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Occupancy model to unveil wildlife utilization at Yeongyang-gun wind farm management road, Korea

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ABSTRACT

Wind power is a rapidly growing renewable energy sector that reduces greenhouse gas emissions and provides sustainable energy. However, environmental destruction in wind power plant areas, particularly in wind farms within forests, is an emerging issue. This study aimed to analyze the impact of wind-farm roads on terrestrial animals in forested areas. A camera trap survey was conducted to investigate the impact of road management on wildlife behavior. We installed 52 cameras along roads connecting wind turbines for three months (1st October to 30th December 2021) on the Yeongyang-gun wind farm in South Korea and evaluated animal occupancy and detection probabilities using an occupancy model. Factors related to terrain and vegetation were used to estimate the occupancy probability (station use). The detection analysis included the presence or absence of guardrails, wind turbines, shrublands, and retaining walls. Additional variables included camera type, number of camera-operating days, and survey time. During the survey period, seven terrestrial mammals (roe deer, wild boar, water deer, raccoon dogs, badgers, leopards, cats, and martens) were captured using cameras. Based on camera trap records, roe deer was the most dominant species, followed by wild boars, raccoon dogs, and water deer, with fewer badgers and martens. The presence of forests in the road area was a significant factor for most species in terms of use probability, and camera type was significant for detection probability. Detecting animals along roads shows that roads are passageways for wildlife, affecting animal behavior during vehicle movement and can cause habitat disconnection. Our results demonstrate that wind farms are indirectly linked to wildlife distribution and welfare. Effective management policies for mitigating wildlife disruption can support sustainable ecosystems and biodiversity. The results of this study can serve as a reference for supporting wildlife conservation, terrestrial ecosystems, and environmental impact assessments.

1. Introduction

Renewable energy sources, such as wind and solar energy, are considered alternative solutions to conventional fossil fuels to meet energy demands. However, some environmental destruction is unavoidable when renewable energy sources are used. As a rapidly

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growing source of renewable energy, wind farms have various adverse effects, including bird death due to direct collisions with turbines, turbine noise, habitat destruction from farm management roads, and other anthropogenic infrastructure (Park et al., 2013; Nazir et al., 2020; Husby and Pearson, 2022).

Most environmental impact studies on wind farms have focused primarily on the habitat and mortality of flying species such as birds and bats (Kunz et al., 2007; Baerwald et al., 2008; Pearce-Higgins et al., 2009; Carrete et al., 2012; Masden et al., 2021). Few studies have evaluated the effects of wind farms on terrestrial animals (Agha et al., 2015; Agha et al., 2017; Hall et al., 2020), yet the construction of wind farms has resulted in habitat destruction and impeded animal movement. Road construction for wind farm installation and maintenance causes habitat fragmentation, fire risk, noise, visual impact, and vibration and requires additional infrastructure, such as power lines and substations (De Lucas et al., 2005; Lovich and Ennen, 2013). Several studies have evaluated the response of terrestrial mammals to wind farms. For example, the response of female pronghorns to wind turbines within their winter ranges was evaluated using Global Positioning System (GPS) collars, which revealed that pronghorns tended to avoid wind generators (Smith et al., 2020). European roe deer and hares were tracked on the camera more frequently as the distance from the wind generator increased (Łopucki et al., 2017).

Camera trapping is a method for detecting passing wild animals using a passive infrared sensor for imaging and recording (Rowcliffe et al., 2008). Because CTs automatically detects and captures images of wild animals, it is widely used for wildlife monitoring as a low-cost, non-invasive technique that requires minimal labor (Kucera et al., 2011; Burton et al., 2015). Camera traps can be used to observe wildlife communities within a target area (Tobler et al., 2008) and are particularly well-suited for monitoring terrestrial mammals that are primarily nocturnal, agile, and difficult to observe (Rich et al., 2016; Mazzamuto et al., 2019). Correlations between camera-captured species behaviors and environmental factors in ecological research have been evaluated using various techniques, ranging from traditional statistical methods, such as linear regression, Bayesian occupancy models, analysis of variance, and other parametric and non-parametric approaches, to machine learning-based methods, such as decision trees, random forests, and neural networks (Dormann et al., 2018; Mohankumar and Hefley, 2022).

