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A modeling framework for biodiversity assessment in renewable energy development: A case study on European bats and wind turbines

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ABSTRACT

Combining renewable energy planning and biodiversity conservation is urgently needed to address the interconnected climate change and biodiversity loss crisis and meet the United Nation's Sustainable Development Goals 7,13, and 15. However, in many countries such as France, current strategies to limit the negative effects of renewable energy on biodiversity still hold major limitations during the planning process that could be overcome with modeling approaches. Here we propose a new modeling-based framework which aims to determine potential threats posed by projects to biodiversity. By capitalizing on large-scale standardized citizen science biodiversity data to create biodiversity benchmarks, this approach aims to better inform the Ecological Impact Assessment (EIA) process at different stages pre- and post-project construction. We demonstrate the practical application of the framework using bats and onshore wind energy development in France as a case study. We reveal that current approaches in renewable energy planning in France failed to identify sites of biodiversity significance with >90 % of wind turbines approved for construction to be placed in sites of high significance for bats. The risks posed by future wind turbines to bats concern all taxa (all protected in the EU), including species with higher collision risks. We highlight how the proposed modeling-based framework could contribute to a more objective evaluation of pre- and post-construction impacts on biodiversity and become a prevalent component of the EIA process. Its implementation could promote a more biodiversity-friendly approach to renewable energy planning, aligning with the Global Biodiversity Framework's target of halting biodiversity loss by 2030.

1. Introduction

It is now well recognized that climate change and biodiversity loss are fundamentally intertwined and that both crises should be addressed collectively [1–3]. Climate change mitigation measures in the energy sector such as the development of renewable energy sources may negatively impact biodiversity [4–6]. The urgent need of moving away from fossil fuel to carbon-free energy production for reducing global CO_2 emission therefore sometimes conflicts with the overreaching global goal of halting and reversing biodiversity loss [7]. This has been referred to as the "green-green dilemma" [6] and is well illustrated by the challenges posed to bats by wind turbine [8]. The negative impacts of onshore wind turbines on bats are well documented and include both fatalities for individuals attracted to the turbines [9] and losses of habitat use for those avoiding them [10,11]. A promising approach to solve this dilemma is to carefully plan the implementation of renewable energy facilities as well as mitigation measures for potential impacts on local biodiversity [12]. For instance, mitigation strategies such as curtailment of turbine operation [13] have proved to be effective in reducing bat fatalities at wind turbines in North America [14]. In many countries worldwide (e.g. EU countries, USA, Canada, Australia, Brazil, etc.) renewable energy projects such as wind turbine installations fall within the mitigation hierarchy. This is a decision-making framework for mitigating ecological impacts by sequentially avoiding, reducing, and, as a last resort, offsetting potential impacts, with the aim of

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Abbreviations

BFC	Bourgogne-Franche-Comté region
BPL:	Bretagne & Pays de la Loire regions
EIA	Ecological Impact Assessment
EU	European Union
NRMSE	Normalized Root Mean Square Error
RF	Random Forest
SDG	Sustainable Development Goal

achieving no net loss of biodiversity [15,16]. By identifying and evaluating the potential impacts of a project on biodiversity and proposing ways to avoid, mitigate or offset these impacts, the ecological impact assessment (EIA) represents a cornerstone of the mitigation hierarchy [17].

In the European Union, the Directive 2011/92/EU outlines the process of EIA which ensures that projects that are likely to have significant impacts on biodiversity are assessed prior to their authorization. In brief, following the screening and scoping stages this typically includes (i) a pre-selection of potential sites based on spatialization and mapping of the impacts, (ii) field-based ecological surveys of protected species and habitats (Habitats Directive 92/43/EEC and Birds Directive 79/409/EEC) on the pre-selected sites to document the EIA, and (iii) an impact analysis in which potential impacts and their strength are identified and quantified and mitigation measures are proposed. In some cases, such as in wind turbine project development, the EIA process extends beyond construction to include post-construction impact assessments, which evaluate the accuracy of predicted impacts and the effectiveness of the mitigation measures implemented. However, while the EIA process is regulatory, it holds major limitations that can lead to serious errors during decision-making processes [18]. For instance, the identification of potential sites using spatialization and mapping tools most often rely on incomplete (e.g. data collected with inadequate sampling effort) and biased biodiversity data (including taxonomic, temporal and spatial biases). While regulatory field-based ecological surveys allow to ground-check this first assessment, their implementations are far from being optimal [18]. These surveys are constrained by financial resources which limit the sampling effort allocated [19,20]. Furthermore, the evaluation of a site's biodiversity significance can be hindered by the limitations of external references, which frequently depend on heterogeneous and non-standardized data. Overall, the whole EIA process crucially suffers through its different stages from the lack of standardization for biodiversity data interpretation and contextualization, resulting in subjective evaluation of pre- and post-construction impacts [21,22].

One potential solution to overcome these last issues that are currently inherent to EIA is to create biodiversity benchmarks [22] that can be defined at different spatial (from local to national and international levels) and temporal (dynamic over time) scales. To achieve this, large-scale ecological models of how species distributions and abundances vary over space and time (i.e. abundance-based species distribution models) could represent an effective tool. Species distribution models are well-established in the scientific literature [23,24] and have already proved to be of great asset for assessing the effectiveness of the EIA procedure [25,26] and guiding conservation planning [27–30]. Nevertheless, building reliable biodiversity benchmarks using species distribution models requires a large amount of biodiversity data collected in a standardized way through space and time. Although there are extensive databases available containing big biodiversity data (e.g. Global Biodiversity Information Facility database), a considerable amount of the data in these databases is obtained opportunistically with unknown collection processes, and is subject to observer's bias, producing biases such as over-sampling of flagship species, favorable areas or habitats [31,32]. These biases are difficult to correct or involve complex analysis [33,34], and together with the lack of sampling effort quantification make the data unsuitable for the intended purpose. In contrast, standardized biodiversity monitoring schemes – especially those that are intended to detect large-scale spatiotemporal trends of abundance and distribution – could be an important source of high-quality data on species abundance. These schemes have been developed in many countries worldwide and for many taxa, including insects (e.g. van Swaay et al. [35]), birds (e.g.Gregory et al. [36]) and mammals (e.g. Van der Meij et al. [37]). They have the advantage of being based on standardized protocols with a fixed sampling effort and allows for comparison among sites without relying on assumptions about observer site or species preferences or adjusting for varying sampling efforts [38]. Depending on their goals, these monitoring schemes aim to represent the current national distribution of habitats and biogeographic context. While financial and logistic constraints may sometimes limit their coverage, biodiversity monitoring schemes that are based on citizen science and adhering to standardized protocols have the potential to provide extensive, standardized biodiversity data [39,40].

