map created from the combination of the Rare Vegetation & High Bird Conservation with the Protected Areas triggered by IUCN classification.

Due to the relevance for bird and conservation, the Final Habitat Sensitivity and Bird Sensitivity maps were combined, preserving the maximum value of each grid cell as follows:

$$Final\ Bird\ Sensitivity\ (x, y) = \max\ (C(x, y), D(x, y))$$

After generating the Final Bird Sensitivity Map, the final step involved reducing the overall contribution of human-induced areas, as this specific land-use information is not represented in the main vegetation map. To address this, we incorporated data from the Catchment Scale Land Use of Australia (CLUM), version 2 (ABARES 2024), which provides a national compilation of catchment-scale land-use data for Australia. CLUM is a seamless raster dataset that integrates land-use information from all state and territory jurisdictions, compiled at a spatial resolution of 50x50 m.

The following land-use classes were selected for adjustment: Intensive horticulture, Intensive animal production, Manufacturing and industrial, Services, Utilities, Transport and communication, Mining, and portions of Plantation forest, Irrigated plantation, and Residential areas. These classes were resampled to match our 5x5 km grid, and a maximum value of 0.5 was subtracted from the Final Bird Sensitivity Map to reflect their reduced suitability for bird conservation.

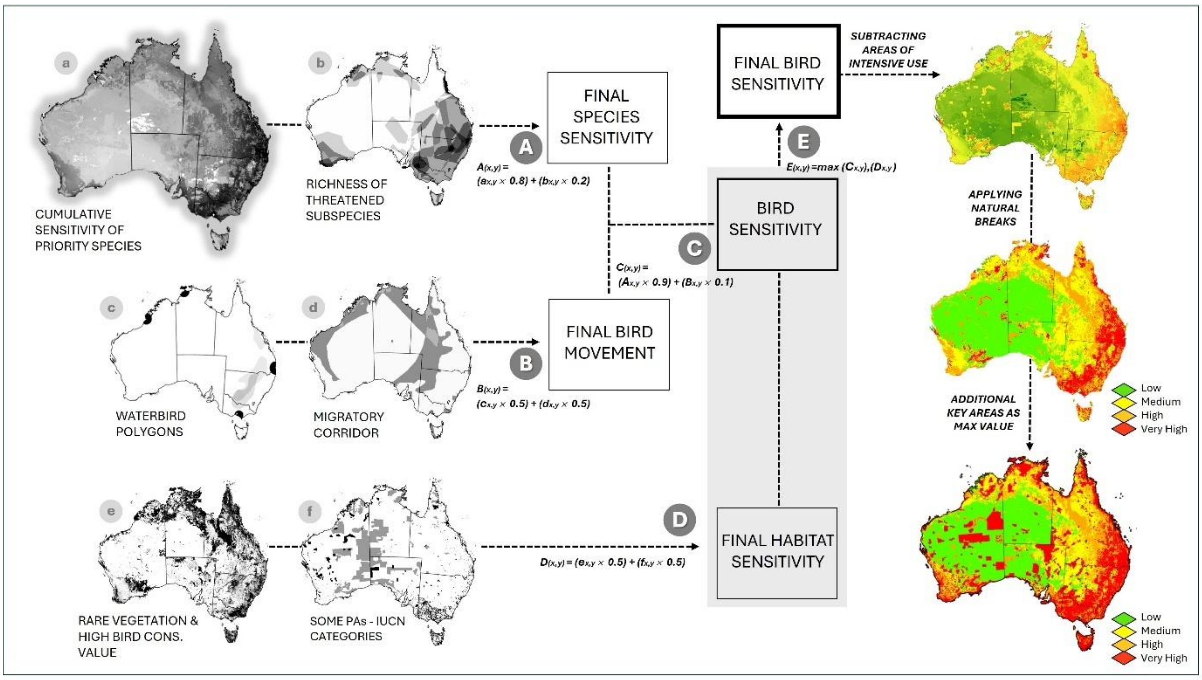

Figure 4. Overall workflow showing the main spatial layers integrated to create the final map displayed on AVISTEP. The same workflow was used for Powerline - High Voltage and Low-Medium Voltage. For these infrastructures, the only difference is the Cumulative Sensitivity map (a), which reflects the respective priority species for each development and impact.

Identifying final sensitivity categories – STEP 5

Classifying the sensitivity value into categories

Our sensitivity data over grid cells display non-uniform distributions with evident clustering data. Thus, we have used Jenks' Natural Breaks algorithm (Natural breaks function, ArcGIS Pro, ESRI 2021) to classify sensitivity values across grid cells into four classes, which we interpret as Low (1), Medium (2), High (3), and Very High (4) bird sensitivity. Natural Breaks minimise the squared deviations of a group's means and are a standard method for splitting spatial datasets. The map shows the four final bird sensitivities in a format that provides meaningful visualisation and is easier to interpret for a range of stakeholders in decision-making processes.

Including Additional key areas

Additional key areas are considered as those already designated for bird conservation purposes or for conservation of their habitats, regardless of whether they focus on a priority species concerning the impacts of energy infrastructure. Examples include some Protected Areas (PAs), Important Bird and Biodiversity Areas (IBAs), Key Biodiversity Areas (KBAs), and Ramsar Areas.

Protected Areas

Specifically, in this step, we considered the 5,605 protected areas identified by bird experts as key areas for birds. We used data from the Collaborative Australian Protected Areas Database (CAPAD) for protected area information. The protected areas selected as additional key areas were not included in any previous step to prevent data redundancy. The protected areas not considered as additional key areas (5,621) were previously considered (see Final Habitat Sensitivity).

Key Biodiversity Areas (KBAs)

For Australia, the Important Bird and Biodiversity Areas (IBAs), which are areas of the greatest significance for birds worldwide (Donald et al., 2019; BirdLife International, 2025), are integrated also as KBAs triggered by birds. KBAs are a global dataset of areas of greatest significance for conserving birds. This dataset is curated by BirdLife International and available through the website (https://datazone.birdlife.org/). The most up-to-date version of this data was used (BirdLife International, 2025).

Ramsar Areas

Ramsar areas are wetlands of international importance designated under the Ramsar Convention (1971). These areas should be safeguarded for various biodiversity reasons, primarily because they serve as safe breeding and feeding grounds for birds and as stopovers during migrations. We considered Ramsar areas in accordance with the Department of Climate Change, Energy, the Environment, and Water (DCCEE, 2025).

Furthermore, other areas already recognised as relevant for bird conservation but not yet officially designated or in the process of implementation, such as Shorebird polygons (BirdLife Australia, 2025a), Bird Colonies (Quade, 2025), and areas of potential occurrence for sensitive species, were considered as additional key areas.

All the above information was rasterised in a resolution of $5km^2$. We combined additional key areas with very high sensitivity (assigned the maximum value of 4) into the final sensitivity layer, which already contained four categories (Figure 5). For each grid cell, the highest sensitivity value was retained. As a result, cells with lower initial sensitivity that overlapped spatially with these additional key areas were upgraded to the maximum sensitivity value. This approach ensures that areas already recognised as important for bird conservation receive the highest sensitivity rating and are avoided from energy planning. Likewise, areas previously classified as highly sensitive remain so when overlapping with additional key areas.

All the maps created in STEP 2, STEP 3, STEP 4 and STEP 5 had the Geocentric Datum of Australia (GDA2020) as the Projected Coordinate System.

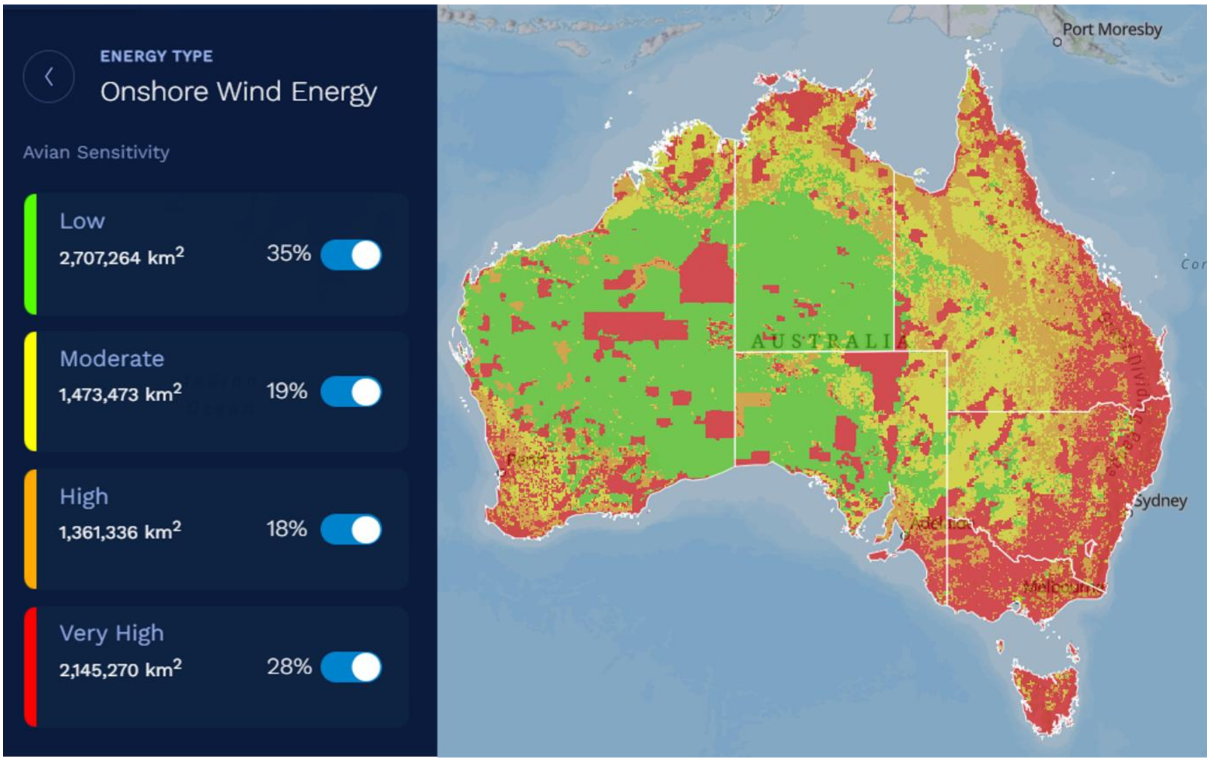

Figure 5. Final Sensitivity Map for Onshore Wind development in Australia. See more in [AVISTEP – Australia.]()

Powerline – High voltage

Calculating species sensitivity – STEP 1

The respective national species lists to be assessed were created in agreement with BirdLife Australia, and other bird experts. The sensitivity index was calculated for each regularly occurring bird species, excluding flightless, vagrant, rare sightings, and restricted seabirds. For Australia, we calculated the sensitivity index for 607 bird species following the formula:

$$Sensitivity\ Index = (PwCo) \times (CnS)^{(1-(Su)/((Su)+0.5))}$$

Collision with energy cables (PwCo). Bird collisions with overhead wires occur during flight when birds fail to see ahead the cables or cannot avoid the collision in time. They represent a significant source of anthropogenic bird mortality (Loss et al., 2014) and are responsible for the decline of different populations (Uddin et al., 2021; Bernardino et al., 2018; Loss et al., 2012).

To assess the species' sensitivity to overhead collision, we used a trait-based approach similar to Wind Farm Onshore, estimating collision mainly from the interaction between Exposure and Susceptibility.

$$\boldsymbol{C}ollision = (Exp \times Suscep) + Ext.risk$$

Bird exposure (Exp) refers to the probability of a bird encountering a powerline tower or an overhead cable, based on the time they fly at heights compatible with the powerline vulnerable height (ranging from 10m to 60m). We classified each species in four different exposure categories:

- **No exposure**: Species that are never or very rarely active at a vulnerable height, representing flightless, terrestrial, and ground-dwelling birds. Birds that rarely fly at height, in open landscapes away from forest vegetation, such as forest dwellers and species that stay low to the ground, were also classified in this category.
- **Low exposure**: Species that are not active daily at a vulnerable height but spend some time during their annual cycle are often represented by migratory and dispersive species, such as migratory honeyeaters and altitudinal migrants.
- **Moderate exposure**: Species that spend less than 50% of their daily active time at a vulnerable height, represented by species that make daily movements across open air space as they commute between roosting and foraging sites. This category includes typically many members of the following families: corvids, parrots, pigeons and doves, waterfowl, gulls and terns, shorebirds, pelicans, cormorants, bustards, cranes, herons and ibis, magpies and birds of prey that hunt from a perch or within forests.
- **High exposure**: Species that spend more than 50% of their daily active time at a vulnerable height, represented by aerial insectivores such as swifts and swallows, and birds of prey that hunt on the wing, often from a high soar. Since a bird can collide only when it is exposed, we work with this set of weights: No exposure (zero); Moderate (0.333); High (0.666); Very high (1).

Bird susceptibility (Suscep) refers to the species' intrinsic characters, which are mainly related to the morpho-behavioural and life-history traits linked with flight behaviour. Theoretically, large, heavy, relatively small-winged birds with poor vision are most susceptible to collision, while small, light, relatively large-winged birds with acute vision are least susceptible (Bevanger, 1998). All volant, terrestrial species are potentially susceptible, and most fall between these extremes.

$$\boldsymbol{Bird\ Suceptibility} = (\boldsymbol{Forag.behav} \times \boldsymbol{Mnvr})$$

Foraging behaviour (Forag.behav.): Variations in visual field topography among birds have been interpreted as adaptations to the specific perceptual challenges posed by the species' foraging ecology. At the same time, visual perception, when combined with specific foraging behaviours during flight, can affect the likelihood of bird collision with different human infrastructures.

Visual topography differs between species, especially in the extent and position of the binocular field relative to the bill, and the extent of blind areas above and behind the head. These differences are primarily correlated with differences in foraging ecology, even among closely related species (Martin & Portugal 2011). Birds differ in the vertical extent of their binocular fields, which results in differences in the extent of the blind areas to the front of the head, the key region for detecting obstacles in flight. These differences must arise primarily due to differences in the positioning of the eyes in the skull. Overall, bird species with more comprehensive coverage of the frontal hemisphere gain full visual coverage of the airspace ahead of them, regardless of the head position adopted in flight. This is likely to contribute to lower vulnerability to collisions. We are interested in the phylogenetic signal for the maximum vertical height of the binocular field and foraging ecology based on the family level. Therefore, we classified birds into four different types of risk of collision according to eye position in the skull, vertical extension of the binocular visual field, foraging behaviour, head position during flying, and diet.

- **Low risk:** Birds with frontal eye position, excellent binocular view, and large vertical extension of the binocular field. They have forward-facing vision, which means that during flying, they forage looking forward, not looking down, catching prey in the air (e.g., some insectivorous birds).
- **Medium risk**: Inside medium risk, we can identify two groups: a) Birds with lateral eye position and those with limited forward vision. Full celestial/hemisphere view is monocular, with almost no blind areas (associated with anti-predator vigilance). Looking for foraging spots when flying. Foraging looking forward, not looking down while flying, represented mainly by tactile/filter foragers. b) Lateral eye position, forward vision limited. Benefit from monocular vision. But have a large vertical extension of the binocular field (small blind area). Looking for foraging spots when flying. Foraging looking forward, not looking down, represented mainly by Pecking foragers, using the bill like pincers (catching seeds or evasive prey).
- **High risk:** More frontal eye position, Excellent binocular vision, but limited vertical extension of the binocular field resulting in extensive blind areas. Forward-facing vision, but forages looking down. Overall, carrion eaters and birds of prey.
- **Very high**: They also benefit from lateral vision. Very limited vertical extension of the binocular field (Even a slight 30-degree head turn can send them flying forward blindly), forward-facing vision often looking down. Overall, a diet based on a range of stationary sources such as seeds, berries, bulbs, and non-evasive animals.

Manoeuvrability (Mnvr). The scientific literature highlights that wing loading (resulting from body mass divided by wing area) is one of the most relevant morphological traits that predicts species' probability of colliding and is associated with high manoeuvrability in flight (Bevanger, 1998; Janss, 2000). However, measures such as wing area or specific measurements necessary to calculate wing area, such as wingspan, are not always available. We demonstrated that wing length is highly correlated with wingspan. When bird weight is divided by the wing length, it produces a proxy valid to infer manoeuvrability (D'Amico et al., 2019; Reid et al., 2023) that could conserve the same relative difference between species as using wing area. Both weight and wing length are commonly recorded measurements and are available for all birds worldwide in Tobias et al. (2022). Therefore, we have:

$$\boldsymbol{Mnvr\_proxy} = \left(\frac{\boldsymbol{weight\ (g)}}{\boldsymbol{wing\ \ length\ (cm)}}\right)$$

Extra risk factor (Ext.risk): Some species possess additional or aggravating risk factors for collisions that cannot be generalised across all species. For example, even a bird with great manoeuvrability and adequate vision can be frequently involved in collisions. In those cases, other intrinsic traits, such as very high flight speeds, or flock-oriented flight patterns, may play a role, especially when combined with low-light conditions typical of crepuscular or nocturnal activity. However, these traits alone do not universally predict collision risk: not all fast-flying, flocking, or nocturnal species are equally affected. Therefore, when we could identify a special trait, we gave some species with at least one of these potential special traits an additional weight = 0,2 as an extra risk factor. Additionally, we assigned an extra weight of 1 to species frequently recorded as victims of overhead cable collisions worldwide. An extra weight of 1 was also given to a few Australian species that faced threats from energy infrastructure in their National Recovery Plan.

*It's important to recognise that any flying species may eventually collide. In addition to intrinsic species characteristics, collisions can occur due to other external environmental and technical factors, and the frequency of recordings may be attributed to population abundance. Therefore, a species that is not prone to collisions, flying in extreme weather conditions such as wind and low light availability, combined with a lack of bird flight diverters, may also collide. Our approach aims to capture collision risk based only on intrinsic aspects of the species.

The second part of our formula is calculated using the same approach and values as for the Wind Offshore.

Conservation Status (CnS) was assigned to each species by integrating information from both the Global Red List (GRL) and the National Red List (NRL). Species were then classified according to their Conservation Status and Population Trend (if population are increasing, stable or decreasing in numbers). To determine the relative importance among different categories, we used the Analytic Hierarchy Process (AHP), applying a Saaty pairwise comparison matrix across categories to evaluate and contrast their relevance to extinction risk. The assessment was conducted in collaboration with colleagues from the IUCN Red List. The weights assigned increased exponentially according to the highest threat category as follows:

- Critically Endangered (CR) + any species with number of mature individuals < 1,000 = **1.00**
- Endangered (EN) + any species with number of mature individuals < 2,500 = **0.59**
- Vulnerable (VU) + any species with number of mature individuals < 10,000 = **0.41**
- Near Threatened (NT) = **0.12**
- Least Concerned (LC) and population trend decreasing = **0.08**
- LC and population trend increasing/stable = **0.06**

We did not have data-deficient (DD) species. The same values were considered for the Global and National Red List categories. Then, the mean value was used as a final CnS since the categories may differ in the global and national assessments.

$$\boldsymbol{CnS} = \left(\frac{\boldsymbol{GRL} + \boldsymbol{NRL}}{\mathbf{2}}\right)$$

Annual adult survival (Su). The population-level impact of a single individual fatality event depends primarily on the species' life history traits. Specific life history traits, such as fecundity, age of maturity, and adult survival, are particularly relevant. K-selected species are characterised by low fecundity, late ages of maturity and high survival; thus, adult mortality impacts these populations (Niel & Lebreton, 2005; Sæther & Bakke, 2000). The species groups with the highest rates of impact from wind development tend to be K-selected species such as Accipitridae, Ciconiidae, or Bucerotidae (Thaxter et al., 2017); thus, it is a factor that must be carefully considered when evaluating impacts on bird conservation. We employed annual adult survival estimated for all bird species to include a metric that could capture these life history factors (Bird et al., 2020). For Australian birds, the adult annual survival ranged from 0.41 to 0.93.

To combine the four parameters above in the formula and balance their contributions to the sensitivity index, we rescaled all values from 0.01 to 1, following the recommendations of Certain et al. (2015).

We ranked all species according to their sensitivity values to identify the priority species for spatial assessment. To identify the subset of species most affected, we split the ranking into different classes using a cluster method proposed by Jiang (2013) for data with heavy-tailed distributions. The method partitions the class intervals and establishes the number of groups through an iterative approach. This approach resulted in five groups, which we interpreted as extremely high, very high, high, medium, and low sensitivity. To be more conservative, we considered the species in all categories different from low sensitivity as priority species, totalling 113 Australian birds (See "AVISTEP_Australia_PW_Collision.xlsx" in Sup. Material).

Mapping the distribution area for priority species – STEP 2

We followed the same approach as for onshore wind farms. Go to STEP 2 to read more.

Creating a multispecies combination map – STEP 3

We created a multispecies combination map by summing the sensitivity maps for all species. For onshore wind in Australia, we combined rasters for 113 priority species. Thus, the final score for each grid cell results from the summed values of all the species present in that cell. The bird sensitivity map captures the cumulative impact over the range of species present in each area. The final cumulative sensitivity map was rescaled in values between 0 and 1 (Figure 6).

$$\sum_{species}^{n} ln(species\ occurence\ probability + 1) * SI$$

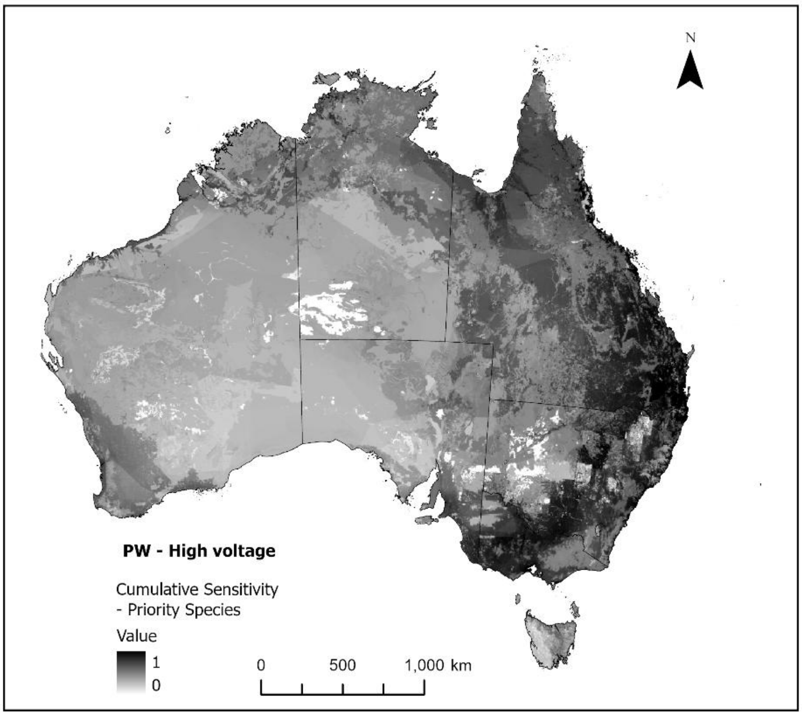

Figure 6. The cumulative sensitivity raster combining the sensitivity layers for 113 priority species facing impacts from Powerlines – High voltage. Values rescaled between zero and 1.

Adding other important areas for birds and conservation – STEP 4

We followed precisely the same approach as for onshore wind farms. Go to STEP 4 to read more.

Identifying final sensitivity categories – STEP 5

We followed precisely the same approach as for onshore wind farms. Go to STEP 5 to read more. The final map is in Figure 7.

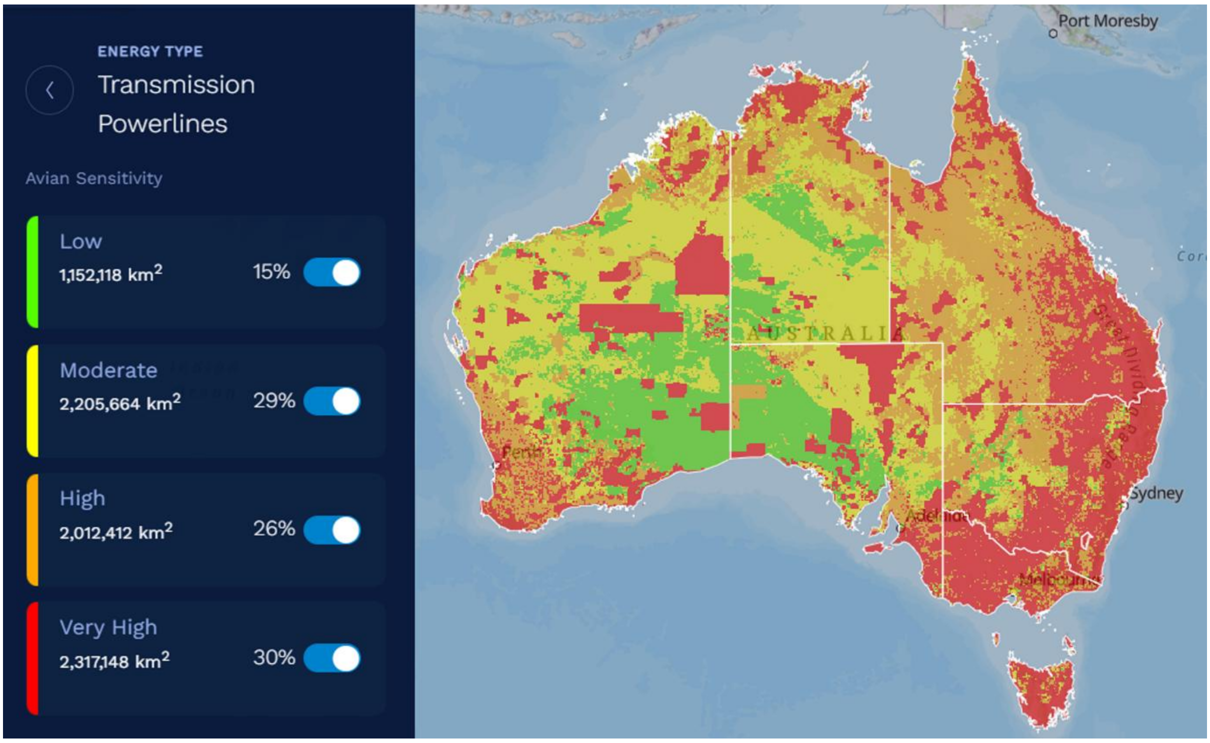

Figure 7. Final Sensitivity Map for Powerlines – High-Voltage Development in Australia. See more in AVISTEP – Australia.

Powerline – Medium and Low voltage

Calculating species sensitivity – STEP 1

Distribution lines primarily impact birds through collisions with overhead cables and electrocution on energy pylons and cables. Therefore, in addition to considering the species most sensitive to collision using the formula mentioned for the High-voltage lines (PwCo), a specific formula for calculating and identifying species sensitive to electrocution was also applied separately:

$$Sensitivity\ Index = (PwElec) \times (CnS)^{(1-(Su)/((Su)+0.5))}$$

To assess the species' sensitivity to electrocution on energy pylons, we also estimated the risk of electrocution from the interaction between exposure and susceptibility.

$$\boldsymbol{Electrocution} = (Exp \times Suscep) + Ext.risk$$

Bird exposure (Exp): To assess behavioural exposure in the electrocution context, we classified each species according to its use of energy pylons and cables for perching or nesting. We used four different exposure categories:

- **No exposure** for birds that never or very rarely encounter powerlines, so they never perch on wires, poles and pylons. Flightless species, terrestrial and ground-dwelling species such as emus, cassowaries, mound builders, lyrebirds, logrunners, and whipbirds were included in this category.
- **Low exposure** for birds that utilise energy cables and pylons but do so infrequently or are of a small size and therefore have a reduced risk of simultaneously contacting live elements. Swallows, swifts, honeyeaters, and Flycatchers are examples.
- **Moderate exposure**: Birds often utilise electricity pylons for hunting, resting and singing, but not to the extent that high exposure species do.
- **High exposure**: birds frequently have daily exposure to live elements. Those include species that routinely roost on powerlines, have a propensity to investigate electrical components, routinely nest on pylons, regularly perch on pylons and have large bodies and/or wingspans. Examples are some raptors, such as eagles, storks, and psittacine birds, such as cockatoos, parakeets and macaws.

Bird susceptibility (Suscep) refers to the species' intrinsic aspects, which are mainly related to the morphological traits. Wingspan is often selected as the best indicator of morphological susceptibility to electrocution in birds (Bevanger, 1998), but it is not available for most species. We used wing length as a proxy because this measure often represents the overall body size better than other univariate traits (e.g., Wiklund, 1996) and correlates well with wingspan in various bird groups (Biasotto et al., 2021). Wing length is available for all birds worldwide in Tobias et al. (2022).

Extra risk factor (Ext. risk): Additionally, Australian species that faced threats from energy infrastructure in their National Recovery Plan and are frequently recorded as victims in other countries had an extra weight of 1.

The second part of our formula is calculated using the same approach and values as for the Wind Offshore.

Conservation Status (CnS) was assigned to each species by integrating information from both the Global Red List (GRL) and the National Red List (NRL). Species were then classified according to their Conservation Status and Population Trend (if population are increasing, stable or decreasing in numbers). To determine the relative importance among different categories, we used the Analytic Hierarchy Process (AHP), applying a Saaty pairwise comparison matrix across categories to evaluate and contrast their relevance to extinction risk. The assessment was conducted in collaboration with colleagues from the IUCN Red List. The weights assigned increased exponentially according to the highest threat category as follows:

- Critically Endangered (CR) + any species with number of mature individuals < 1,000 = **1.00**
- Endangered (EN) + any species with number of mature individuals < 2,500 = **0.59**
- Vulnerable (VU) + any species with number of mature individuals < 10,000 = **0.41**
- Near Threatened (NT) = **0.12**
- Least Concerned (LC) and population trend decreasing = **0.08**
- LC and population trend increasing/stable = **0.06**

We did not have data-deficient (DD) species. The same values were considered for the Global and National Red List categories. Then, the mean value was used as a final CnS since the categories may differ in the global and national assessments.

$$\boldsymbol{CnS} = \left(\frac{\boldsymbol{GRL} + \boldsymbol{NRL}}{\boldsymbol{2}}\right)$$

Annual adult survival (Su). The population-level impact of a single individual fatality event depends primarily on the species' life history traits. Specific life history traits, such as fecundity, age of maturity, and adult survival, are particularly relevant. K-selected species are characterised by low fecundity, late ages of maturity and high survival; thus, adult mortality impacts these populations (Niel & Lebreton, 2005; Sæther & Bakke, 2000). The species groups with the highest rates of impact from wind development tend to be K-selected species such as Accipitridae, Ciconiidae, or Bucerotidae (Thaxter et al., 2017); thus, it is a factor that must be carefully considered when evaluating impacts on bird conservation. We employed annual adult survival estimated for all bird species to include a metric that could capture these life history factors (Bird et al., 2020). For Australian birds, the adult annual survival ranged from 0.41 to 0.93.

To combine the parameters above in the formula and balance their contribution to the sensitivity index, we rescaled all values from 0.01 to 1, following recommendations from Certain et al. (2015).

We ranked all species according to their sensitivity values to identify the priority species for spatial assessment. To identify the subset of species most affected, we split the ranking into different classes using a cluster method proposed by Jiang (2013) for data with heavy-tailed distributions. The method partitions the class intervals and establishes the number of groups through an iterative approach. This approach resulted in five groups, which we interpreted as extremely high, very high, high, medium, and low sensitivity. To be more conservative, we considered the species in all categories different from low sensitivity as priority species, totalling 135 Australian birds (See “AVISTEP_Australia_PW_Electrocution.xlsx” in Sup. Material).

Mapping the distribution area for priority species – STEP 2

We followed the same approach as for onshore wind farms. Go to STEP 2 to read more.

Creating a multispecies combination map – STEP 3

We created a multispecies combination map by summing the sensitivity maps for all species. For onshore wind in Australia, we combined rasters for 135 priority species for electrocution impact. Thus, the final score for each grid cell results from the summed values of all the species present in that cell. The bird sensitivity map captures the cumulative impact over the range of species present in each area. The final cumulative sensitivity map was rescaled in values between 0 and 1.

$$\sum_{species}^{n} ln(species\ occurence\ probability + 1) * SI$$

Since power distribution lines are causing both bird collisions and electrocution, as a precautionary approach, we combined the cumulative priority species map for electrocution (considering 135 species and their respective Sis, Figure 8, left) with the priority species map for powerline collision (113 species and their respective Sis, Figure 8, right), conserving the maximum value for each grid cell (Figure 9).

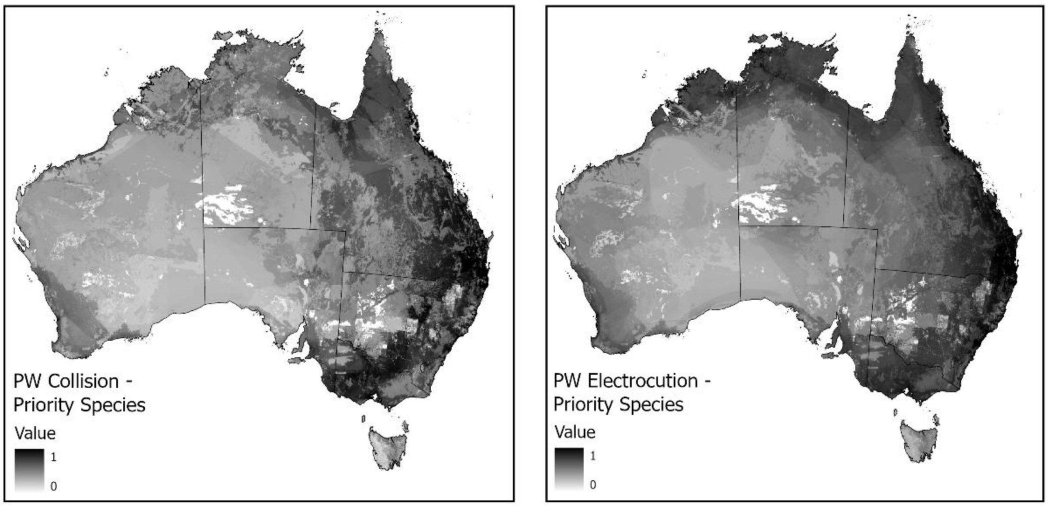

Figure 8. Left panel showing the cumulative priority species map for electrocution (considering 135 species and their respective SI; Right panel showing the cumulative priority species map for powerline collision (113 species and their respective SI).

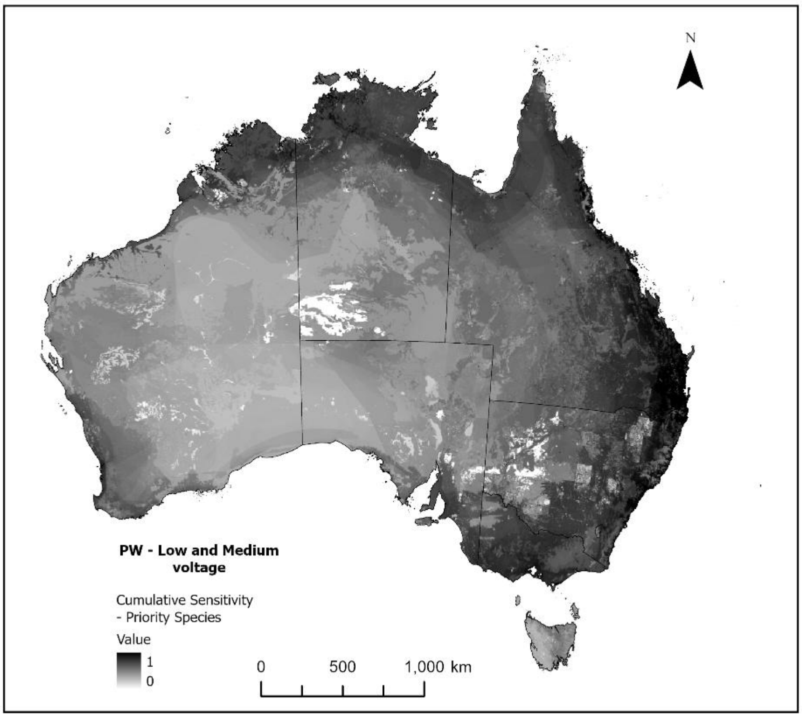

Figure 9. Cumulative Sensitivity map considering both Collision with Powerlines and Electrocution priority species. Collision and Electrocution were mapped individually and combined, preserving the maximum value in each grid cell. Values rescaled between zero and 1.

Adding other important areas for birds and conservation – STEP 4

We followed precisely the same approach as for onshore wind farms. Go to STEP 4 to read more.

Identifying final sensitivity categories – STEP 5

We followed the same approach as for onshore wind farms. Go to STEP 5 to read more. The final map is in Figure 10.