While biodiversity benchmarks derived from modeling approaches hold significant potential to address many limitations in the EIA, there is currently no modeling framework that demonstrates their practical application or evaluates their effectiveness using empirical data. Such modeling framework is crucially needed to guide stakeholders navigating the green-green dilemma – especially with bats and wind turbines – and minimizing conflicts between Sustainable Development Goals set by the United Nations in 2015, namely SDG 7: 'affordable and clean energy' and SDG 13: 'climate action' with SDG 15: 'life on land' [41]. Here, the aim of the study was to demonstrate how biodiversity benchmarks derived from large-scale standardized citizen science biodiversity monitoring programs could be used to inform decision-making processes at various stages of the mitigation hierarchy process. We developed an applied modeling-based framework to (i) determine prior to field-based ecological surveys whether projects proposed for development are in areas of biodiversity conservation significance and (ii) evaluate post construction whether the project complies with the mitigation hierarchy framework. The modeling framework is illustrated in Fig. 1 and includes five main steps: (i) identifying large-scale citizen-science programs and determining relevant predictors (e.g. environmental and bioclimatic variables) known to shape the spatial distribution of the target species potentially occurring in the study area; (ii) modeling species abundance using biodiversity data from large-scale citizen science programs in relation to previously identified relevant predictors; (iii) predicting species abundance at random points to build a standardized benchmark of species abundance; (iv) predicting species abundance at the proposed/built sites and comparing the prediction to the standardized benchmark of species abundance to evaluate potential risks posed by the proposed/built projects; (v) identifying sites of potential biodiversity significance threatened by the proposed/built projects.

We developed and tested the modeling framework using bats and onshore wind energy development in France as a case study. France represents an ideal case study as (i) it is one of the largest wind energy contributors in the EU and experiencing a rapid acceleration in wind turbine installations, and (ii) it holds the largest national-scale standardized citizen-science bat monitoring program in Europe. According to the mitigation hierarchy established in the Article 6 of the EU Habitats Directive 92/43/EEC, we predicted that wind turbines approved by local environmental planning authorities for construction (i.e. projects that have undergone an EIA) would be localized in areas of low bat activity levels for all taxa and especially for taxa with higher collision risks. Building on more than two decades of research into the impacts of wind turbines on bats and strategies to mitigate them, we provide through this case study a concrete illustration on how the modeling framework can be applied in EIA to inform the decision-making process. This

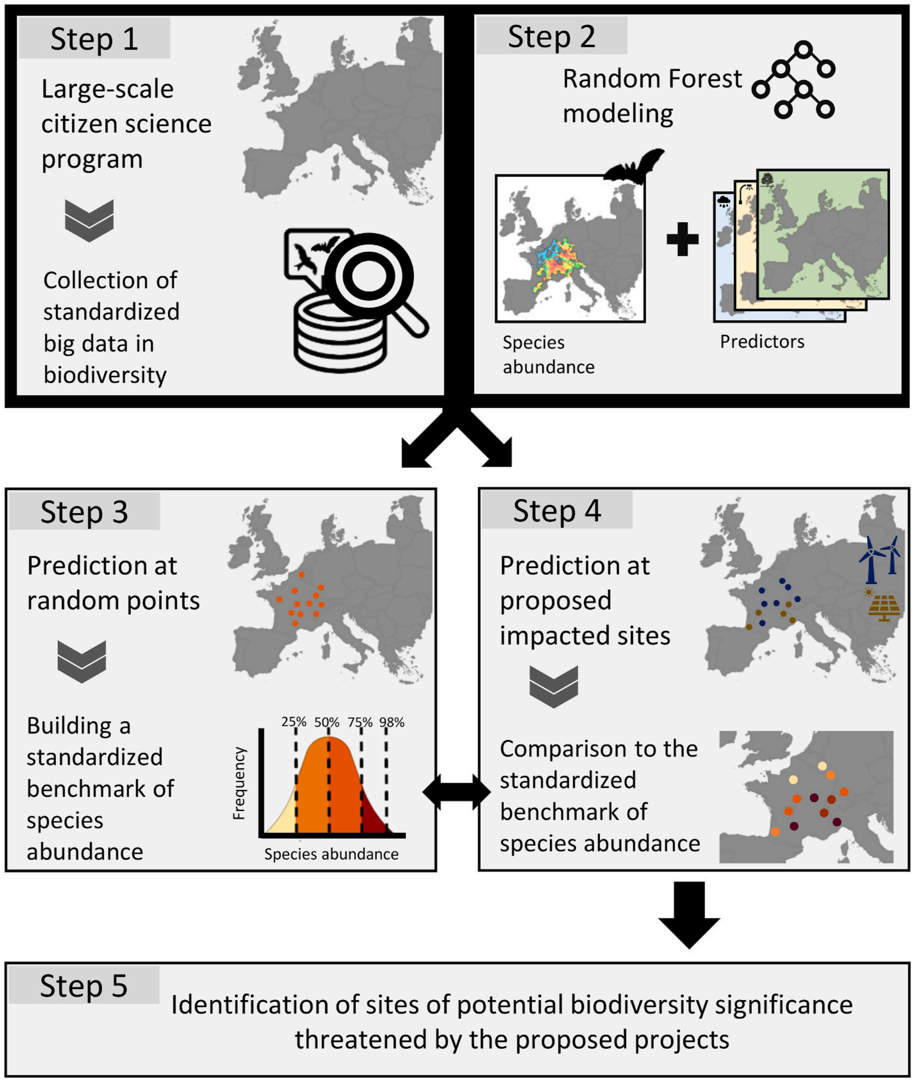

Fig. 1. Conceptual modeling-based framework proposed to be implemented within the ecological impact assessment process.

framework is of relevance globally and could be applied to other taxa (e.g. birds), other types of renewable energy infrastructures (e.g. solar farms), and other countries.

2. Material and methods

2.1. Study areas

The case study focused on two areas in France with contrasting past and current wind farms development, namely the region Bourgogne-Franche-Comté (BFC, eastern France, 47°12′ N, 4°57′ E, 47,783 km^2, altitude: 52 to 1495 m a.s.l.) and the regions Bretagne and Pays de la Loire (BPL, western France, 48°12' N, 2°55 W, 59,290 km^2, altitude: 0–416 m a.s.l.). The BFC region is mainly covered by forests (36 %) and grassland (32 %) while two-thirds of the BPL area consist of agricultural lands – with 36 % of arable lands and 31 % of grassland. By mid-2020, a total of 388 and 1105 wind turbines were operational in BFC and BPL, respectively, and 233 and 766 were approved by local environmental planning authorities for construction in BFC and BPL, respectively.

2.2. Modeling framework for assessing potential ecological impact: case study with bats and wind turbines

2.2.1. Step 1a: using large-scale database and evaluation of their representativeness

We used data from the French national-scale citizen-science bat monitoring program "Vigie-Chiro" [42]. We retrieved bat activity data from surveys conducted between 2015 and 2020 following the stationary points protocol (see Refs. [43–45] for more details). In brief, trained volunteers acoustically sampled bats during at least one full night (from 30 min before sunset to 30 min after sunrise) when weather conditions were optimal for bats to forage. Volunteers surveyed either specific sites or randomly selected ones within a systematic 2-km square grid. Although volunteers could select their recording devices for bat sampling, trigger settings were standardized among recorders to minimize heterogeneity in detectability. Species identification was conducted using Tadarida software [46]. Tadarida automatically detects and extracts sound parameters of recorded echolocation calls within a 5-sec file (i.e. a bat pass) and classifies them into bat taxa with an associated confidence index. We followed the method proposed by Barré et al. [47] to account for potential automated identification errors, i.e. we used the confidence index to retain two separate datasets: (i) one dataset of bat passes with maximum error risk tolerance of 10 %; and (ii) another dataset of bat passes with maximum error risk tolerance of 50 %. The first threshold is cautious, aiming to minimize false positives, while the second one is less conservative, allowing for a larger amount of data to be retained. Bat activity per night corresponded to the sum of bat passes recorded.

We restricted our selection to sites (i) sampled between May and October (i.e. period of highest bat activity), (ii) with microphones placed at <5 m height, (iii) located away (>200 m) from known roosts, and (iv) at lower altitude (<800 m a.s.l.) to avoid excessive heterogeneity due to mountainous environmental characteristics. In total, 711 sites corresponding to 1186 detector-nights and 643 sites corresponding to 880 detector-nights were retained in BPL and BFC, respectively [48]. Although the sites sampled are nationally representative [44], they were chosen through a participatory process, which may result in spatial distribution heterogeneities at the local or regional level. A preliminary step was to evaluate the potential impact of this heterogeneity on representativeness and to develop appropriate strategies to address any spatial structure issues. Regarding the representativeness, the amount of major land-cover classes around the sampling sites was representative of the two study areas, except for BFC where deciduous forests were slightly over-sampled [48]. Similarly, gradients of environmental variables and anthropogenic pressures around the sampling sites matched the gradients observed within the two study areas. Furthermore, there was no confounding effect between the habitat type surveyed and the detector type used [48]. Because sampling sites (especially in BPL) were clustered, we developed in step 2 (see section 2.2.3) models using the full dataset and models using a subset of the dataset containing only sites that were located >500 m away from each other to account for potential spatial structure issues. We conducted the analysis on 12 bat species or species groups (due to current challenges in species identification using acoustic monitoring) recorded in the two study areas. A summary of the bat data used in the modeling is reported in Table 1.

2.2.2. Step 1b: determining relevant predictors

We collected 40 predictor variables that are relevant for predicting bat activity in human-modified landscapes [49–52]. These variables were contiguously available at high resolution for the two study areas and include (i) two topographic predictors (altitude and slope), (ii) eight environmental and land-uses variables (the proportion and Euclidean distance to deciduous forests and linear small woody features, the density of rivers and distance to the nearest freshwater body, the edge density and Shannon's diversity index of major land-cover classes), (iii) 11 predictors related to anthropogenic stressors (artificial night-time light brightness, amount and distance to urban areas and croplands, the density and distance to major roads and operational wind turbines, human population density, quietness suitability index), and (iv) 19 bioclimatic predictors. For BPL which is bordered by the Atlantic Ocean, we also derived the distance to the coastline. Predictor type, source, temporal coverage and resolution are presented in Table 2.

Bats are mobile taxa that respond to environmental variables and anthropogenic stressors across spatial scales, from local to landscape levels [49]. We therefore implemented a multi-scale approach and derived area-based variables across ten spatial scales. We used ArcGIS Desktop v10 (ESRI, Redlands, CA, USA) to create ten buffers of 0.05, 0.10, 0.25, 0.50, 1.00, 2.00, 3.00, 4.00, 5.00, and 10.00 km radius around each sampling site. The large scales were selected considering the mean and maximum daily foraging movement of European bat species [53] whereas the small ones allow us to have a fine-scale description of the near environment of the sampling sites. The density of operational wind turbines was calculated for the six largest spatial scales only as most sites (>75 %) were located >1 km away from wind farms. Given the recent increases in wind turbines installation between 2015 and 2020 in France, we considered the two predictors related to wind turbines as dynamic [54], i.e. we calculated the density and distance to wind turbines of a given site using only wind turbines that were operational at the time of the bat survey.

2.2.3. Step 2: modeling species abundance

We used Random Forest (RF; [58]) implemented in the R package randomForest [59] to model bat activity in relation to topographic, environmental, anthropogenic and bioclimatic predictors variables in each study area (BFC and BPL). RF models were parameterized with the recommended default values (ntrees = 500, cutoff = 1/k = 1/3). We added temperature at night, Julian day and the site coordinates in the final list of predictors to consider spatiotemporal variation in bat activity. We used participant ID and site ID as strata to account for the stratified structure of the citizen-science data. While RF can operate with large numbers of variables and is largely insensitive to multicollinearity, it is recommended to proceed to variable selection to improve overall model performance [60]. We therefore conducted a variable selection procedure using the package vsurf [61] and retained the smaller set of variables sufficient for prediction purposes. In this process, predictor variables were assessed for their individual impact on model performance and the resulting list of selected predictors was refined by eliminating redundancy. Final models that included the selected variables explained higher variance (here referred to as a measure of how well the out-of-bag predictions capture the variability of the target variables in the training set) than full models [48] and were therefore retained to proceed to model performance evaluation and prediction. We assessed model performance using the Normalized Root Mean Square Error statistic (NRMSE) derived from a fivefold cross-validation procedure. NRMSE measures the divergence of the predictions generated by the models (using a training set) from observations of a test set. We iterated 500 times the fivefold cross-validations to calculate NRMSE, with a training set consisting of 80 % of the observations randomly selected at each iteration and a testing set corresponding to the remaining 20 % observations. We provide an Overview, Data, Model, Assessment and

Table 1
Summary of percentage of occurrence and mean bat activity per night across sites of the 12 bat taxa studied in the two study areas. Values are given considering an identification of bat passes with a maximum error risk tolerance of 50 %.