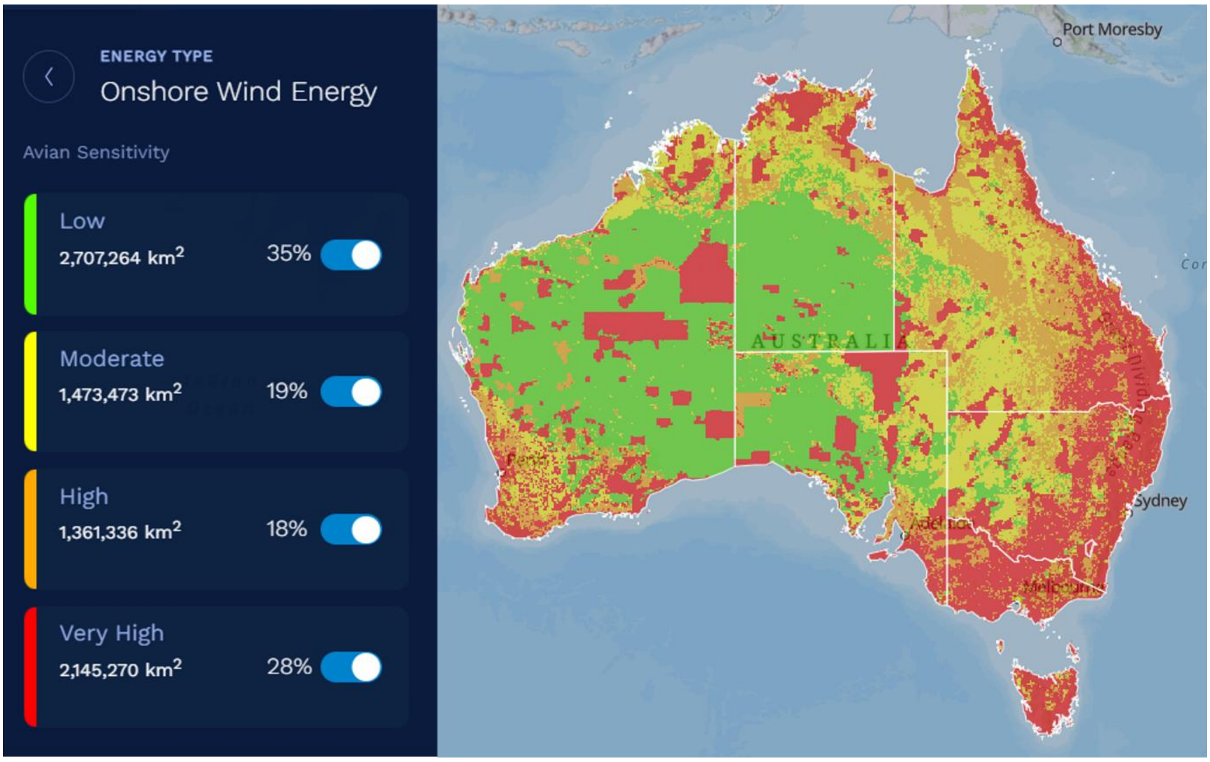

Figure 10. Final Sensitivity Map for Powerlines – Low- and Medium-Voltage Developments in Australia. See more in AVISTEP – Australia.

Solar Photovoltaic (PV)

The species-specific sensitivity based on different impacts created for the other types of energy developments does not apply to the context of solar photovoltaic energy. We have used a precautionary approach, considering that the presence of solar photovoltaics would result in habitat loss and/or degradation for all species that occur in the area, although some species can indeed coexist with solar PV installations.

Calculating Sensitivity for all species occurring in the country – STEP 1

We considered a list of all species occurring in the country, individually weighted by their respective Conservation Status. For Australia, we worked with a total of 607 species.

Conservation Status (CnS) was assigned to each species by integrating information from the Global Red List (GRL). Species were then classified according to their Conservation Status and Population Trend (i.e., whether populations are increasing, stable, or decreasing in numbers). To determine the relative importance among different categories, we used the Analytic Hierarchy Process (AHP), applying a Saaty pairwise comparison matrix across categories to evaluate and contrast their relevance to extinction risk. The assessment was conducted in collaboration with colleagues from the IUCN Red List.

The weights assigned increased exponentially according to the highest threat category as follows:

- Critically Endangered (CR) + any species with number of mature individuals < 1,000 = **1.00**
- Endangered (EN) + any species with number of mature individuals < 2,500 = **0.59**
- Vulnerable (VU) + any species with number of mature individuals < 10,000 = **0.41**
- Near Threatened (NT) = **0.12**
- Least Concerned (LC) and population trend decreasing = **0.08**
- LC and population trend increasing/stable = **0.06**

We did not have data-deficient (DD) species.

Mapping the species distribution according to the Sensitivity – STEP 2

We used a version of the area of habitat (AOH) maps explicitly created for Australian terrestrial birds (the data are under review and available on request). The AOH maps represent the utilised habitats within a species' range and can be considered an intermediate step between the Extent of Occurrence (EOO) and Area of Occupancy (AOO). These maps were created with a 100x100m grid cell resolution using a modelling approach based on the Australian National Vegetation Information System (NVIS v.6). The NVIS classes were translated to species' habitat preferences according to Garnet et al. (2015) inside species distribution maps combining BirdLife International & Australian Bird Guide ranges. The AOH maps were created using binary information representing presence and absence, and were based only on breeding, non-breeding, and resident distribution.

A raster layer was produced for each species (607), representing the species' occurrence probability as the proportion of suitable habitat area in each grid cell. More specifically, since our assessment was conducted at a 5x5 km grid cell resolution, we transformed the original AOH maps to match our resolution, calculating the total percentage of AOH present in each cell.

We adapted the formula by Bradbury et al. (2014) to weight the raster for each species by its respective sensitivity index and the amount of habitat in each grid cell. The final species sensitivity value was assigned for each grid cell following the formula below:

$$Species\ Sensitivity\ core = ln(\%\ AOH\ by\ grid + 1) * CnS$$

Creating a species richness map weighted by Conservation Status – STEP 3

We created a multispecies combination map by summing the sensitivity maps for all species. Thus, the final score for each grid cell results from the summed values of all the species present in that cell. The bird sensitivity map captures the cumulative impact over the range of species present in each area. The final cumulative sensitivity map was rescaled in values between 0 and 1 (Figure 11).

$$\sum_{species}^{n} ln(\%\ AOH\ by\ grid + 1) * SI$$

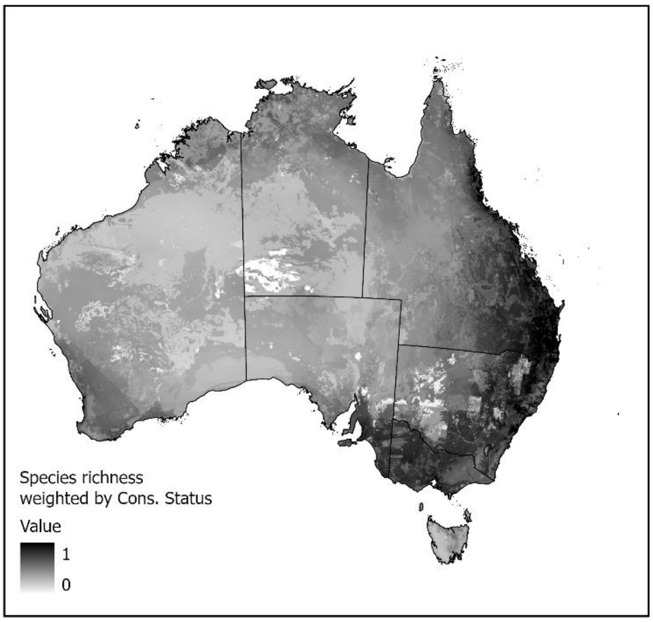

Figure 11. Bird species richness map weighted by Conservation Status.

Adding other important areas for birds and conservation – STEP 4

To mitigate the impact of renewable energy, it is crucial to focus development away from natural habitats and important areas for biodiversity and towards areas with low ecological value, such as those already heavily modified by human activity (Kiesecker et al., 2019). For this purpose, in addition to the priority species cumulative surface, we also integrated various spatial information regarding areas relevant to bird and biodiversity conservation, which were integrated using Multicriteria Analysis – MCA. First, for Australia, we worked on different levels to map bird sensitivity (Figure 12).

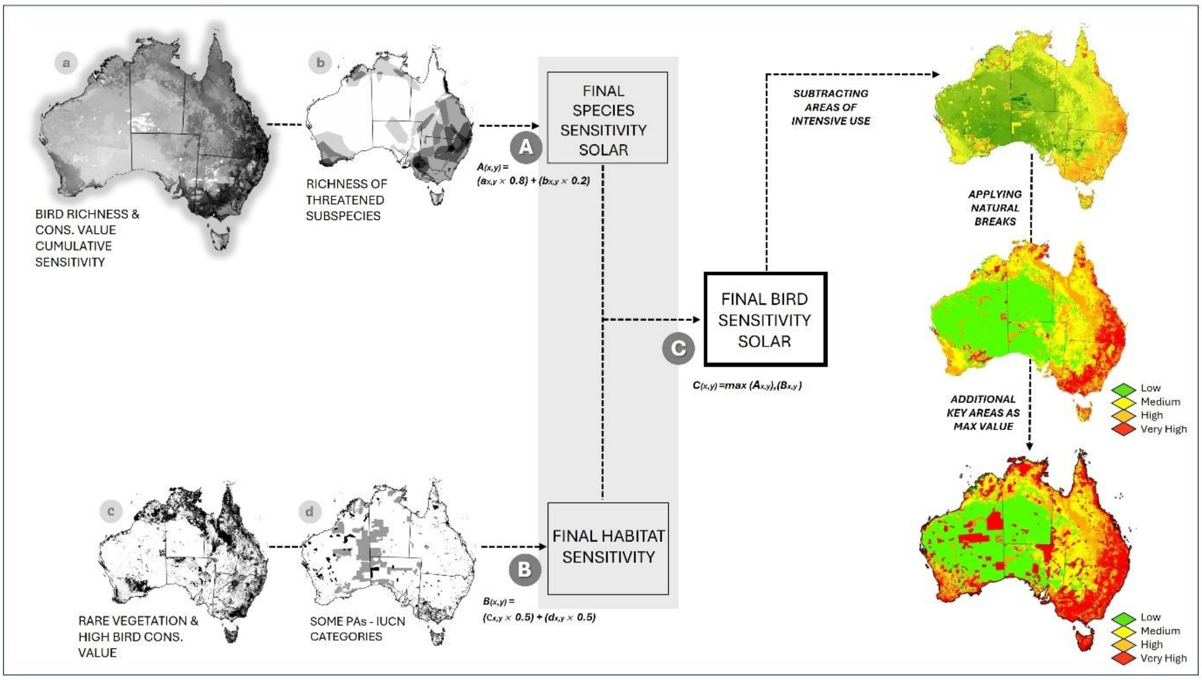

Figure 12. Overall workflow showing the main spatial layers integrated to create the final solar photovoltaic map displayed on AVISTEP.

A) Due to a combination of geological, climatic, and evolutionary factors, Australia hosts many endemic bird subspecies distributed across diverse habitats, from tropical rainforests in the north to deserts, temperate forests, and alpine zones in the south and east. Although many of these subspecies may not be directly affected by impacts from energy infrastructures, they are very rare and have a restricted distribution. Therefore, they warrant priority in conservation efforts and spatial planning to avoid their distribution areas. To account for these subspecies, we developed a spatial layer representing the "Richness of Threatened Subspecies", based on polygons delineating the distribution areas of 84 subspecies classified under the threat categories Near Threatened (NT), Vulnerable (VU), Endangered (EN), and Critically Endangered (CR). To produce a Final Species Sensitivity (A), this layer was combined with the priority species cumulative map, but with less weight (contributing with only 20%) since the polygons are less accurate regarding the probability of finding the species when compared to the information used to prepare the cumulative map of priority species (contributing with 80%). All the maps were rescaled into 0 and 1.

$$Final\ Species\ Sensitivity\ Solar = (Cumulative\ Sensi. \times 0.8) + (Richness\ of\ Threatned\ subsp\ \times 0.2)$$

B) To identify habitats most relevant for bird conservation, we used data from the National Vegetation Information System (NVIS) Version 7.0, which provides delineations of 32 major Vegetation Groups representing native vegetation classes across Australia at a 100 m resolution. We developed a bird richness map based on 609 Australian bird species, weighting each species according to its global Conservation Status as follows: Critically Endangered (CR) + any species with number of mature individuals < 1,000 = 1.00; Endangered (EN) + any species with number of mature individuals < 2,500 = 0.59; Vulnerable (VU) + any species with number of mature individuals < 10,000 = 0.41; Near Threatened (NT) = 0.12; Least Concerned (LC) and population trend decreasing = 0.08; LC and population trend increasing/stable = 0.06. For each grid cell, the cumulative value of bird richness & conservation status was calculated, and the final values were rescaled to a range of zero to one.

Vegetation classes were ordinated using Principal Component Analysis (PCA), considering the proportion of each vegetation class in Australia, the median bird richness and conservation status, and the maximum richness value within each class. Bartlett's test of sphericity (Bartlett, 1951) was applied to evaluate the suitability of the data for factor analysis. Composite scores were obtained by multiplying the factors derived from the first ordination axis by that axis's shared variance. Based on these results, eleven vegetation classes were identified as being important for bird conservation: 1)Eucalypt Open Forests, 2)Eucalypt Tall Open Forests, 3)Eucalypt Woodlands, 4)Rainforests and Vine Thickets, 5)Casuarina Forests and Woodlands, 6)Mangroves, 7)Tussock Grasslands, 8)Callitris Forests and Woodlands, 9)Eucalypt Low Open Forests, 10)Heathlands, and 11)Inland Aquatic - freshwater, salt lakes, lagoons (Figure 13). To support this assessment, we also referred to the EPBC Act List of Threatened Ecological Communities and the Australian National Botanic Gardens – Centre for Australian National Biodiversity Research.

The NVIS map was subsequently reclassified by assigning a value of 1 to the 11 vegetation classes selected and a value of 0 to all others. The percentage of important vegetation within each 5x5 km cell was then calculated following the same procedure as in Step 2. Consequently, cells with a higher proportion of important vegetation received higher sensitivity scores.

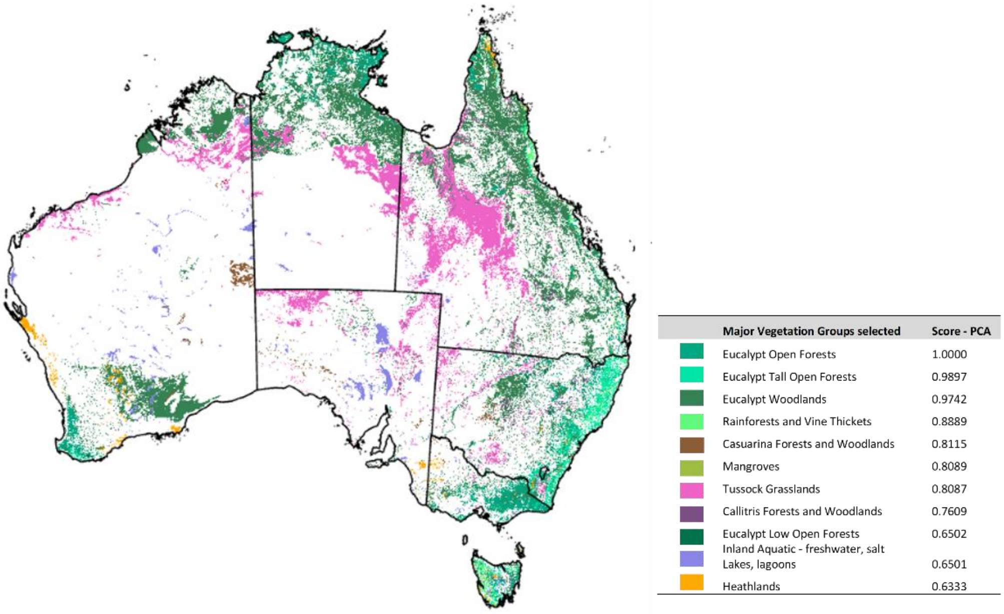

Figure 13. Eleven classes selected to represent the rarest vegetation in Australia in accordance with PCA rank analysis, EPBC Act List of Threatened Ecological Communities and the Australian National Botanic Gardens – Centre for Australian National Biodiversity Research.

To complement the habitat assessment, in addition to creating the Rare vegetation & high bird conservation map, we also included the Protected Areas database from Collaborative Australian Protected Areas Database (CAPAD 2024). This database provides spatial information on Australia's protected areas at national, state, and territory levels, including IUCN categories (i.e., categories Ia to VI), which classify protected areas according to their management objectives (Dudley, 2008).

First, all protected areas (PAs) that were designated specifically for bird conservation or that represent essential habitats for certain bird species were identified. This resulted in a set of 5,605 PAs, which were extracted and carried forward to the next step (see STEP 5). From the remaining PAs, different weights were assigned according to the IUCN management categories. PAs classified as Ia (Strict Nature Reserve), Ib (Wilderness Area), II (National Park), III (Natural Monument or Feature), and IV (Habitat/Species Management Area) were given the highest weight of 1.0. In contrast, PAs under categories V (Protected Landscape or Seascape) and VI (Protected Area with Sustainable Use of Natural Resources) were considered lower priorities for bird conservation, as they allow a broader range of human activities. These were assigned a weight of 0.4. The set of weights was determined using the Analytic Hierarchy Process (AHP).

All the above information was rasterised at a resolution of 5 km^2. The final habitat sensitivity map was created by combining the Rare Vegetation & High Bird Conservation Value map with the IUCN-triggered PA map, both given the same weight in the MCA combination according to the equation:

$$Final\ Habitat\ Sensi. = (Rare\ veg.\&high\ bird\ cons.value\ \times 0.5) + (PAs_{IUCN}triggered\ \times 0.5)$$

C) Due to the relevance for bird and conservation, the Final Habitat Sensitivity and Bird Sensitivity maps were combined, preserving the maximum value of each grid cell as follows:

$$Final\ Bird\ Sensitivity\ (x,y) = \max\ (A(x,y), B(x,y))$$

After generating the Final Bird Sensitivity Map, the final step involved reducing the overall contribution of human-induced areas, as this specific land-use information is not represented in the main vegetation map. To address this, we incorporated data from the Catchment Scale Land Use of Australia (CLUM), version 2 (ABARES 2024), which provides a national compilation of catchment-scale land-use data for Australia.

CLUM is a seamless raster dataset that integrates land-use information from all state and territory jurisdictions, compiled at a spatial resolution of 50x50 m.

The following land-use classes were selected for adjustment: Intensive horticulture, Intensive animal production, Manufacturing and industrial, Services, Utilities, Transport and communication, Mining, and portions of Plantation forest, Irrigated plantation, and Residential areas. These classes were resampled to match our 5x5 km grid, and a maximum value of 0.5 was subtracted from the Final Bird Sensitivity Map to reflect their reduced suitability for bird conservation.

Identifying final sensitivity categories – STEP 5

Classificando o valor de sensibilidade em categorias

Our sensitivity data over grid cells display non-uniform distributions with evident clustering data. Thus, we have used Jenks' Natural Breaks algorithm (Natural breaks function, ArcGIS Pro, ESRI 2021) to classify sensitivity values across grid cells into four classes, which we interpret as Low (1), Medium (2), High (3), and Very High (4) bird sensitivity. Natural Breaks minimise the squared deviations of a group's means and are a standard method for splitting spatial datasets. The map shows the four final bird sensitivities in a format that provides meaningful visualisation and is easier to interpret for a range of stakeholders in decision-making processes.

Including Additional key areas

Additional key areas are considered as those already designated for bird conservation purposes or for conservation of their habitats, regardless of whether they focus on a priority species concerning the impacts of energy infrastructure. Examples include some Protected Areas (PAs), Important Bird and Biodiversity Areas (IBAs), Key Biodiversity Areas (KBAs), and Ramsar Areas.

Protected Areas

Specifically, in this step, we considered the 5,605 protected areas identified by bird experts as key areas for birds. We used the data from the Collaborative Australian Protected Areas Database: protected area data (CAPAD). The protected areas selected as additional key areas were not included in any previous step to avoid data redundancy. The protected areas not considered as additional key areas (5,621) were considered previously (STEP 4).

Key Biodiversity Areas (KBAs)

For Australia, the Important Bird and Biodiversity Areas (IBAs), which are areas of the greatest significance for birds worldwide (Donald et al. 2019; BirdLife International, 2025), are integrated also as KBAs triggered by birds. KBAs are a global dataset of areas of greatest significance for conserving birds. This dataset is curated by BirdLife International and available through the website (https://datazone.birdlife.org/). The most up-to-date version of this data was used (BirdLife International, 2025).