Taxa	Abbreviation	Bourgogne-Franche-Comté (N = 643)		Bretagne - Pays de la Loire (N = 711)	
		% of occurrence	Mean bat activity	% of occurrence	Mean bat activity
Barbastella barbastellus	B.bar	68	12	74	17
Eptesicus serotinus	E.ser	78	45	65	18
Myotis nattereri	M.nat	65	7	68	14
Myotis spp. (excluding *M. nattereri*)	Myo.spp	84	73	78	50
Nyctalus leisleri	N.lei	72	21	52	7
N. noctula	N.noc	40	6	21	10
Pipistrellus pipistrellus	P.pip	99	709	100	786
P. nathusii/kuhlii	P.natkuh	79	82	95	176
P. pygmaeus/Miniopterus schreibersii	P.pygM.sch	33	3	23	1
Plecotus spp.	Plec.spp	39	2	63	5
Rhinolophus ferrumequinum	R.fer	23	2	28	6
R. hipposideros	R.hip	47	5	29	8

Table 2
List of the predictors with their source and their temporal coverage and resolution (when applicable) included in the models.

Predictor	Source	Temporal coverage	Resolution
Altitude (m a.s.l.)	IGN BD Alti https://geoservices.ign.fr/bdalti	2020	75 m
Slope (°)	IGN BD Alti https://geoservices.ign.fr/bdalti	2020	75 m
% of deciduous forests	CES OSO land cover data https://osr-cesbio.ups-tlse.fr/~oso/	2018	10 m
Dist. to deciduous forests (m)	CES OSO land cover data https://osr-cesbio.ups-tlse.fr/~oso/,	2018	10 m
% Linear small woody features	Copernicus https://land.copernicus.eu/pan-european/high-resolution-layers/small-woody-features	2014–2016	5 m
Dist. to linear small woody features (m)	Copernicus https://land.copernicus.eu/pan-european/high-resolution-layers/small-woody-features	2014–2016	5 m
Density of rivers (m/ha)	Eaufrance BD Carthage https://www.data.gouv.fr/fr/datasets/cours-deau-metropole-2017-bd-carthage	2017	vector
Dist. to freshwater body (m)	Eaufrance BD Carthage https://www.data.gouv.fr/fr/datasets/plans-deau-metropole-2017-bd-carthage	2017	vector
Edge density of major land-cover classes[a]	CES OSO land cover data https://osr-cesbio.ups-tlse.fr/~oso/	2018	10 m
Shannon's diversity index of major land-cover classes[a]	CES OSO land cover data https://osr-cesbio.ups-tlse.fr/~oso/	2018	10 m
Artificial night-time light brightness	NOAA https://ngdc.noaa.gov/eog/viirs/download_dnb_composites.html	2016	350 m
% of urban areas	CES OSO land cover data https://osr-cesbio.ups-tlse.fr/~oso/	2018	10 m
Dist. to urban areas (m)	CES OSO land cover data https://osr-cesbio.ups-tlse.fr/~oso/	2018	10 m
% of croplands	CES OSO land cover data https://osr-cesbio.ups-tlse.fr/~oso/	2018	10 m
Dist. to croplands (m)	CES OSO land cover data https://osr-cesbio.ups-tlse.fr/~oso/	2018	10 m
Density of major roads (m/ha)	IGN Route 500 https://geoservices.ign.fr/route500	2020	vector
Dist. to major roads (m)	IGN Route 500 https://geoservices.ign.fr/route500	2000–2020	vector
Density of operational wind turbines (no/ha)	Bretagne: https://geobretagne.fr/mapfishapp/ Pays de la Loire: https://www.sigloire.fr/ Bourgogne-Franche-Comté: https://cartes.ternum-bfc.fr/	2000–2020	vector
Dist. to operational wind turbines (m)	Bretagne: https://geobretagne.fr/mapfishapp/ Pays de la Loire: https://www.sigloire.fr/ Bourgogne-Franche-Comté: https://cartes.ternum-bfc.fr/	2000–2020	vector
Human population density (no/km^2)	GHSL https://ghsl.jrc.ec.europa.eu/ghs_pop.php	2015	250 m
Quietness suitability index	EEA https://www.eea.europa.eu/data-and-maps/figures/quietness-suitability-index-qsi-2/quiet_areas_suitability_qsi.eps	2016	100 m
Bioclimatic variables	CHELSEA database v1.2 Karger et al. [55], Karger et al. [56]	1979–2013.	30 arc sec (~1 km)

[a] Calculated in R with *landscapemetrics* package [57].

Prediction [62] in Froidevaux [48].

Using citizen-generated acoustic data to model bat activity comes with some challenges that need to be addressed during the modeling process. First, we accounted for uncertainties in bat identification by modeling bat activity using two separate datasets (hereafter referred to as "acoustic datasets") having different error risk tolerance thresholds in acoustic identification (10 vs 50 %) [47]. Second, because some Vigie-Chiro sites were spatially clustered (especially in BPL) - thus potentially leading to an overestimation of model performance - we also ran the final models using two datasets (hereafter referred to as "spatial datasets") that included either all the sites or only spatially independent ones, i.e. a subset of the full dataset containing only sites that were located >500 m away from each other (N_{BPL} = 473, N_{BFC} = 546).

2.2.4. Step 3: building a standardized benchmark of species abundance

We built a bat activity benchmark for each study area in three steps. First, within each area, we randomly selected the same number of random points as there were wind turbines approved for construction (i.e. 233 in BFC and 766 in BPL). We employed a random stratified approach: random points were located (i) within a 50 km radius from wind turbines approved for construction, for encompassing areas with similar environmental and bioclimatic conditions, (ii) > 150 m from each other (with >98 % of points located >500 m); and (iii) outside urban and protected areas because wind turbines sitting in such area is not permitted. We were not able to exclude other restricted areas (e.g. zones of aeronautical easements) as GIS layers were not publicly available. Second, we used the final RF models to predict species-specific bat activity at these random points. Third, we built the bat activity benchmark using the ordered value of bat activity predicted at random points. We used percentile threshold [22,63] with the following five categories: (i) low activity: 0-25th percentiles; (ii) medium-low: 25-50th percentiles, (iii) medium-high: 50-75th percentiles, (iv) high: 75-98th percentiles, and (v) extremely high: 98-100th percentiles.

2.2.5. Steps 4 and 5: predicting species abundance and assessing potential risks posed by wind turbines to bats

To provide a concrete illustration through this case study on how the final steps of the modeling-based framework can be applied in EIA to inform the decision-making process, we assessed whether wind turbines approved by local environmental planning authorities for construction (i.e. projects that have undergone an EIA) were in areas of low bat activity levels. We expected that the approved wind turbines would be sited away from important foraging and commuting habitats for bats since bats are strictly protected in the European Union (Habitats Directive of the European Union 92/43/EEC) and are considered in the mitigation hierarchy process during wind turbines planning since several years in France. We used the final RF models developed in step 2 to predict species-specific bat activity at the wind turbines approved for construction by local environmental planning authorities. These predictions were then compared to the standardized benchmarks of bat activity, established in step 3, for each taxon at the regional level. This comparison allowed us to quantify potential risks that the approved wind turbines posed to bats.

We finally evaluated species-specific patterns in risks posed by wind turbines to bats as the type of impacts of wind turbines on bats are largely species-specific, with mortality events by collision mainly affecting high-flying species [64]. We tested whether future wind turbines planned for areas with high bat activity would primarily affect bat species with low collision risks, as expected if the mitigation hierarchy effectively avoids direct impacts. To evaluate this, we independently calculated the proportion of wind turbines that would be built in areas with high and extremely high bat activity levels for each species. Then, we tested the relationship between the proportion obtained for each species in relation to their collision susceptibility index (in a logarithmic scale to the base two due to the large spread of values) using beta regression models [65]. Collision susceptibility index was obtained from Roemer et al. [64]. Models were checked using the performance package [66].

3. Results and discussion

3.1. Overview of random forest models

The modeling-based framework was developed and tested using 12 bat taxa which were monitored through the French national-scale citizen-science bat monitoring program "Vigie-Chiro" in two distinct areas in France – Bourgogne-Franche-Comté (BFC) and Bretagne-Pays de la Loire (BPL). We built 96 RF models, i.e. one per taxa and per area and considering (i) two separate acoustic datasets having different error risk tolerance thresholds in acoustic identification (10 vs 50 %), and (ii) two spatial datasets that included either all the sites or only spatially independent ones (full vs subset dataset). The predictive performances of random forest models were overall satisfying with most NRMSE values below 20 % [67], even though predictive performance varied to some extent with respect to species, area and spatial dataset, as shown in Fig. 2. Given the overall predictive performance of the RF models developed and for sake of clarity and concision, results of subsequent analyses are only reported for the 50 % full dataset.

The variable selection procedure (step 2) led to different combinations of predictor variables for the 12 taxa in the two study areas. These combinations are reported in Fig. 3. The top ranked predictors retained in >25 % of models included climate variables, quietness suitability index and amount of cropland at different spatial scales, distance to water, and Julian day. Other key predictors included the amount of deciduous forest, small woody features, urban areas as well as river density at several spatial scales, and distance to cropland and wind turbine. Overall, environmental variables retained in the final models fit with our expectations regarding bat ecology and their responses to anthropogenic stressors [50]. For instance, the results are in line with Azam et al. [68] who demonstrated that the amount of cropland in the landscape was the main factor negatively affecting four common bat species in France. Similarly, several studies demonstrated that proximity

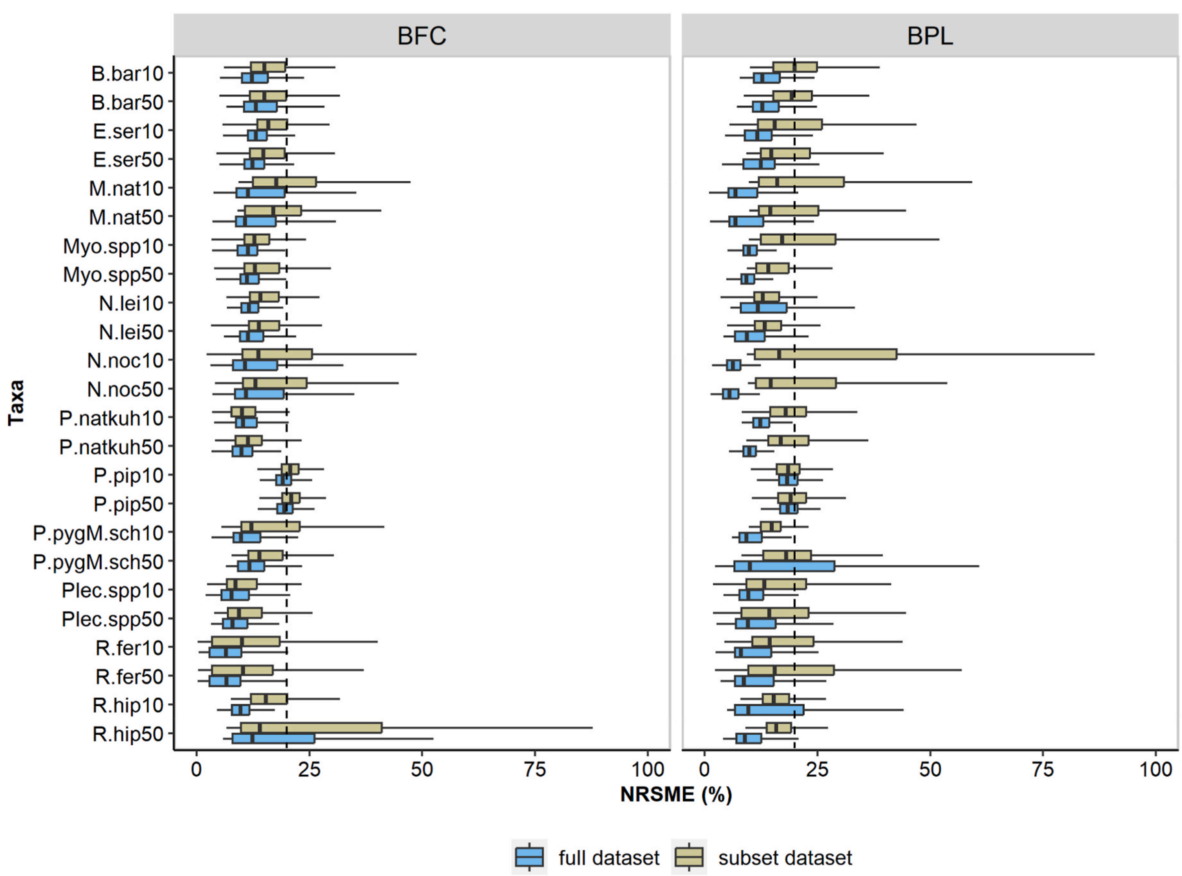

Fig. 2. Boxplot of Normalized Root Mean Square Error statistic derived from a fivefold cross-validation procedure iterated 500 times to assess predictive performance of the random forest models. The boxplots display the interquartile range box (top line = 75 % of the data ≤ this value; middle line = median; lower line = 25 % of the data ≤ this value) and the lower and upper whiskers (minimum and maximum data points). Lower NRMSE values indicate higher performance, and the dashed line represents the 20 % threshold. NRMSE were calculated for each final random forest, i.e. one per taxa and per area (BFC: Bourgogne-Franche-Comté, BPL: Bretagne-Pays de la Loire) and considering two acoustic datasets (10 vs 50 % maximum error risk tolerance) and two spatial datasets (full vs subset dataset with spatially independent sites). See Table 1 for full species names.