Ramsar Areas

Ramsar areas are wetlands of international importance designated under the Ramsar Convention (1971). These areas should be safeguarded for various biodiversity reasons, primarily because they serve as safe breeding and feeding grounds for birds and as stopovers during migrations. We considered Ramsar areas in accordance with the Department of Climate Change, Energy, the Environment, and Water (DCCEE, 2025).

Furthermore, other areas already recognised as relevant for bird conservation but not yet officially designated or in the process of implementation, such as Shorebird polygons (BirdLife Australia, 2025a), Bird Colonies (Quade, 2025), and areas of potential occurrence for sensitive species, were considered as additional key areas.

All the above information was rasterised in a resolution of 5km2. We combined additional key areas with very high sensitivity (assigned the maximum value of 4) into the final sensitivity layer, which already contained four categories (Figure 14). For each grid cell, the highest sensitivity value was retained. As a result, cells with lower initial sensitivity that overlapped spatially with these additional key areas were upgraded to the maximum sensitivity value. This approach ensures that areas already recognised as important for bird conservation receive the highest sensitivity rating and are avoided from energy planning. Likewise, areas previously classified as highly sensitive remain so when overlapping with additional key areas.

All the maps created in STEP 2, STEP 3, STEP 4 and STEP 5 had the Geocentric Datum of Australia (GDA2020) as the Projected Coordinate System.

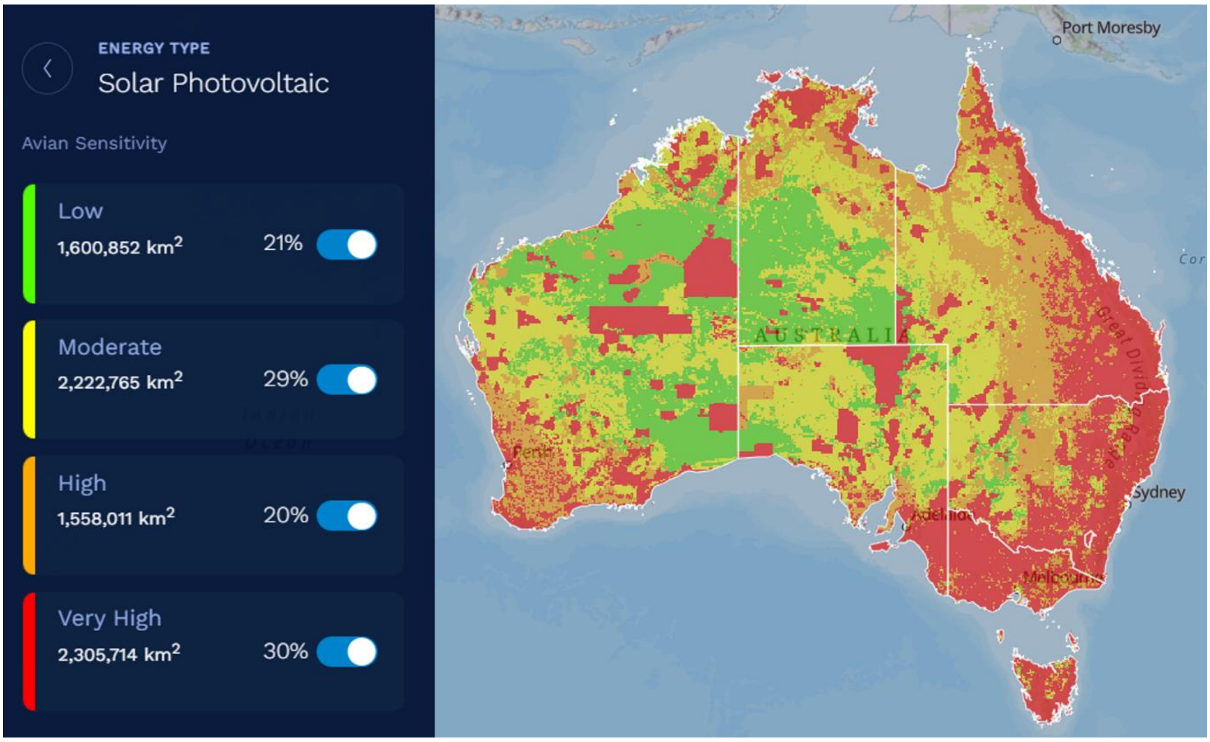

Figure 14. Final Sensitivity Map for Solar - Photovoltaic developments in Australia. See more in AVISTEP – Australia.

Offshore Wind Energy

Delineate Area of Interest (AOI) – STEP 1

The first step in our offshore sensitivity analysis was delineating our Area of Interest (AOI). For Australia, the extent of the entire Exclusive Economic Zone (EEZ) was not considered a suitable boundary for analysis. Australia has a large EEZ, with some areas located very far the mainland, including around external territories such as Norfolk Island, Christmas Island and Macquarie Island. These remote offshore areas are unlikely to face offshore wind development in oncoming years. Therefore, the AOI boundary was manually defined in ArcGIS.

First, we excluded areas lacking available wind resource data (World Bank Group, globalwindatlas.info/en/). Second, areas around external territories that were not connected to the main wind resource data surrounding the coast of mainland Australia and Tasmania were removed. Using this reduced layer, maximum distances from the coast were estimated at various points from the coast of mainland Australia and Tasmania. From this, the typical distance across the coast was calculated and a buffer distance of 200km was selected. Using the coastline of mainland Australia and Tasmania, as well as two large islands in the Bass Strait (King Island and Flinders Island), a 200km extension from the coast was made using the *Buffer* tool in ArcGIS Pro, cropped to the extent of the EEZ. The AOI boundary was then rasterised to a 5x5km grid using a suitable projection (Australian Albers Equal Area, GDA94) to form the basemap of our analysis. This boundary was used to screen species and data to be included in subsequent analysis (Figure 15).

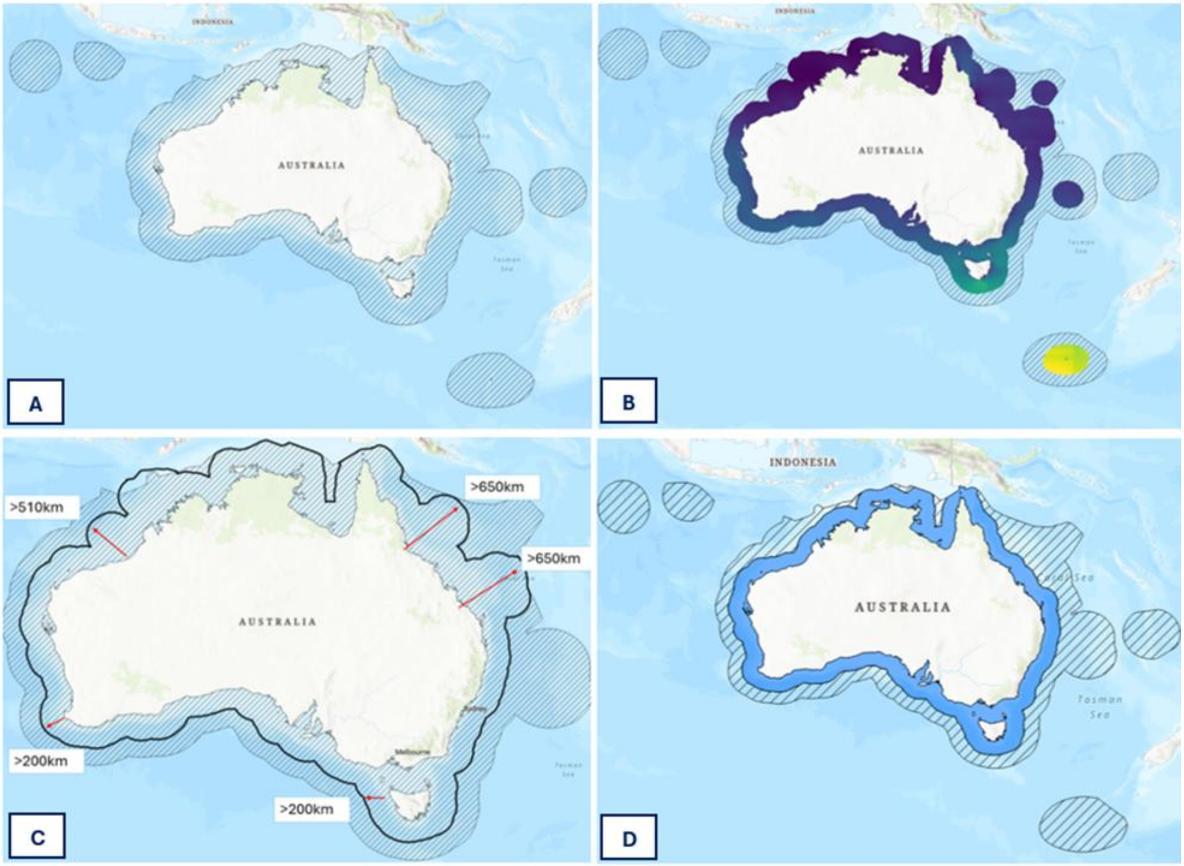

Figure 15: The process of delineating the Area of Interest (AOI) for the AVISTEP offshore analysis in Australia in ArGIS. Step one, the full extent of the Australian Exclusive Economic Zone (A) was reduced based on the available wind data (Global Wind Atlas) for the region (B). wind data for external territories was excluded. Next, an average estimate of distance from the coast was taken to determine a suitable buffer(C). A buffer of 200km was extended from the coast and then clipped to the extent of the EEZ along the northern boundary in ArcGIS (D).

Selecting Species for Analysis – STEP 2

For Australia, we identified marine species that were "regularly occurring" within the AOI. The flow chart below shows the range of sources we consider before a species is ultimately included or excluded (see Figure 16). Collating the seabird species list for offshore analysis is a process that we validate with local partners and experts where available. First, we obtained a comprehensive working list of all bird species in Australia from the BirdLife partner in the region (BirdLife Australia, 2022). We selected the marine species from this list and investigated the regularity of occurrence for each species within the selected AOI. This required a review of range maps for each species (HBW & BirdLife International, 2024) and local literature to further inform details of individual species distribution and frequency of occurrence (this includes field guides for Australia, rare birds lists and telemetry data or scientific papers that included the spatial distribution of relevant species). Some species listed as seabirds can exhibit both marine and onshore activity in their ranges (for example, species such as Cormorants, Terns and Grebes). For these groups, their distribution was checked within the AOI using available evidence and expert elicitation. Our species list was reviewed by BirdLife Australia and other local experts on various occasions before being finalised. After review, 83 species were selected for analysis (Table 1).

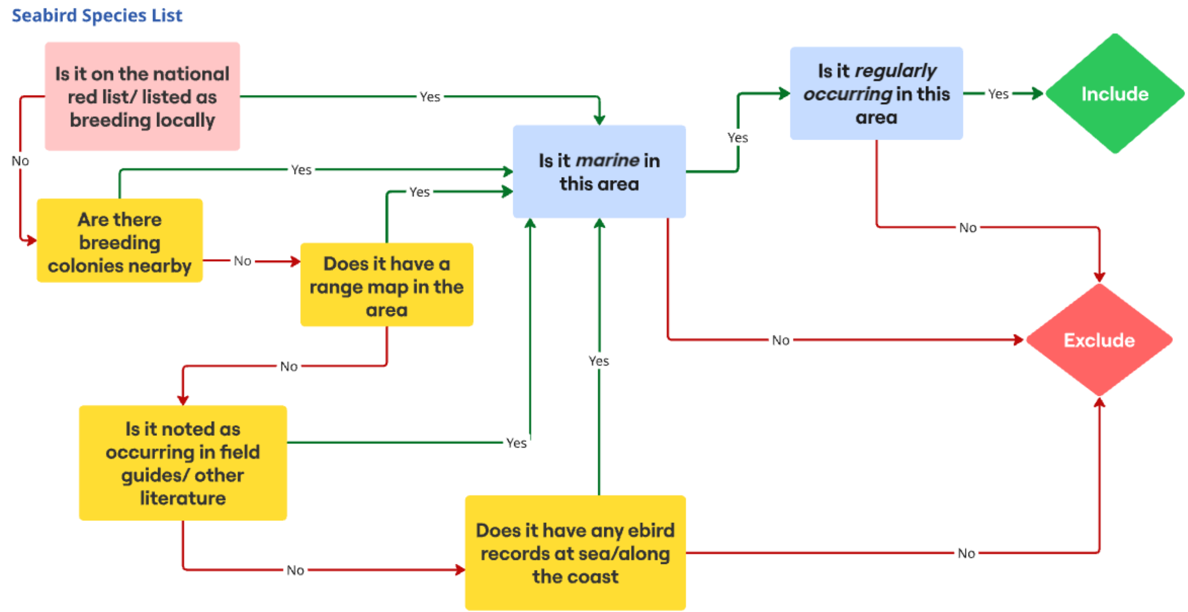

Figure 16: Flowchart of the decision-making process for seabird species selection in AVISTEP offshore analysis. The process starts with key sources (in red), additional corroborating sources are in yellow, country-specific distribution requirements are in blue. The process ends with a species being included or excluded from the species list.

Table 1: A list of all analysed species for AVISTEP offshore wind sensitivity maps in Australia, grouped by family. This includes 83 seabird species and 10 families.

Diomedeidae	**Sulidae**	**Hydrobatidae**	Little Shearwater	**Stercorariidae**
Amsterdam Albatross	Australasian Gannet	Matsudaria's Storm-Petrel	Mottled Petrel	Arctic Jaeger
Antipodean Albatross	Brown Booby	**Spheniscidae**	Northern Giant-Petrel	Brown Skua
Black-browed Albatross	Masked Booby	Little Penguin	Providence Petrel	Long-tailed Jaeger
Buller's Albatross	Red-footed Booby	**Procellariidae**	Short-tailed Shearwater	Pomarine Jaeger
Campbell Albatross	**Laridae**	Antarctic Prion	Slender-billed Prion	**Oceanitidae**
Grey-headed Albatross	Black Noddy	Black-winged Petrel	Soft-plumaged Petrel	Grey-backed Storm-Petrel
Indian Yellow-nosed Albatross	Black-naped Tern	Blue Petrel	Sooty Shearwater	White-faced Storm-Petrel
Light-mantled Albatross	Bridled Tern	Buller's Shearwater	Southern Fulmar	Wilson's Storm-Petrel
Northern Royal Albatross	Brown Noddy	Bulwer's Petrel	Southern Giant-Petrel	**Phaethontidae**
Salvin's Albatross	Caspian Tern	Cape Petrel	Streaked Shearwater	Red-tailed Tropicbird
Shy Albatross	Common Tern	Common Diving-Petrel	Wedge-tailed Shearwater	White-tailed Tropicbird
Snowy Albatross	Fairy Tern	Cook's Petrel	White-chinned Petrel	
Sooty Albatross	Greater Crested Tern	Fairy Prion	White-headed Petrel	
Southern Royal Albatross	Gull-billed Tern	Flesh-footed Shearwater	White-winged Petrel	
White-capped Albatross	Kelp Gull	Fluttering Shearwater		
Phalacrocoracidae	Lesser Crested Tern	Grey Petrel		
Black-faced Cormorant	Lesser Noddy	Grey-faced Petrel		
Fregatidae	Little Tern	Great-winged Petrel		
Great Frigatebird	Pacific Gull	Herald Petrel		
Lesser Frigatebird	Roseate Tern	Hutton's Shearwater		
	Sooty Tern	Kerguelen Petrel		
	White-fronted Tern	Kermadec Petrel		

Calculating Sensitivity for all Selected Species – STEP 3

Following the selection of species, we calculated sensitivity for all listed species. We estimated the individual risk factors collision (Co) and displacement (Di), along with the population level susceptibility (PopS). Using a trait-based approach, we estimated the level of sensitivity to offshore wind development for each species. As with previous projects, collision and displacement were calculated separately as these are distinct pressures (Furness et al., 2013; Bradbury et al., 2014; Certain et al., 2015). Both were then combined with a population susceptibility score (PopS) to create an overall sensitivity to both collision (CoSI) and displacement (DiSI). As there is much more certainty regarding conservation status than collision and displacement, the population susceptibility score was given a higher weight in our calculations.

Contributing factors were divided into primary, aggravating and additional factors. Primary factors are inherently risky behaviour, traits, or other parameters that directly contribute to a species' sensitivity. Aggravating factors exacerbate an existing risk but have no inherent risk of their own (Certain et al., 2015). Additional factors are factors that reflect a known risk for a species that cannot be captured by primary or aggravating factors but should still be reflected in the calculation of the sensitivity index. For Australia, the only additional risk included was for evidence of collision

Population Susceptibility (PopS) was used as a factor to address the disparity in vulnerability of different seabird populations. Seabird species that are at a high-risk for extinction are very vulnerable to threats which may further population decline.

Population susceptibility was calculated as follows:

$$PopS = CnS \times Su$$

Conservation Status (CnS): We classified the primary population-level risk for a species as their conservation status. Values were attributed according to their Red List status, population size and population trend. The Global Red List categories were defined as follows:

- Critically Endangered (CR) + any species with number of mature individuals < 1,000 = **1.00**
- Endangered (EN) + any species with number of mature individuals < 2,500 = **0.59**
- Vulnerable (VU) + any species with number of mature individuals < 10,000 = **0.41**
- Near Threatened (NT) = **0.12**
- Least Concerned (LC) and population trend decreasing = **0.08**
- LC and population trend increasing or stable = **0.06**

To determine the relative importance among different categories, we used the Analytic Hierarchy Process, applying a Saaty pairwise comparison matrix across categories to evaluate and contrast their relevance to extinction risk. The assessment was conducted in collaboration with colleagues from the BirdLife International Red List Team who are responsible for assessing all bird species for the IUCN Red List. Weights assigned increased approximately exponentially according to the highest threat category.

We calculated mean of the values for the Global Red List and the National Red List (Garnett & Baker, 2021). If the species was Least Concern, scores are given according to the global population trend. The Australian Environment Protection and Biodiversity Conservation Act 1999 (EPBC Act) includes Red List assessments for a subset of species. We added 0.05 if a species was listed as a Threatened Species under the EPBC act with a more severe threat status than the mean of the Global and Australian Red List statuses (according to the Species Profile and Threats Database accessed September 2025).

Annual Adult Survival (Su): Populations of long-lived, slow breeding species have limited ability to recover from additional moralities or poor breeding success. We used species' annual adult survival as an aggravating factor to capture these life history traits (Bird et al., 2020), by multiplying Su by the conservation status (CnS).

Collision (Co): Offshore structures are novel additions to the marine environment that can pose a risk of fatal collisions for seabirds. Such collisions may occur either with the moving rotor blades of turbines or with the stationary components of the structure below. In recent years, collision risk has been the focus of windfarm sensitivity analysis in areas with established offshore wind industries (Garthe & Hüppop, 2004; Furness et al., 2013; Bradbury et al., 2014; Certain et al. 2015). Despite ongoing research into collision, there is still uncertainty surrounding the drivers and the frequency of collision of seabirds. As a result, risk of collision is estimated by scoring various behavioural and morphological traits of individual species.