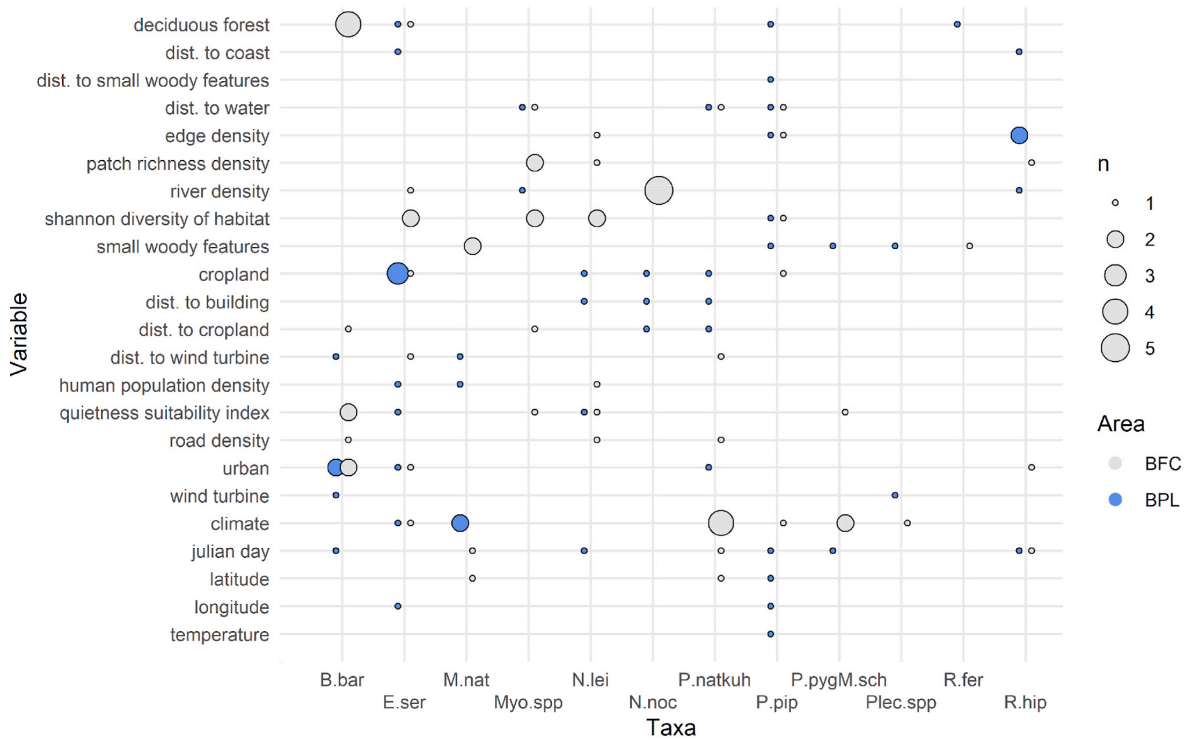

Fig. 3. Summary of the variables retained in the final random forests built for 12 bat taxa in two study areas (BFC: Bourgogne-Franche-Comté, BPL: Bretagne-Pays de la Loire). The presence of a dot at the intersection between a given variable and a given species means that the variable was retained in the final random forest model built for that species. The color of the dots indicates the two study areas (gray: BFC, blue: BPL). The dot size corresponds to the number of retained spatial scales for environmental variables and the number of selected climate variables for the climate variable. See Table 1 for full species names. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

to resources such as freshwater sites is a key driver of bat activity [69–71]. The variable selection process also emphasized the importance of considering the quietness suitability index when modeling bat activity, which is consistent with increasing field-based evidence regarding the effects of anthropogenic noise on bats [72,73]. In addition to noise, quietness suitability index may encompass other urban-related stressors (e.g. major road density, artificial night-time light brightness, impervious surface) making it a crucial predictor to consider when modeling bat activity.

The reliable predictive performance of models, along with consistent species responses corroborating findings in the literature, reinforce the notion that citizen science-based biodiversity monitoring schemes adhering to standardized protocols could provide high-quality big data [39,40]. The use of standardized acoustic data collected through the national-scale citizen-science bat monitoring program Vigie-Chiro in combination with high-resolution climatic and environmental variables has proved to be valuable for modeling bat activity. The development of such models would not have been possible with other sources of data since standardized abundance/activity data on bats are scarce or not centralized and often limited in spatiotemporal extent, thus hampering large-scale modeling studies. Scaling up the Vigie-Chiro program to a European level through collaboration with other bat citizen science initiatives (e.g. Barlow et al. [74] and Torre et al. [75]) could improve large-scale bat biodiversity analysis and advance research on the ecological impacts of renewable energies across the continent. Nevertheless, combining data from acoustic, capture and roost monitoring programs would be required to adequately model the abundance of species that are difficult to detect acoustically. Furthermore, we acknowledge several limitations associated to the use of citizen science data as they can be subject to spatiotemporal and observer biases [40]. Although the use of passive acoustic methods together with algorithms for species identification may prevent from observer bias, they could also lead to some uncertainty in species identity. Here, we scrutinized for any potential spatiotemporal and species-related bias before building the models and accounted for by modeling different subsets of the dataset and by including key predictors into the models (see sections 2.2.1 and 2.2.3). Finally, while RF models performed relatively well to model bat species activity, predictions beyond the topographic, environmental, and climatic conditions of the training data are likely to be unreliable [24]. This could pose challenges in scaling the modeling framework to broader geographic extents.

3.2. *Failure in current mitigation hierarchy process highlights the crucial need of adopting a modeling-based approach*

The comparison of predicted species-specific bat activity at the wind turbines approved by local environmental planning authorities for construction (step 4) to the standardized benchmark of bat activity (step 3) highlighted that a considerable proportion of wind turbines will be placed in areas with high or extremely high bat activity levels, as illustrated in Fig. 4a. While this proportion varies among species, we found that only less than 10 % of wind turbines will be placed in areas where no high or extremely high bat activity levels of any taxon is expected. On the other side of the spectrum, more than 25 % of wind turbines will be in areas of high and extremely high activity for one-third of the bat assemblage. When investigating in more detail species-specific pattern, we found no significant relationship (BFC: $P = 0.19$, estimate ± SE = -0.06 ± 0.05; BPL: $P = 0.34$, estimate ± SE = -0.04 ± 0.05; relationships displayed in Fig. 4b) between the percentage of wind turbines in areas of high and extremely high activity and the collision susceptibility index of the taxa that will be affected by the wind turbines. In other words, wind turbines will be built in areas where even species with higher collision risks are expected to be very active. For *Nyctalus* spp. which are the most sensitive species to collision, activity recorded at ground level correlates with bat activity at nacelle height [64], and we can assume that higher activity of high-flying species leads to higher

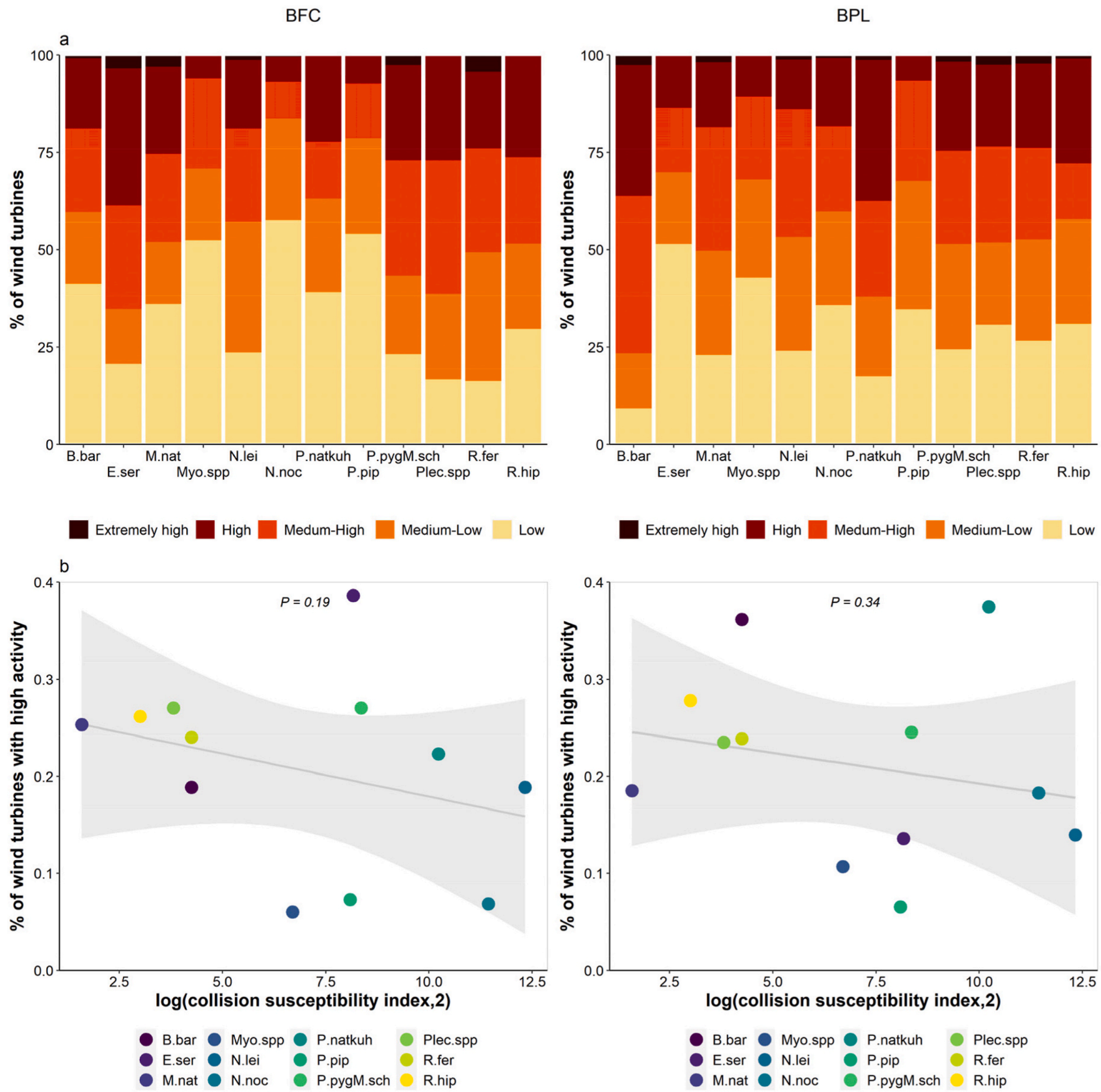

Fig. 4. Potential risks posed to bats by wind turbines approved by local environmental planning authorities for construction in the two study areas (BFC: Bourgogne-Franche-Comté, BPL: Bretagne-Pays de la Loire). **(a)** Stacked bar plots depicting the percentage of wind turbines that will be placed in areas of low, medium-low, medium-high, high, and extremely high levels of activity for each bat species. **(b)** Relationship between the percentage of wind turbines with high and extremely high bat activity and the collision susceptibility index (on a logarithm scale to the base 2) of the taxa that will be affected by the wind turbines. See Table 1 for full species names.

fatalities, as demonstrated in Germany [76] and North America [77]. This could potentially threaten bat population viability if no mitigation measures are implemented [78]. If the current mitigation hierarchy process was truly effective in avoiding the direct impacts of wind turbines on bats, we would have expected to observe a much lower proportion of wind turbines located in areas of high or extremely high bat activity for species with higher collision risks. Thus, the results corroborate those of Lintott et al. [18] who provided empirical evidence that ecological impact assessments fail to reduce risk of bat casualties at wind farms in the United Kingdom. Nevertheless, we acknowledge that information regarding the presence of curtailment – i.e. a reduction measure consisting of operational restriction of the turbines during high bat activity – were not provided. In addition, the more subtle effect of habitat loss due to wind turbine avoidance by some bat species [10,11] were not considered in the analysis due to the lack of consideration of this type of impact in past and current EIA process [79], even though avoidance behaviour has been documented in many taxa [80].

Given failures in the current mitigation process, this study case demonstrates the crucial need of adopting a modeling-based approach to derive robust biodiversity benchmarks and guide planning authorities in their decision-making processes. We represent the potential contributions and adding values of integrating the proposed modeling-based framework in the ecological impact assessment process in Fig. 5. More specifically, the whole modeling-based framework could be implemented as a toolbox for stakeholders (e.g. ecological consultants, environmental planning authorities) to help assisting during spatialization and mapping of the impacts prior to regulatory ecological ground surveys and determining whether the projects proposed for development are in area of biodiversity conservation significance. This approach could also help identifying infrastructures already sited in areas of predicted high species abundance and advise on targeted post-construction surveys and the implementation of mitigation measures for poor-sited ones [81]. For instance, if not already in place, wind turbine curtailment strategies should be implemented at high-risk sites.