Collision was calculated as follows:

$$Co = FliB \times \left(\frac{FliM + Noct}{2}\right) + AddR$$

Flight Behaviour (FliB): We used a species-level trait-based approach to identify the primary risk for seabird collision. For previous offshore maps, this factor was a measurement of time spent flying in the rotor swept zone based on estimates of flight height and flight time information from literature (please review manuals prior to 2025). However, due to lack of good quality flight height information and the possibility of collision with static structures under the rotor swept zone (defined here as 30-350m) we categorised levels of risky flight behaviour which included flight below the rotor-swept zone. Based on values used in Reid et al. (2023) and Reid & Baker (2025), the rotor-swept zone is assumed to be 30-350m. Using an existing risk assessment that measured and categorised flight behaviour according to flight height and foraging type, we established 6 categories of exposure (Reid et al. 2023; Reid & Baker, 2025). Based on local expert advice, adjustments were made on a species-by species basis.

Flight behaviours were categorised as follows:

Flight Behaviour	Species groups	Score
Very High Risk	Gannets, Boobies	1.00
High Risk	Frigatebirds, Noddies, Frigatebirds, Skuas, Terns	0.85
Moderate Risk	Cormorants, Gadfly Petrels, Gulls, Tropicbirds	0.70
Low Risk	Shearwaters, Petrels, Prions, Fulmars	0.55
Very Low Risk	Albatrosses, Northern Storm-petrels, Southern Storm-petrels	0.40
No Risk	Penguins	0

Flight Manoeuvrability (FliM) & Nocturnal Activity (Noct): Once flying at a dangerous height, there are factors that may impact an individual's ability to avoid possible collision. Based on previous work on collision sensitivity factors (Garthe & Hüppop, 2004; Furness et al., 2013; Bradbury et al., 2014; Certain et al., 2015), flight manoeuvrability and nocturnal activity were identified as aggravating factors for collision. The application of aggravating factors assumes that, when all other factors are equal, a less manoeuvrable species or a species that is more active at night may be more vulnerable to collision. When combining factors, how they interact determines how best to include them. As nocturnal activity and flight manoeuvrability are considered to aggravate the risk of flying near offshore turbines, we consider them as interactive with the exposure risk values for each species. Therefore, this factor is multiplied by the risk of exposure to rotor blades due to flight behaviour (FliB). Since there is a lack of evidence suggesting that manoeuvrability and nocturnal activity interact dependently in relation to collision risk, we used the average between the two (Certain et al., 2015).

Flight manoeuvrability was calculated dividing body mass Dunning (2007) by wing length (Tobias et al., 2022) as a proxy for wing loading. Wingspan and wing width are usually used to calculate wing loading, but these measurements are not always available and recorded consistently for seabird species. As wing length is typically very well recorded for most species, we used this measurement for our analysis. In Australia, wingspan data was used from Handbook of Australian, New Zealand and Antarctic Birds (HANZAB, Marchant et al., 1990-2006) to plot the correlation between the available wingspan measurements and wing length data from Avonet (Tobias et al., 2022). We were satisfied that the correlation between wing length and wingspan was sufficient to use wing length as a proxy.

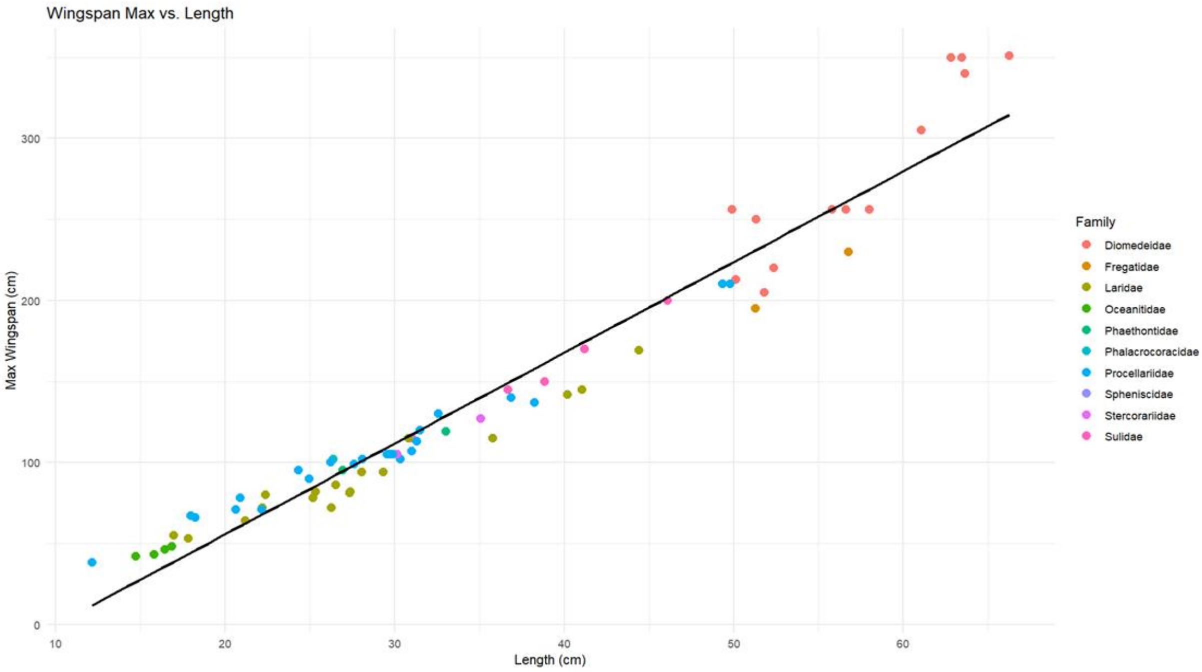

Figure 17: Relationship between wingspan (maximum values from HANZAB) and wing length (AVONET) for seabird species. Points are coloured by family, and a linear regression line is shown.

For nocturnal activity, we categorised species into types of night activity. These were nocturnal activity, partially active at night and diurnal activity. The categories based on flight information from a literature review, including data from a recent review of Procellariform flight height and nocturnal activity carried out in Australia (Miller et al., 2025). All categories were given a score between 0.5-1 as shown below.

Nocturnal Category	Score
Nocturnal Activity	1
Partially Nocturnal Activity	0.75
Diurnal	0.5

Additional Risk (AddR): Despite over four decades of collision risk modelling and its central role in Environmental Impact Assessments for offshore wind developments in the Northern Hemisphere, much remains unknown about the factors that contribute to seabird collisions (Madsen & Cook, 2016; Cook et al., 2025). As a result, the primary and aggravating factors above (exposure to offshore structures, flight manoeuvrability and nocturnal activity) may not fully encapsulate traits or behaviours that impact an individual's risk of collision. To address this, we include an additional risk factor for collision. Where there has been documented evidence that species in Australia can collide onshore (Hull et al., 2013), an extra risk value is added. As we cannot establish from event records alone why these collisions occur, we treat the factor as additive. There was no evidence of collision at offshore sites in Australia, therefore the maximum score applied was 0.2.

Evidence of Collision	Value	Species	Sources
Offshore Collision	1	*Not applicable*	
Onshore collision	0.2	Australasian Gannet, Common Diving-petrel, Grey-backed Storm-petrel, Short-tailed Shearwater, White-faced Storm-petrel, Wilson's Storm-petrel	Hull et al., 2013
No evidence of collision	0	*All remaining species*	

Displacement (Di): The presence of offshore development may also deter seabirds from areas or cause them to alter their movements and behaviours. Changes in distribution of seabirds in response to offshore windfarm development have often been recorded. The strength of this response often varies between taxa, breeding seasons, spatial and temporal extent of the disturbance and this response can be attraction or avoidance (Searle et al., 2018; Lamb et al., 2024). Avoidance behaviour may adversely impact seabirds the most where it displaces them from key foraging areas or notably changes their time-energy budgets.

Displacement can be split into three types (Figure 18):

1. Macro-avoidance is where birds avoid an entire windfarm
2. Meso-avoidance is where birds will enter a windfarm but avoid all the turbines.
3. Micro avoidance is where birds move in and around the turbines but avoid the blades.

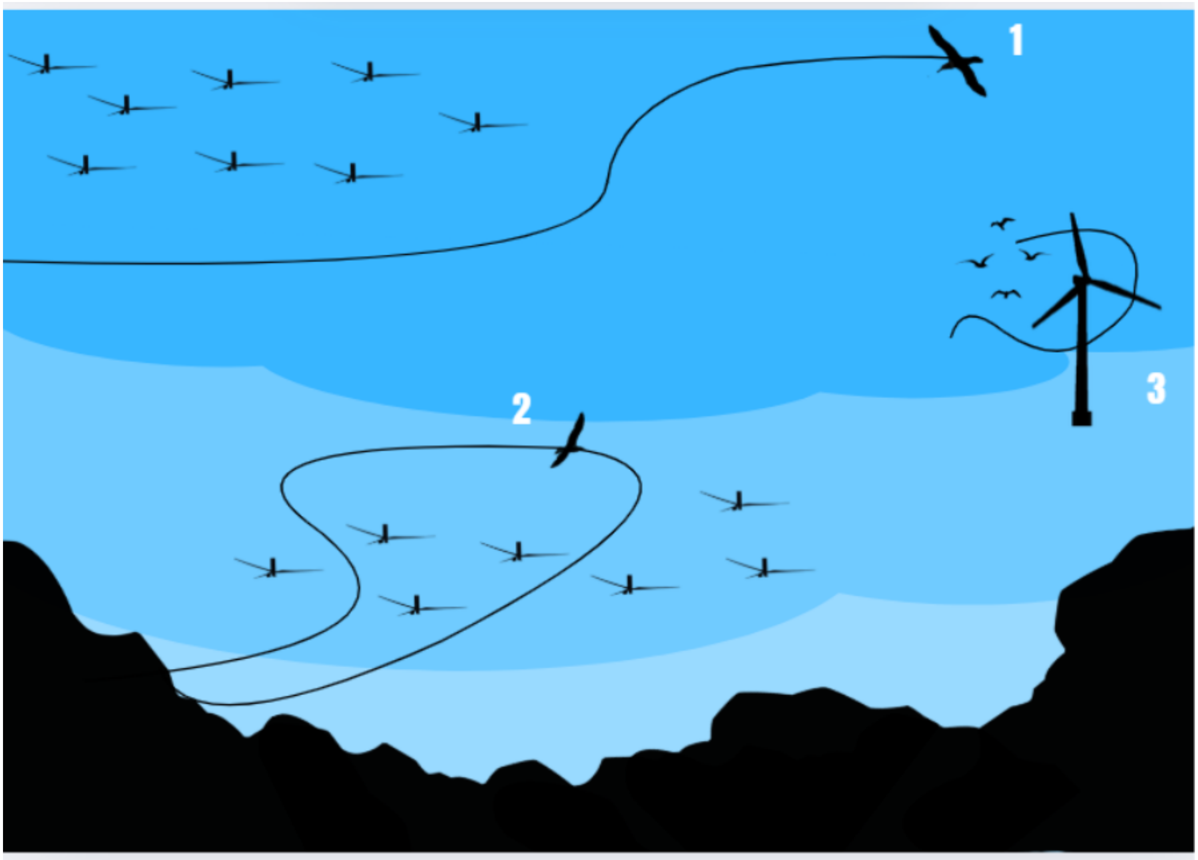

Figure 18: Diagram explaining the differences between macro, meso, and micro avoidance. Macro-avoidance (1) is where individuals avert from and entire windfarm area when flying. Meso-avoidance (2) is where individuals fly into a

windfarm but fly between turbines once they enter. Micro-avoidance (3) is where individuals fly amongst the turbine blades of individual turbines but carry out flight manoeuvres in order to avoid collision.

Displacement was calculated as follows:

$$Di = \left(\frac{DiMT + DiSt}{2}\right) \times Flex$$

Disturbance from Marine Traffic (DiMT) and Static Structures (DiSt) are the primary factors for calculating displacement for seabirds. In line with the onshore approach, we applied a literature review looking for articles published regarding bird displacement to understand how likely different bird families are to be impacted. Some authors do not distinguish between these types of disturbances. However, since marine traffic (i.e., vessels and helicopters) is expected to increase during construction and operation of offshore wind farms, we include them separately. For some species we did not find information about both disturbance types, but only for fixed structures; on those occasions, we scored both parameters equally. As these factors may operate independently, an average of the two is used to estimate disturbance.Disturbance from static Structures was divided into four categories. Disturbance from marine traffic was divided into three categories. For both factors, disturbance scored from 0.5 (low disturbance response) to 1 (high disturbance response).

Category of disturbance from Static Structures	Species Groups	Risk Score
1	Albatrosses, Cormorants, Frigatebirds, Petrels, Shearwaters, Southern Storm-Petrels,	0.5
2	Gulls, Terns, Noddies, Skuas, Tropicbirds, Penguins,	0.67
3	Boobies	0.83
4	Gannets, Boobies	1

Category of disturbance from Marine Traffic	Species Groups	Risk Score
1	Frigatebirds, Gulls, Northern Storm-Petrels, Southern Storm-Petrels, Tropicbirds	0.5
2	Albatrosses, Boobies, Cormorants, Gannets, Noddies, Petrels, Shearwaters, Skuas, Terns	0.75
3	Penguins	1

Habitat Flexibility (Flex) is the aggravating factor used for displacement. While the marine environment is dynamic and habitats often change overtime, the flexibility of foraging habitat use and diet specialisation varies from species to species. As flexibility influences the severity of the impacts of displacement, it is multiplied by the primary disturbance risks. Local reports were used to categorise the species in Australia (Garnett et al., 2015; Reid et al., 2023; Reid & Baker, 2025). Where no data was available for the species, proxy species were used to estimate factors. Habitat flexibility was categorised into four groups from 0.5 (high habitat flexibility) to 1 (low habitat flexibility) and multiplied by the primary factor as shown below.

Habitat Flexibility Category	Risk Score
1	0.5
2	0.67
3	0.83
4	1

Overall Sensitivity:

Once collision, displacement and population susceptibility were all individually scored, collision and displacement were both multiplied the population susceptibility (PopS) to produce a collision sensitivity index (CoSI) and a displacement index (DiSI) as shown below.

$$CoSI = Co \times PopS$$

$$DiSI = Di \times PopS$$

Because population susceptibility was considered more certain than individual risks of collision and displacement, the individual factors were scaled to a lower range of values. Consequently, population susceptibility had a stronger influence on the overall calculations. All collision and displacement factors were scored between 0.4 or 0.5 and 1, while conservation status (CnS) and annual adult survival (Su) retained their full scoring range.

Table 2: Summary of sensitivity factors used to assess seabird sensitivity to offshore wind for the AVISTEP offshore maps in Australia, categorised by risk type (population or individual), associated pressure (collision or displacement), and factor type (primary, aggravating, or additional), with corresponding scoring scales.

Risk Type	Pressure	Factor Type	Factor	Scale
Population	Population Susceptibility	Primary	Conservation Status	0.06-1
		Aggravating	Annual Adult Survival	data
Individual	Collision	Primary	Flight Behaviour	0.4-1
		Aggravating	Flight Manoeuvrability	0.5-1
			Nocturnal Flight Activity	0.5-1
		Additional	Evidence of Collision	0.2
	Displacement	Primary	Disturbance to Marine Traffic	0.5-1
			Disturbance to Static Structures	0.5-1
		Aggravating	Habitat Specialisation	0.5-1

Mapping distribution for all seabird species– STEP 4

Seabird distributions change over their annual cycle, and a variety of spatial information is available to estimate areas used across the year by seabird species for offshore AVISTEP maps in Australia (such as breeding colony information, known core migratory areas, tracking data and at-sea observations). As with onshore, distribution maps are rasterised into a 5x5km grid. Each species distribution is split into areas of breeding distribution and their all-year distributions.

Seaward extensions

This analysis uses foraging range estimates and colony abundance counts to produce density estimates of abundance extending from breeding sites. These seaward extensions were then used to estimate breeding distribution around the coast of mainland Australia and Tasmania.

First, colony size and location data was collated for all breeding species. This included a summary colony count dataset for island breeding sites in Australia (Quade, 2025), and Fairy Tern *(Sternula nereis*) and Little Tern (*Sternula albifrons*) site counts from BirdLife Australia. For sites with multiple years of data, only the most recent counts were used. The relative abundance of mature breeding individuals was estimated for each species using the following approach:

- Count x 2 for
    - counted in burrow
    - on nest
    - chicks for species with one clutch
- Count x 2/3
    - for individual counts
    - for total population counts where a mix of count methods have been used for the species across the dataset.
    - for chicks counts for a species with maximum clutch of 3
- Count x1
    - for chicks counts for a species with maximum clutch of 2
    - for total population counts where only total population counts have been used for estimating abundance for that species across all colonies in the dataset
- All counts rounded *up* to the nearest whole number

Once breeding sites were identified and relative abundance counts were calculated, a literature review was carried out to collate the recorded foraging ranges for each breeding species. Where multiple records in the region were available, the "mean maximum" values were taken. Where not all records were from studies in the region, preference was given to records within the region. Where no maximum estimates were available, mean values were used. Where there were no suitable records, values from a suitable comparable species were used.

Using these values, gridded density maps extending from the colonies were produced for 37 species. These were made using a log decay function, which assumes that marine space use reduces as distance from the colony via sea increases, limited to the foraging range estimate for each species and not including areas over land. Each colony was run for all species on a 5x5km grid, and all colony extensions were summed so that larger colonies contributed more to the species layer and areas within reach of multiple colonies had higher densities than those only within the foraging range of one colony. Layers were then scaled between 0-1 to produce a layer of relative use of marine areas per species (see Figure 19).

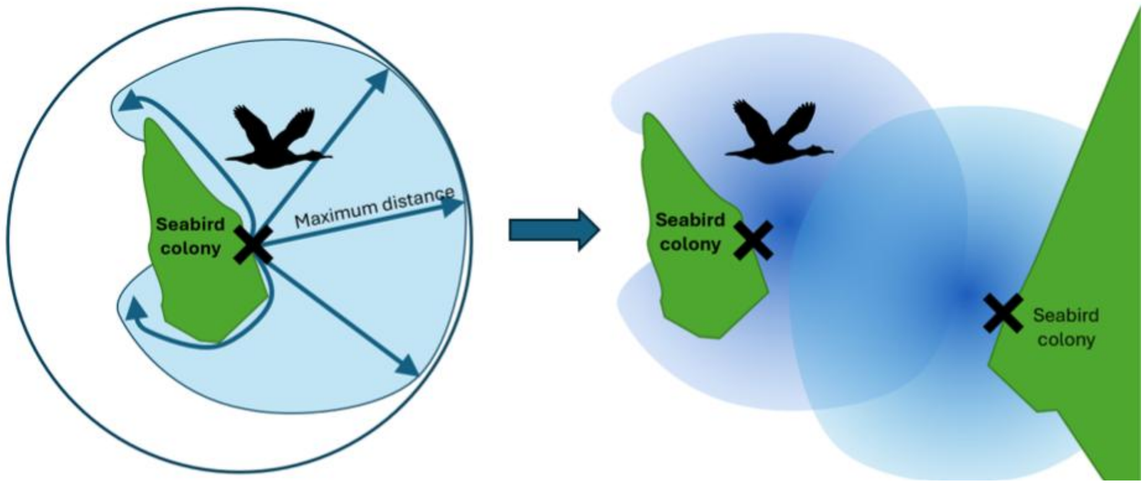

Figure 19: Method for estimating kernel density estimates (KDE) for multiple colonies using foraging range estimates and weighting by colony abundance.

Seabird tracking data

To investigate high use areas both inside and out of the breeding season, tracking data was collated and analysed. Platforms such as the Seabird Tracking Database and Movebank were used to search for available data, and a literature review was also conducted to identify potential data owners. Global Positioning System (GPS), Platform Transmitting Terminal (PTT) and light-based geolocation loggers (GLS) data were all requested where it was found that tracks overlapped with the selected AOI. GPS data has the lowest error, followed by PTT and then GLS has by far the highest error. We assessed each dataset for quality and sample size, and decided the most appropriate use. High-quality data from the breeding season was used to refine our density maps that represent the space use of birds from the breeding colony. While for some datasets, we used tracks only to validate and edit species range maps (see following section).

For tracking data used in analysis, we cleaned the data by removing any duplicate records and ran a McConnel speed filter with a suitable speed for each species. Tracks were then assigned to data groups to ensure that any spatial aggregation patterns exhibited by a species during breeding stages only are captured and not diluted by inclusion of data from outside the breeding period with potentially very different distributions. We interpolated tracks to obtain locations at regular intervals because this is required for kernel density analysis, choosing interpolation intervals to minimise difference from the original dataset. We removed sections of tracks with very large time gaps between actual locations. For each species, we then used kernel density estimation (KDE) using the *adehabitatHR* R package as described in the *Track2KBA* package (Beal et al., 2021). The smoothing parameters used for kernel densities were determined according to bird behaviour (larger smoothing parameters were used for species that travel further and faster than others) and the accuracy of the data available.

Tracking data that was available for breeding individuals were analysed and weighted by relative colony abundance. These outputs were compared with the seaward extension produced for this site, and substituted seaward extension estimates where appropriate (e.g. Figure 20). All tracking data from non-breeding individuals was analysed using the same weighted kernel density estimations from the *Track2KBA* package (Beal et al., 2021) and used to investigate species distribution outside of the breeding period.

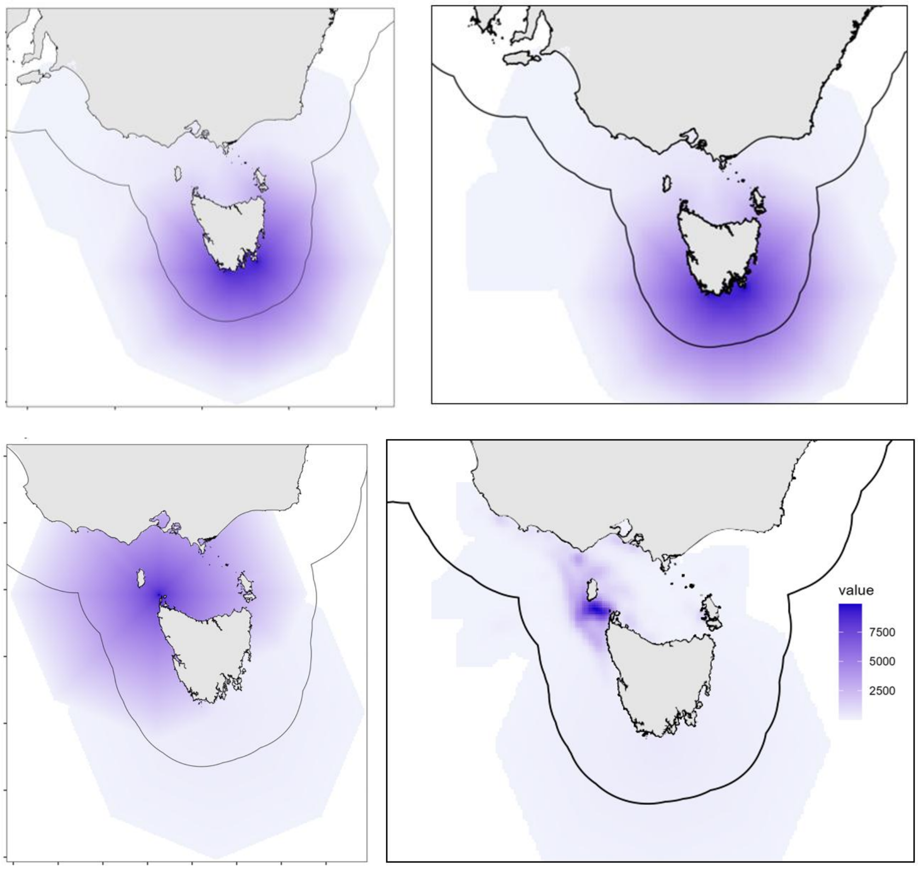

Figure 20. Example for the Fairy Prion, with the seaward extension method only (top left) and the distribution layer after replacing the distribution for Kanowna Island with kernel density map created using a GPS tracking dataset (data.seabirdtracking.org/dataset/2054) contributed by John Arnould (top right). Example for the Shy Albatross, with the seaward extension method only (bottom left) and the distribution layer after replacing the distribution for Albatross Island with kernel density map created using a GPS tracking dataset (data.seabirdtracking.org/dataset/1381) contributed by Kris Carlyon (bottom right).

Range Maps

For Australia, range maps were used to establish the year-round distribution of the listed species. Global range maps were sourced from BirdLife International as used in the IUCN Red List assessments (HBW & BirdLife International, 2024). These maps contain information about resident, passage and breeding areas for seabirds. We also had access to range maps delineated by BirdLife Australia in 2014, with some updates since (BirdLife Australia, pers. comm.). These maps show areas of vagrant and core usage within Australia (e.g. Figure 21) Differences in spatial extent between both maps was investigated for each species and compared with seabird tracking data and observation records from eBird (eBird, 2025) and Birdata (BirdLife Australia, 2025b). A suitable distribution was decided on a species-by-species basis in consultation with BirdLife Australia, but preference was given to the range maps produced by local experts. These core and vagrant areas were incorporated into our analysis, with core areas contributing with double the numerical value of vagrant areas. Where no local maps were available, IUCN range maps were used and treated as vagrant areas. For one species, the Amsterdam albatross (*Diomedea amsterdamensis*), the species range was determined from analysing a large sample of geolocator (GLS) data as no other sources were available. A conservative threshold was used to delineate this area (50% of the kernel density analysis) which was treated as a vagrant area.

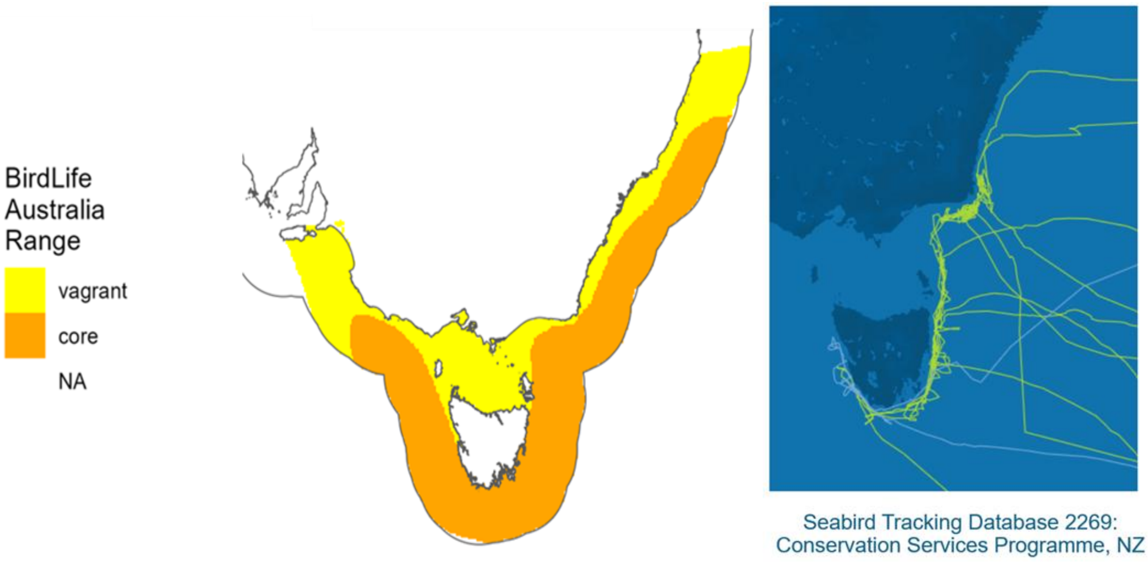

Figure 21: Example of core and vagrant ranges used for Buller's albatross (Thalassarche bulleri) around the coast of Tasmania and southeast coast of mainland Australia, and the corresponding tracking dataset used to verify the ranges (data.seabirdtracking.org/dataset/2269). Cells in yellow indicate a lower value for areas of vagrant distribution (0.5) and darker cells in orange indicate a higher weighting of cells, for core areas (1).

Applying Sensitivity Scores to Species Distribution

Breeding distribution maps were created by merging breeding tracking kernel density outputs and colony seaward extensions together and getting the total sum values for each species. Each species breeding layer was then scaled to 0-1 to create a map of relative use of the marine area during breeding periods. At this point in the analysis, CoSI and DiSI scores were applied to the individual species breeding layers. For each species, the higher of the two scores was multiplied by the distribution values in the breeding layer. Once complete, all species layers were then combined and summed in each overlapping cell to create a single layer. This output layer for each species had the total of the CoSI or DiSI values for each breeding species. This was then scaled between 0 and 1 to create a breeding sensitivity layer (Figure 22).

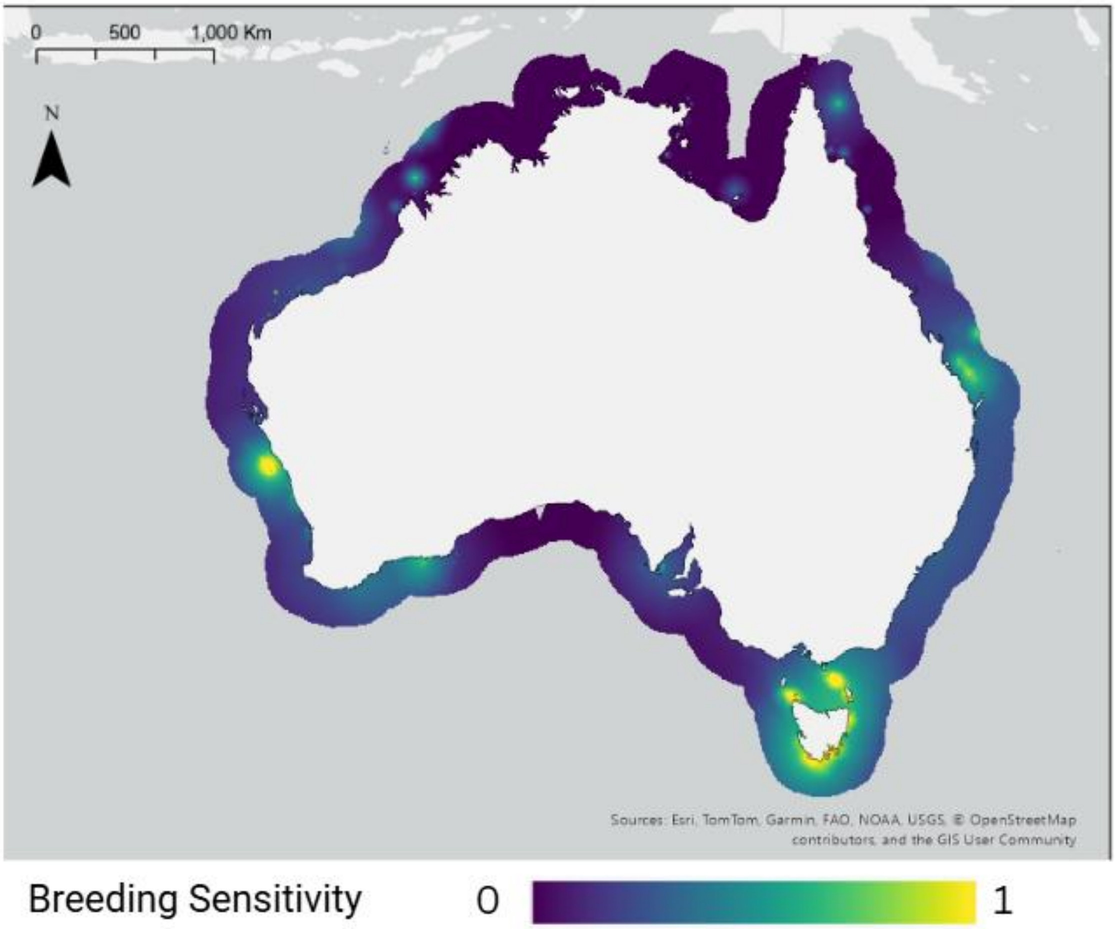

Figure 22: Output breeding sensitivity for Australia AVISTEP Offshore sensitivity mapping at a 5x5km resolution. Scaled between 0-1, this shows the relative usage of marine areas within the Area of Interest (AOI) for breeding periods combined with Collision Sensitivity (CoSI) or Displacement Sensitivity (DiSI). Kernel density analysis of colony foraging estimates (seaward extensions) and suitable tracking data (GPS) were produced and merged for 37 species

All year distribution maps were created by overlapping all range maps that have core and vagrant distributions were delineated and valued as 0.5 (vagrant) or 1 (core). At this point in the analysis, CoSI and DiSI scores were applied to the individual species layers. For each species, the higher of the two scores was multiplied by the core or vagrant distribution values. Once complete, all species layers were then combined and summed in each overlapping cell to create a single layer. This output layer for each species had the total of the CoSI or DiSI values for the core and vagrant areas of all listed species This was then scaled between 0-1 to create a single all year sensitivity layer (Figure 23).

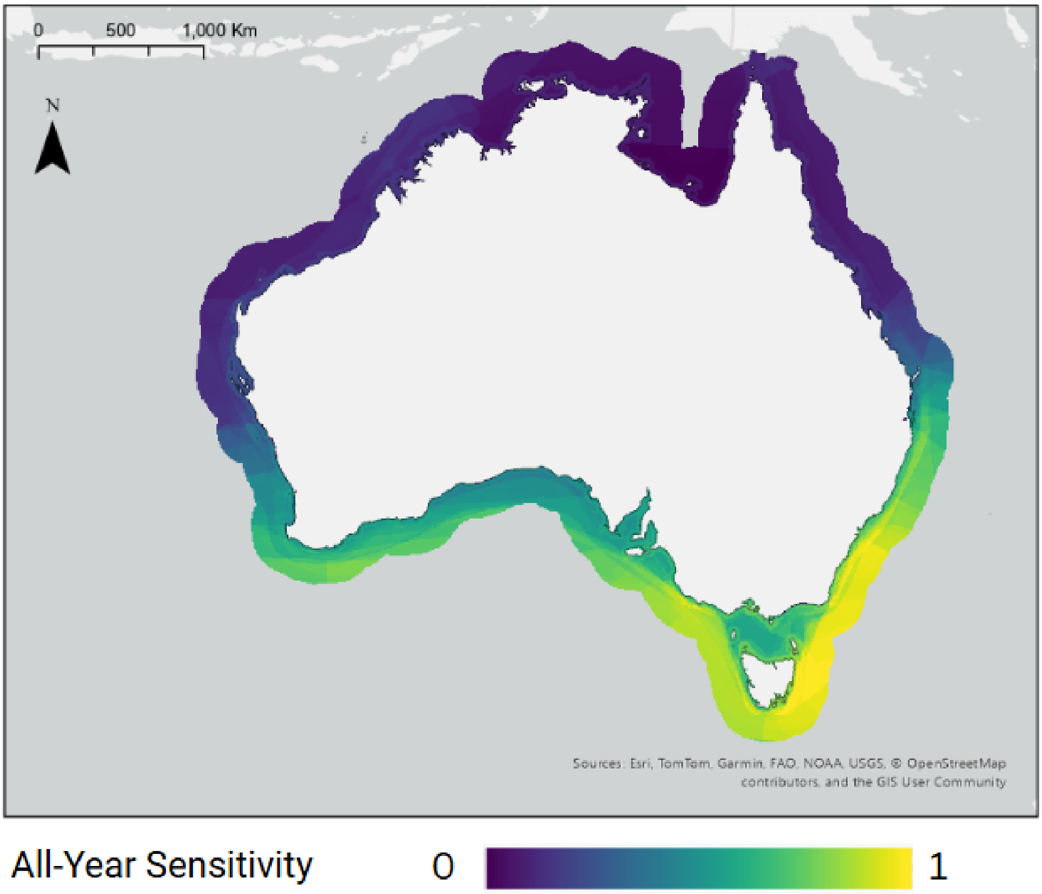

Figure 23: Output for the year-round sensitivity for Australia AVISTEP Offshore sensitivity mapping at a 5x5km resolution. Scaled between 0-1, this shows the combined core and vagrant distribution of all listed species with Collision Sensitivity (CoSI) or Displacement Sensitivity (DiSI) values applied to each cell.

Finally, the two distribution maps were combined to produce a cumulative species sensitivity map. The maps were overlaid, and the maximum value from each cell was retained, resulting in sensitivity scores ranging from 0 to 1 for all species. This output represents the highest sensitivity value from either total breeding sensitivity or year-round sensitivity within each cell (Figure 24).

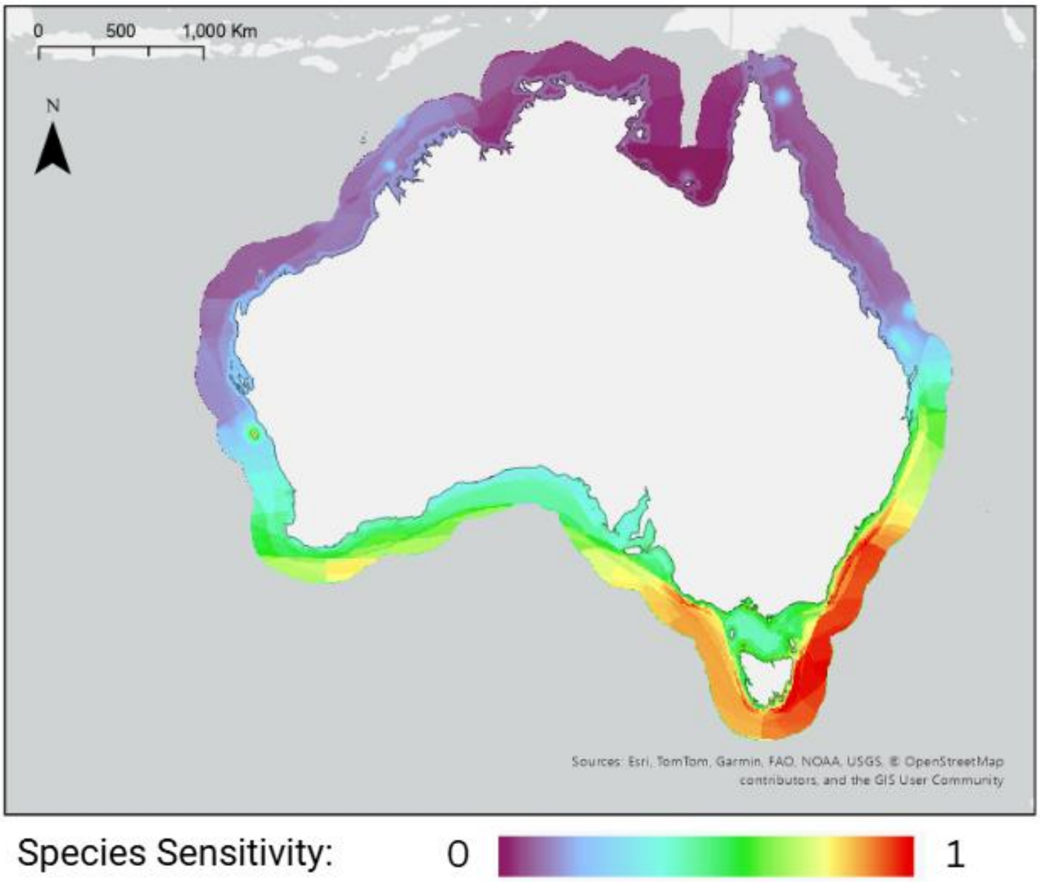

Figure 24: Map of the cumulative species sensitivity for Australia AVISTEP Offshore sensitivity mapping at a 5x5km resolution. Scaled between 0-1, this shows the overall gradation of sensitivity when breeding and year-round sensitivities are combined. When merged, the maximum value was taken from either layer in every overlapping cells

Mapping distribution for non-marine species– STEP 5

Migratory wader tracking data

Although less studied and conspicuous than migratory routes in other regions such as the American and African-Eurasian flyways (Chambers, 2008; Yong et al., 2021; Shi et al., 2022), understanding the movement of avian species in Australia is critical to understanding connectivity between critical stopover sites, breeding and feeding grounds. Australia is home to species possessing various movement strategies, from typical full annual cycle, seasonal migration, to partial migration and full nomadism with irregular paths and unpredictable timing (Chan, 2001; McGinness et al., 2024a, 2024b).