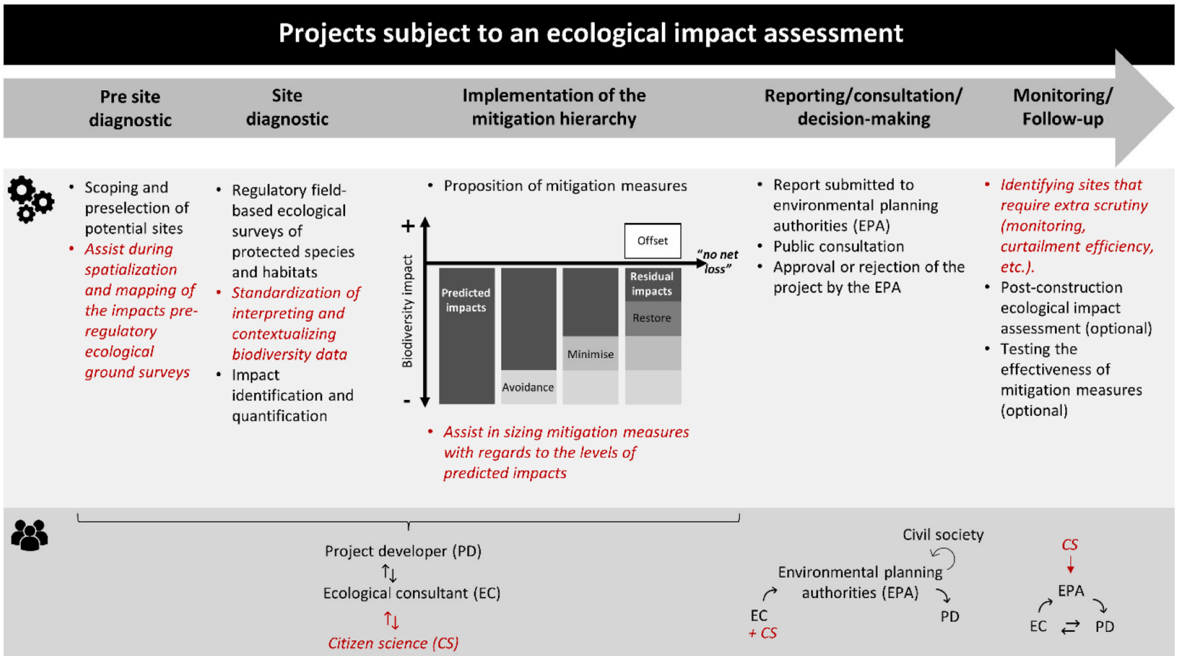

Fig. 5. Potential contributions and adding values (in red) of integrating the proposed modeling-based framework in the ecological impact assessment process. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Conventional curtailment based on a unique combination of wind and temperature thresholds are commonly used and can show significant yet varying effectiveness [14]. More recent and sophisticated methods based on predictive algorithms or real-time bat monitoring offer the best approach moving forward [82–84].

This approach is intended to be complementary, not substitutional, of the current EIA stages during renewable energy infrastructure planning. Indeed, regulatory field-based ecological surveys are crucial for capturing site-specific variations in species abundance driven by the unique characteristics of a given area. Yet, they are often constrained by financial and logistical limitations, resulting in limited temporal and spatial coverage. The modeling-based approach proposed could therefore complement these surveys as it incorporates data collected over larger areas and longer time periods. Taken together, they could provide a more complete assessment of the potential risks posed to bats by wind turbines.

In light of the ongoing debate on whether important conservation areas are effective proxies for predicting the impact of renewable energy expansion on biodiversity [41,85,86], the proposed modeling-based framework is well-suited to identify areas of biodiversity significance both inside and outside these priority conservation areas. Finally, future research should aim to include various taxa affected by wind turbines (e.g., birds, bats, insects) within a unified modeling framework to provide stakeholders with a holistic view of potential ecological impacts of such infrastructure.

3.3. Towards contemporary, dynamic, and multi-season biodiversity benchmarks

The method described for determining biodiversity benchmarks is similar to the contemporary reference state approach outlined in McNellie et al. [87]. This approach offers the advantages of (i) reevaluating and adjusting the biodiversity benchmarks when additional data become available, and (ii) adapting the benchmarks in a context of rapid biodiversity change [88] caused by climate and land-use changes [89–91]. For instance, benchmarks of bat activity levels in Europe should be dynamic to better consider spatial and demographic responses of bats to global changes at a continental scale [92,93]. Nevertheless, we acknowledge that this approach only aids in spatially identifying sites of potential biodiversity significance based on current data without considering any past impacts. There is a trade-off between adapting the benchmarks due to rapid biodiversity change in the Anthropocene and accounting for issues related to shifting baseline syndrome [94]. This trade-off should be considered on a case-by-case basis depending on the targeted species and areas, as well as data availability. For instance, we suggest refraining from using dynamic biodiversity benchmarks in highly anthropogenic areas, especially for species exhibiting rapid ecological or behavioral responses to anthropogenic activities.

Biodiversity benchmarks should also account for seasonal changes in species distribution and abundance which reflect key life-history events and seasonal species responses to climatic and environmental factors in both migratory and non-migratory species [95–97]. Given the increasing amount of within-year temporal biodiversity data in biodiversity monitoring programs and the increasing availability of climatic and environmental layers at high spatiotemporal scales [98], building robust multi-season biodiversity benchmarks will soon become an achievable target.

3. Conclusions

We demonstrated how biodiversity benchmarks modeled from large-scale standardized citizen science biodiversity monitoring programs can identify sites of potential biodiversity significance threatened by renewable energy projects. While using bats and wind turbines as a case study, we developed a modeling-based framework applicable to other species and energy infrastructures such as solar farms, hydropower plants, and power lines. Our findings revealed that fewer than 10 % of wind turbines approved in France would be placed in low-significance sites for bats, exposing shortcomings in the current mitigation hierarchy process. The risks posed by wind turbines affect all bat taxa, including species with higher collision risks.

Adopting a modeling-based approach within the EIA process seems crucial to better assess project impacts and comply with the mitigation hierarchy framework with the ambition of no-net-loss to biodiversity. In addition to assisting in spatialization and mapping of the impacts of pre-regulatory ecological ground surveys, the modeling-based approach enables the standardization of interpreting and contextualizing biodiversity data. Thus, it contributes to a more objective evaluation of impacts, ultimately leading to biodiversity-friendly renewable energy planning aligned with the world-leading target to halt biodiversity decline by 2030 [99,100]. By fostering biodiversity-friendly planning, this approach could also help resolve the green-green dilemma by addressing conflicts between SDGs 7 (affordable and clean energy), 13 (climate action), and 15 (life on land). We therefore urge policy shifts toward mandatory inclusion of biodiversity modeling in the EIA process.

Authorship contribution statement

CK and ILV secured the funding from the SAD–Région Bretagne; JSPF, KB and CK conceived the modeling-based framework; JSPF analyzed the data and performed the case study; JSPF led the writing of the manuscript; All authors critically contributed to the drafts and gave their final approval for publication.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT and deepL Write to improve readability of a few sections of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication. We followed the recommendations made by University Paris 1 Panthéon-Sorbonne for the use of AI in research projects.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data and codes are available in Zenodo: https://doi.org/10.5281/zenodo.14226137

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