To map important areas for migratory terrestrial birds and waders, we used a combination of satellite tracking data and observations. First, we searched for published tracking data and could access datasets of sufficient quality for two migratory waders, the Bar-tailed Godwit (*Limosa lapponica*) and Far Eastern Curlew (*Numenius madagascariensis*).

To clean the data, we removed duplicate records, ran a McConnel speed filter with a speed of 100 kmh^{-1}, and removed individuals that did not have sufficient locations in the AOI. We interpolated to obtain locations at regular intervals because this is required for kernel density analysis, choosing interpolation intervals to minimise difference from the original dataset. We removed sections of tracks with very large time gaps between actual locations. We cropped the tracks to the AOI plus a buffer larger than the smoothing parameter. For each species, we then used kernel density estimation (KDE) in the *adehabitatHR* R package (Beal et al., 2021) to identify key stop over sites, which have very high density of time spent by tracked birds. We extracted the contours of the highest density of time spent by tracked birds as polygons to be included in the final map at the highest sensitivity as sensitive sites for terrestrial bird migration. We repeated this step until all stopover sites were accounted for. The remaining kernel density raster for each species then represented the migratory movements across the marine environment, indicating the relative density of time spent by tracked birds in each 5x5 km grid cell. We rescaled the rasters values to have a maximum value of 1 and combined the rasters for the two species together by taking the maximum values from each (Figure 25).

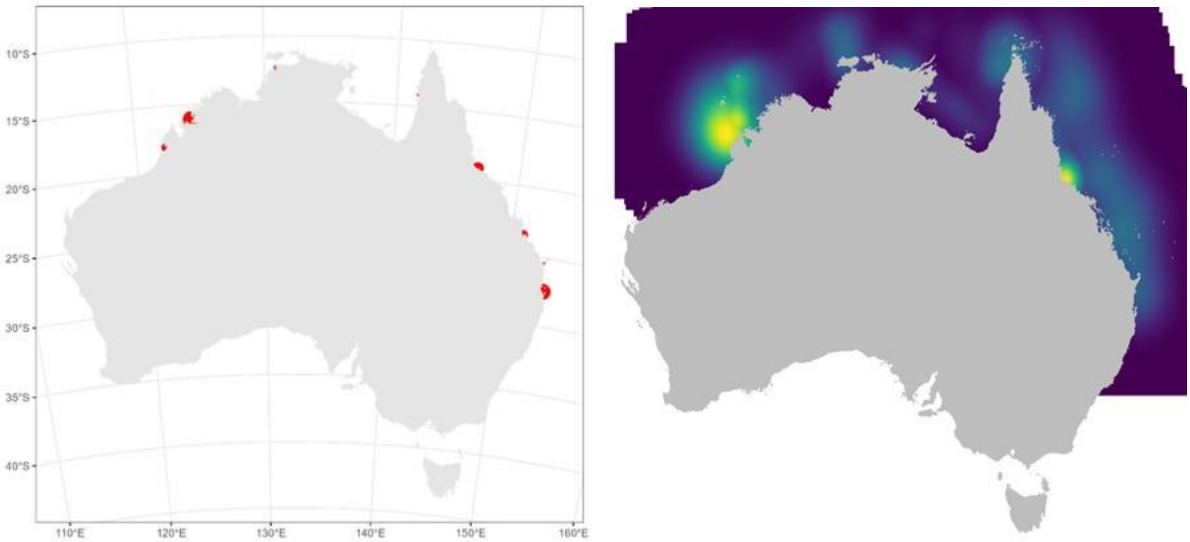

Figure 25. For tracked migrating waders, important wintering/stopovers sites in red (left) and migratory routes across marine areas with yellow indicating the highest importance (right).

Terrestrial bird migration observation data

To integrate terrestrial bird migration across open water, we adapted the population-level migration modelling framework developed by La Sorte et al. (2016), which used citizen science observations to infer large-scale avian migration routes across the Americas. Their approach demonstrated that occurrence data can reliably capture population-level movement dynamics while integrating individual variation in timing and routing. We applied and extended this framework to the Australian context, where bird movements are influenced by more variable and event-driven environmental conditions.

We identified three generalised movement categories among Australian birds, based on ecological literature (Hawkins et al., 2005; Corriveau et al., 2020; Becker et al., 2023) and discussions with experts, separated by movement predictability and spatial separation of seasonal distributions:

- Classic seasonal migrants. Species exhibiting consistent, directional seasonal movements between distinct breeding and non-breeding regions
- Partial or facultative migrants. Species with population-specific strategies showing both resident and migratory behaviours
- Nomadic and irregular movers. Species responding to episodic resource pulses (e.g. rainfall, fire, vegetation growth) with variable timing and directional

Data Acquisition and Preparation

We obtained bird observation data from the eBird Basic Dataset (Sullivan et al., 2009; eBird, 2025), a global citizen science database containing over 1 billion observations, and BirdLife Australia's Birdata platform (BirdLife Australia, 2025b). Records were filtered to complete checklists allow researchers to calculate reporting rates, as they distinguish true absences from simple non-reported species. This infers a presence-absence dataset, rather than presence only (Strimas-Mackey et al., 2023). We applied a multi-stage filtering protocol via the auk R package (Strimas-Mackey et al., 2025); retaining checklists with standardised survey protocols only and survey durations between 5 and 300 minutes, distance travelled 0–35 km, keeping only observations recorded between 2005 and July 2025. Data included observations across the East Asia Australasia Flyway (Bangladesh, Brunei, China, Japan, Cambodia, South Korea, North Korea, Laos, Mongolia, Myanmar, Nepal, Philippines, Russia, Singapore, Thailand, Taiwan, Timor-Leste and Vietnam).

Spatial Framework

We established a hexagonal grid framework using the discrete global grid system (DGGS) approach (Sahr, 2011), as these provide superior spatial properties (less distortion across longitude and latitude) and reduced edge effects in spatial analyses. Grid resolutions were determined to reflect species-specific migration type. For typical migrants, we generated grids at 15,000 km^2, whereas nomadic species required smaller grid cells (5,000 km^2). Each eBird checklist was assigned to its corresponding hexagonal cell.

Temporal Framework

The study period was partitioned into fixed 14-day windows. Each observation was assigned to its corresponding temporal window, which were classified by Austral season definitions (summer = December to February, autumn = March to May, winter = June to August, spring = September to November). However, for trans-equatorial migrants that breed in boreal regions, we aligned the seasons with Northern Hemisphere breeding phenology.

Grid-Time Combination Matrix

A fundamental space-time analytical unit was created by cross-multiplying spatial grids with temporal windows, producing combinations of hexagon cells and time periods. This grid-time matrix forms the basis for all subsequent node detection analyses, with each space-time unit representing a specific geographic area during a specific time period.

Effort Correction

Raw detection rates are confounded by spatial and temporal variation in observer effort, with longer checklists and larger observer parties increasing detection probability independent of true species abundance (Kéry & Royle, 2015). To obtain reporting rates that reflect species occurrence patterns, we implemented effort correction at: checklist level, accounting for the impact of effort duration and number of observers; and cell-level, calculating a simple and effort-weighted reporting rate:

$$reporting\ rate_w = \frac{\sum(detection_i\ *\ effort\ weight_i)}{\sum(effort\ weight_i)}$$

The weighted reporting rate increases the weighting for high-effort checklists over low-effort, providing a more robust estimate of true detection probability.

Node Detection

To account for spatial heterogeneity in eBird sampling intensity, we implemented density-adaptive bandwidth for Gaussian kernel spatial smoothing (Worton, 1989; Lilleyman et al., 2024). This method varies the smoothing extent inversely with local data density, applying tighter smoothing in well-sampled areas and “borrowing” more information from neighbours in sparsely sampled regions. This adaptive approach is more appropriate than fixed-bandwidth methods for citizen science data, due to the larger variation in spatial sampling effort. For each cell, we calculated observation density by averaging total observations (all checklists, including non-detections) across the temporal windows, to ensure stable density estimates. The overall mean density across all cells was calculated with observations greater than zero to serve as the reference point for adaptive scaling. For each cell, *i*, bandwidth was calculated as:

$$bandwidth_i = base\ bandwidth \times \sqrt{\left(\frac{global\ mean\ density}{local\ density_i}\right)}$$

Where base bandwidth is a tier-specific parameter (Classic migrants: 20 km; Partial migrants: 10 km; Nomadic: 10 km) chosen to align with grid cell sizes and species movement scales. This formula produces narrower bandwidths in high-density areas where local density exceeds the global mean, and wider bandwidths in low-density areas where local density falls below the global mean.

We applied minimum and maximum bandwidth constraints to prevent biologically unrealistic smoothing scales. For most species, the minimum bandwidth was set to 5 km to prevent over-fitting to single-cell sampling noise, and the maximum to 50 km to maintain meaningful spatial structure. For pelagic or highly mobile species, we adjusted these limits to 20 km minimum and 150 km maximum to reflect their larger movement scales. For cells with no observations, typically occurring at range edges or in poorly sampled regions, we assigned the maximum bandwidth value under the conservative assumption that uncertainty is highest where data are absent.

Distance Weights

To enable computationally efficient spatial smoothing across temporal windows, we precomputed a weight matrix describing the spatial relationships among all hexagon cells. We calculated great-circle distances between all pairs of hexagon centroids using the Haversine formula implemented in the *geosphere* R package. For each cell pair, we calculated Gaussian kernel weights based on the adaptive bandwidth for the source cell. The weight function assigned maximum weight to a cell itself (weight = 1 when distance = 0) and exponentially decreasing weight to more distant cells according to the standard Gaussian kernel formula. Because Gaussian weights become negligible beyond approximately three standard deviations, we applied a weight threshold of 0.01 below which weights were set to zero, and enforced a maximum distance cut-off of three times the maximum bandwidth. Each row of the weight matrix was normalised to sum to 1 to ensure proper averaging behaviour during smoothing, dividing each weight by the row sum. For isolated cells with no neighbours within the maximum distance threshold, we set the diagonal weight to 1, meaning these cells retained their original reporting rate without spatial smoothing.

Spatial Smoothing

We applied spatial smoothing independently to each temporal window to preserve temporal patterns while reducing spatial noise. For each temporal window, we created a vector of reporting rates for all cells and applied matrix multiplication with the precomputed weight matrix. This operation computed the weighted average of reporting rates across neighbouring cells for each target cell, with weights determined by the adaptive bandwidth structure described above.

Statistical Threshold-Based Node identification

High-use nodes were identified by applying statistical percentile thresholds to smoothed reporting rate distributions, combined with temporal stability analysis and bootstrap uncertainty quantification. The threshold was calculated as the 95th percentile of smoothed reporting rates across all grid-time combinations, identifying the top 5% highest use space-time units (cells). This percentile-based approach provides a conservative, statistically defensible, and species comparable definition of high-use areas. Prior to threshold application, we filtered grid-time combinations to retain only those meeting minimum data quality standards. We required at least five checklists per grid-time combination by default, adjustable to three for rare species or ten for common species, and at least one species detection. Each grid-time combination was then classified as a high-use node if its smoothed reporting rate equalled or exceeded the calculated threshold.

To distinguish consistently important areas from transient hotspots or sampling artefacts, we calculated temporal stability metrics for each spatial location across years. For each hexagon cell, we calculated detection frequency as the proportion of years in which the location was identified as a node, and the stability coefficient as the coefficient of variation of annual mean reporting rates. We classified locations as stable if they were detected in at least half of available years and in at least two distinct years. We also calculated seasonal consistency as the number of distinct seasons (out of four Austral seasons) in which the location was identified as a node.

We quantified node identification uncertainty through bootstrap resampling with 500 iterations by default. For each iteration, we resampled checklists within each grid-time combination with replacement using 80% of the original sample size, recalculated smoothed reporting rates and thresholds on the resampled data, identified nodes using the same threshold approach, and recorded whether each original node was detected in the bootstrap iteration. For each original node, we calculated the bootstrap detection rate as the proportion of iterations in which the node was identified, and assigned bootstrap confidence classifications of high (detection rate ≥80%), medium (50-80%), low (20-50%), or unreliable (<20%). Unreliable nodes were excluded from final conservation recommendations.

We combined temporal stability and bootstrap confidence into a composite reliability score calculated as the average of the stability score and bootstrap detection rate, each weighted equally. Nodes were classified as high reliability if the composite score was 0.8 or greater, medium reliability if between 0.5 and 0.8, low reliability if between 0.2 and 0.5, and unreliable if below 0.2. Only nodes classified as high or medium reliability were retained for subsequent movement corridor inference analyses. The values of reliability are low to ensure that sufficient data was included in the model.

Node Characterisation

For each spatial location, we identified the months during which the location was classified as a node and mapped these months to Austral seasons (e.g. Figure 26 and Figure 27). Locations were classified by their temporal patterns of use, such as spring and autumn, suggesting migration corridors, three-season or year-round suggesting extended residence or multiple functional roles. Tier specific seasonal cycle definitions were applied where appropriate, such as boreal seasons for trans-equatorial migrants.

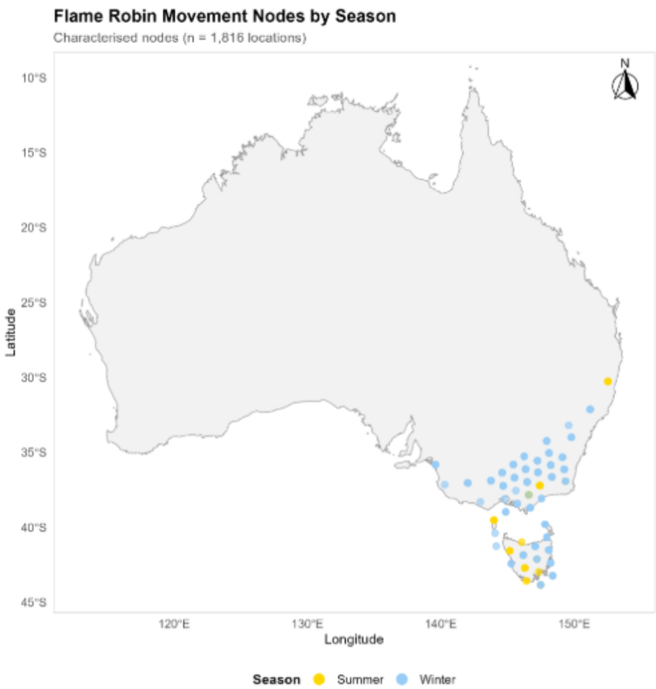

Figure 26. Example of high use nodes, calculated for Flame Robin, showing recorded observations for summer breeding and wintering.

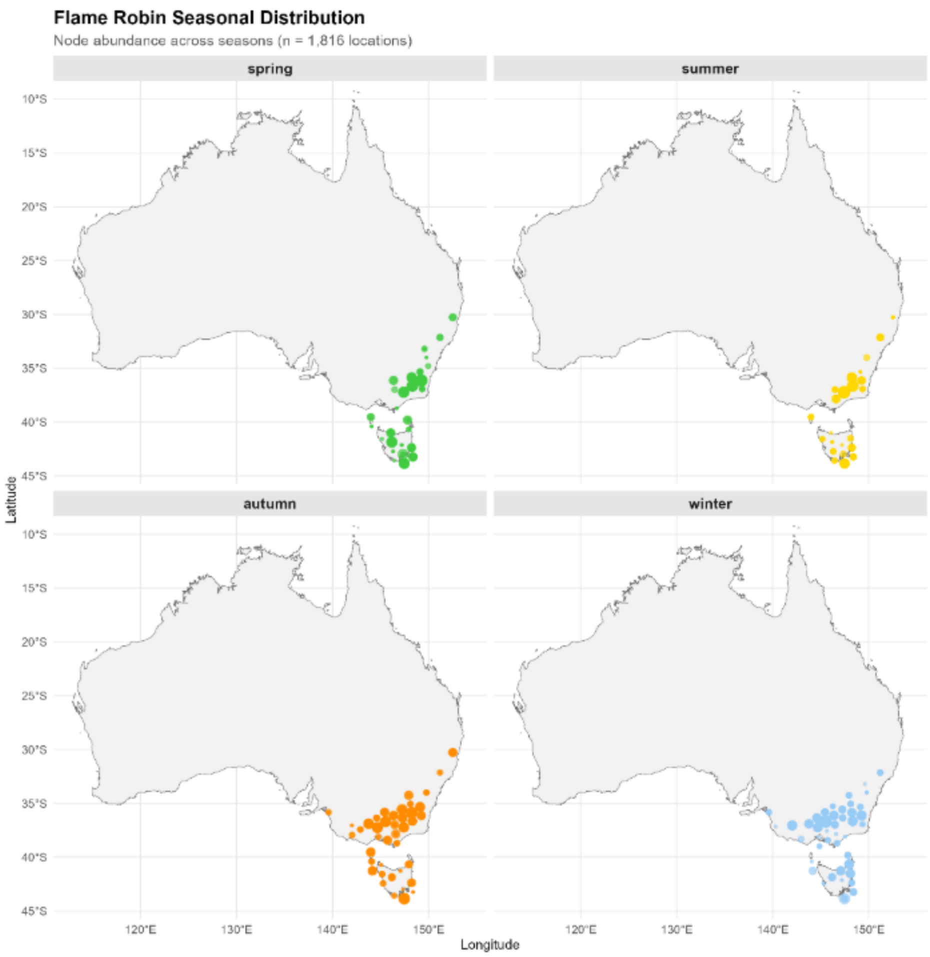

Figure 27. High use node distributions for Flame robin across seasons. Size of points represent total abundance relative to time window t.

Identifying Potential Flight Paths/Areas

To estimate potential movement corridors between key high-use areas identified from eBird data, we generated potential paths between nodes representing robust, regularly used sites. There were not sufficient observations for the Orange-bellied Parrot (*Neophema chrysogaster*) to allow nodes to be identified, but their range is restricted to seven small patches for the non-breeding season and a single small patch for the breeding season, so we used the centroids of range polygons in place of nodes.

To identify least-cost paths, we create a grid and assigned resistance values of 10 for terrestrial areas and 1 for open water to represent relative preference of movement across each habitat. We also created rasters of the direction to and distance from each point using the *Distance Accumulation* tool in ArcGIS Pro (ESRI, 2025). Least-cost paths were then calculated using the *Optimal Path As Line* tool in ArcGIS Pro between each pair of nodes from one month or season to the next (e.g. Figure 28). As the Orange-bellied Parrot, Swift Parrot (*Lathamus discolor*) and Flame Robin (*Petroica phoenicea*) do not use coastal habitats, we then cropped the cost paths to within 15km of the coast.

To represent the spatial density of potential flight activity between these nodes, we applied the *Line Density* tool in ArcGIS Pro to the least-cost paths. The tool calculates a kernel density surface where each cell's value is proportional to the sum of path lengths within a specified search radius, weighted by distance from the path line. We used a 150km search radius for species crossing Bass Strait (Orange-bellied Parrot, Swift Parrot and Flame Robin), and a 200km search radius for the Whimbrel (*Numenius phaeopus*) because the scale of movement was larger. This produced a smoothed, gridded surface representing relative corridor use likelihood (e.g. Figure 28). The resulting raster for each species was normalised and an all-species raster was created by combining by the maximum value for each grid cell.

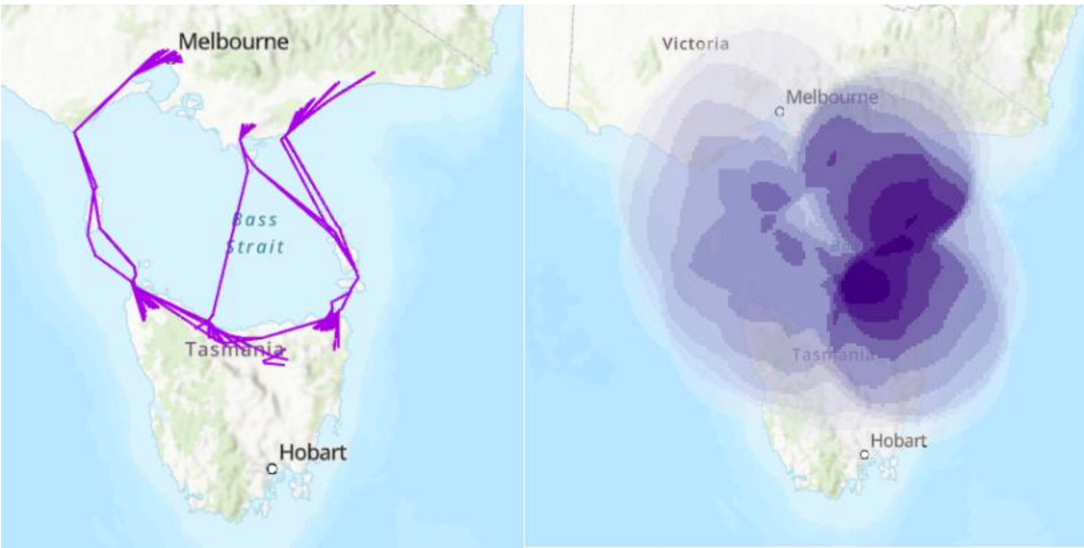

Figure 28. Example for the Flame Robin of all least cost lines cropped to Bass Straight plus a 15km terrestrial buffer (left), and the results of the line density tool (right).

The layer created from the least cost-path line densities was then combined with the maximum values from the raster created from the tracking data. We used Jenks natural breaks with 8 categories to produce a final migration layer for combination with other inputs (Figure 29).

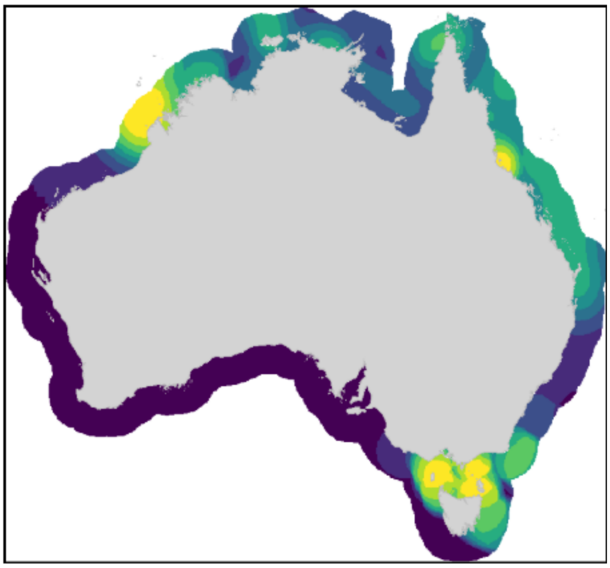

Figure 29. Importance of marine areas for non-marine migrating birds produced from a combination of tracking data and modelling from observations, with yellow indicating the most important areas.

Categorising Sensitivity– STEP 6

Once the cumulative seabird species sensitivity result layer was produced, the migratory bird map was applied to create the preliminary species sensitivity results (for more details see Step 7). Next, we categorised the results into four categories of low-high sensitivity. This was a classed raster with all cells values from 1 to 4 (green to red). This was done using Jenks natural breaks in the *ClassInt* R package (Bivand, 2024). Due to the large area contained within the offshore AOI of this project, 2 additional subcategories were input into the existing four categories using Jenks natural breaks again. As shown in Figure 30, this created eight overall categories from green to red (very low risk, low risk, low to moderate risk, moderate risk, high risk, high to very high risk, very high risk and extremely high risk).

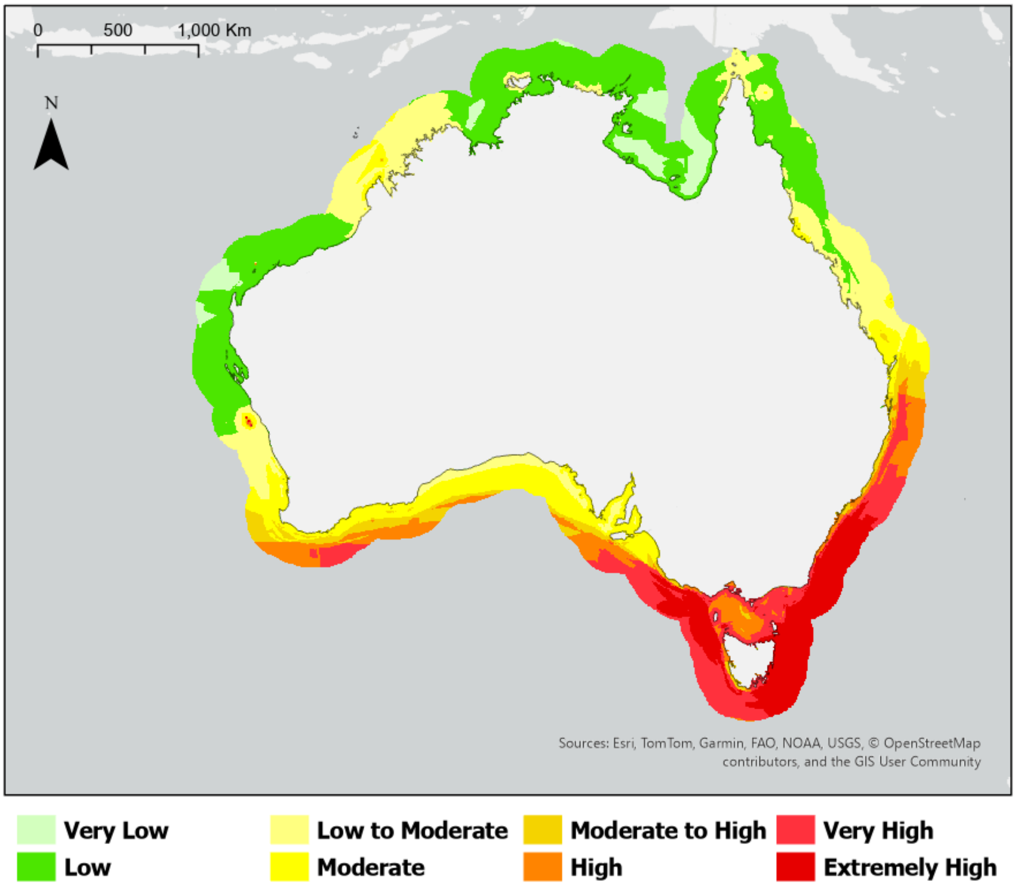

Figure 30. Areas of low to high sensitivity to offshore wind development in Australia categorised into 8 categories by Jenks natural breaks after bird migration weighting is applied to the cumulative species sensitivity layer

Adding Other Important Areas for Birds and Conservation– STEP 7

As with onshore, areas that were determined to be key concern for bird conservation were included in our analysis for offshore wind. Shapefiles of selected areas were overlapped with the project fishnet and overlapping cells were rasterised to match the 5x5km project grid. These areas were split into two types, 1) highly weighted important bird or conservation and 2) important bird or conservation areas added at the highest sensitivity.

Highly Weighted Areas

These are areas that are weighted against the existing underlying values before or after Jenks natural breaks are calculated. For Australia, a land bird migration layer was applied to the preliminary species sensitivity results before Jenks natural breaks was applied. On the other hand, a select number of Marine Protected Areas (MPAs) were applied after the sensitivity classes had been estimated with Jenks natural breaks.

Bird Migration

Using the values from the migratory bird layer, an additional weighting of up to 25% was applied directly the primary species sensitivity layer. Therefore, the resulting score for a cell overlapping with a selected site was dependent upon the underlying sensitivity of the species output for that cell. This step was made before the sensitivity categories were estimated.

Marine Protected Areas

Australia has designated 45.4% of its waters as Marine Protected Areas (MPAs) (WDPA, 2025), a large proportion of which is contained within our area of analysis. Given the large area and that protected areas are not solely designated for birds, it was not appropriate to automatically assign all cells overlapping with the MPA network as the highest level of sensitivity. To determine the best approach, the level of protection and habitat or species designation was investigated as part of our analysis. It was determined that MPAs would be weighted according to their IUCN categories. Any MPAs that were Ia, Ib, or II sites were selected.

Fo Australia, areas which overlapped with relevant MPAs were given a higher weighting rather than automatically being set as highest sensitivity. An additional weighting of 5% was applied after sensitivity was categorised using Jenks natural breaks. Therefore, the resulting score for a cell overlapping with a selected site was dependent upon the underlying sensitivity of the species output for that cell. This step was made before the sensitivity categories were estimated.

We used the World Database of Protected Areas (WDPA) from the Protected Planet website (www.protectedplanet.net). This database is updated regularly by governments and curated by UNEP-WCMC and includes the most up-to-date information on protected areas. The latest version from 2022 was used for the remaining countries. All protected areas classified as coastal or marine were included.

Additive Areas

These are areas that have been rasterised at the highest sensitivity (value of 1). They were combined to form a single additive layer which was then added on top of the total classed sensitivity layer to produce the finalised map. The addition of these sites did not influence the relative sensitivity of the surrounding cells.

For Australia, the sites considered were seabird breeding sites, important areas of conservation, seascape features and oceanic habitats. Important marine oceanic habitats and seascapes were included due to their importance for seabirds and marine ecosystems in general. The important conservation areas included were and Key Biodiversity Areas and Ramsar sites.

Breeding Colony Buffers: We included a 5km buffer around all breeding seabird colonies at the maximum sensitivity, regardless of species or colony size. This is to account for foraging for some species, and other behaviours that occur close to the colony for other species, such as preening (e.g. gulls), rafting (e.g. shearwaters) and kleptoparasitism (e.g. frigatebirds).

Key Biodiversity Areas (KBAs): KBAs are a global dataset of areas of greatest significance for the conservation of the world's birds. They cover about 6.7% of terrestrial area, 1.6% of marine area and 3.1% of the total surface area of the Earth (Donald et al., 2019). This dataset is curated by BirdLife International and available through their website (datazone.birdlife.org/site). Our analysis included the most up-to-date version of this data from 2025 (Birdlife International, 2025). We included all KBAs catalogued as marine by BirdLife International plus those listed as coastal KBAs. In total 166 sites overlap with our offshore AOI. These areas were all rasterised on a 5x5km grid and were given the highest sensitivity value.

Ramsar Sites: Ramsar areas are wetlands of international importance designated under the Ramsar Convention (1971). These areas should be safeguarded for various biodiversity reasons, but mainly because they represent safe breeding and feeding grounds for birds and stopovers during migrations. We considered Ramsar areas according to the Department of Climate Change, Energy, the Environment and Water (DCCEE, 2025).

Ocean habitats: The analysis contains information on the distribution of marine habitats that are of special importance for marine organisms and ecosystems. Overlapping cells with any of these habitats were given the maximum sensitivity value.

Mangroves, coral reefs, submarine canyons and seagrass habitats were included in this analysis. Habitats such as coral reefs, mangroves and seagrasses are known to benefit seabirds during key periods of their annual life cycle (Unsworth & Butterworth, 2021; Benkwitt et al., 2023; Berr et al., 2023; Appoo et al., 2024). Seabird presence at these sites has been shown to act as a beneficial connector of nutrients between terrestrial and marine ecosystems (Unsworth & Butterworth, 2021; Jones et al., 2025). Meanwhile submarine canyons and seamounts were included as important potential marine hotspots (De Leo et al., 2010; Morato et al., 2010; Huang et al. 2014).

- **Mangroves.** This dataset was created mostly from satellite imagery and shows the global distribution of mangroves. It was produced as a joint initiative of several international organizations (Spalding et al., 2010).
- **Coral reefs.** This dataset shows the global distribution of coral reefs in tropical and subtropical regions. It is the most comprehensive global dataset of warm-water coral reefs to date (UNEP-WCMC et al., 2021).
- **Seagrasses.** This global dataset of seagrass distribution was created from multiple sources (in 128 countries and territories), including maps (of varying scales), expert interpolation and point-based samples (UNEP-WCMC & FT Short, 2021).
- **Submarine canyons.** This is a dataset of Australian canyons manually digitised using a variety of bathymetry datasets (Huang et al., 2014)
- **Seamounts.** This is a dataset of seamounts of biological importance included in the 'Marine Key Ecological Features' dataset produced by the DCCEEW in Australia (2013).

This information is curated by UNEP-WCMC and available through the Ocean Data Viewer on their website (https://data.unep-wcmc.org/).

Applying Additional Sites

All additional site layers were rasterised to a 5x5 km grid and assigned a value of 1. These layers were then combined by taking the maximum value from each cell, producing a single high-sensitivity layer with binary values (1 or 0). This layer was subsequently overlaid with the MPA-weighted output, using the maximum value from each layer to generate the final sensitivity output. This process did not alter the relative sensitivity of surrounding cells and had no effect on the Jenks natural breaks classification.

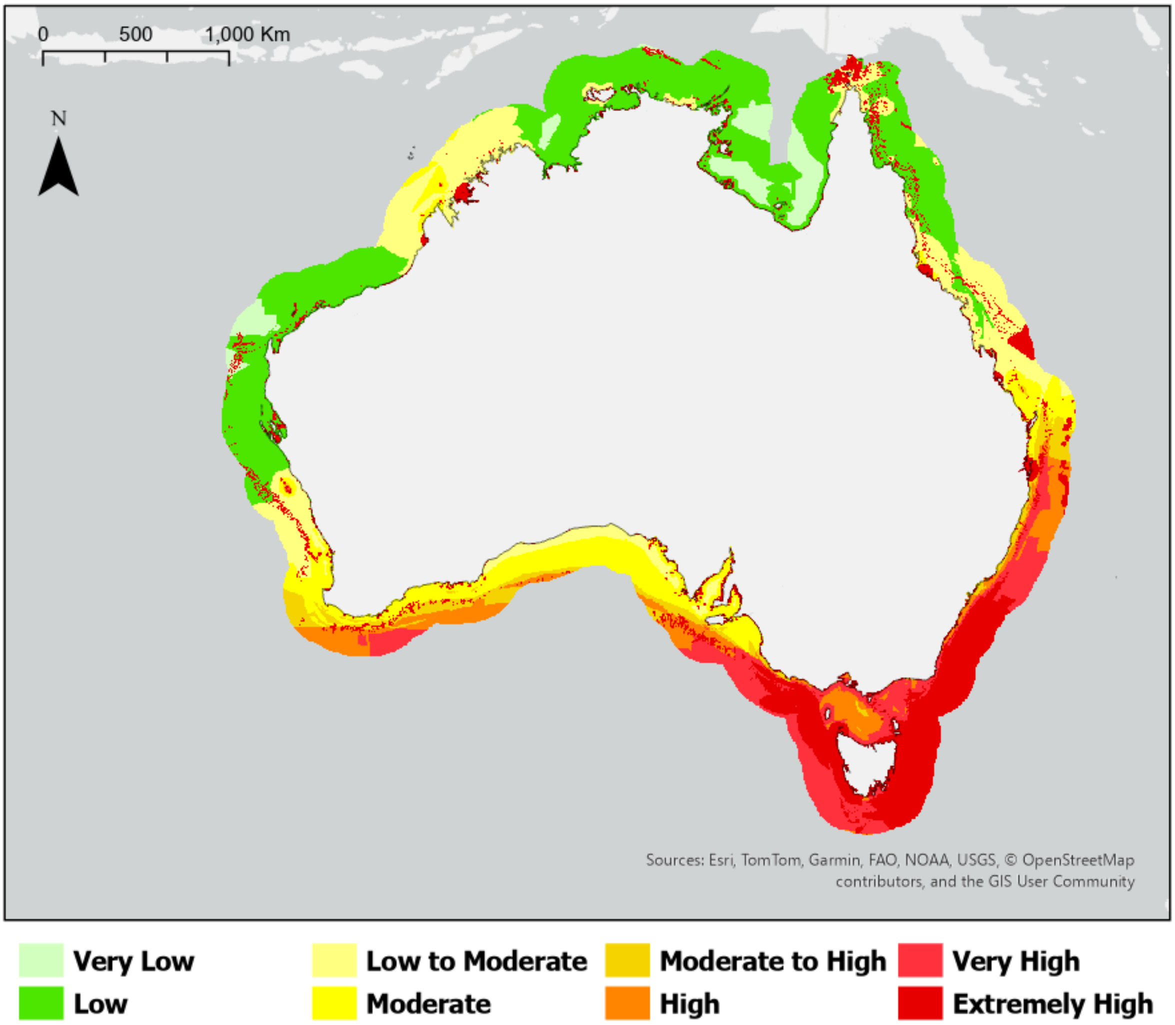

Figure 31. The final sensitivity categories for Australia AVISTEP Offshore sensitivity mapping at a 5x5km resolution after the application of weighted MPAs and the addition of highly sensitive areas to the preliminary sensitivity categories.

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