Occupancy models identify species occupancy based on spatial variations in living environments. These models are frequently employed in ecological research, particularly in conservation biology, where they help guide conservation planning and management by identifying regions crucial for preserving a particular species (MacKenzie and Nichols, 2004; MacKenzie et al., 2017). For example, an occupancy model was used to analyze the impact of habitat loss and fragmentation on the giant anteater (*Myrmecophaga tridactyla*) using a single-season dataset (MacKenzie et al., 2002).

The single-season occupancy model in the PRESENCE program (MacKenzie et al., 2017) was used to study tufted-tailed rats (*Eliurus* spp.), red forest rats (*Nesomys* spp.), greater hedgehog tenrecs (*Setifer setosus*), and common tenrecs (*Tenrec ecaudatus*) to explain the differences in occupancy according to habitat characteristics and habitat degradation (Murphy et al., 2017). A single-species, single-season occupancy analysis was performed using the unmarked R package (Fiske and Chandler, 2011) to estimate the probability of

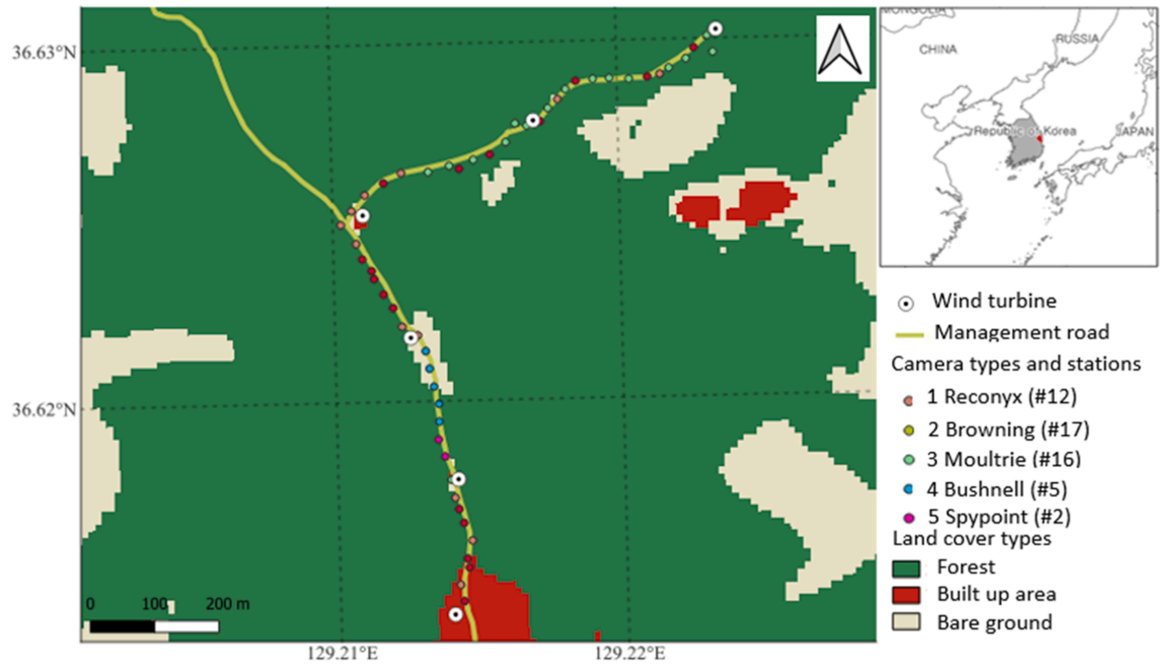

Fig. 1. Study area (GS-Wind farm) in Yeongyang-gun, South Korea. Colored dots indicate the locations of different brands of cameras installed on the wind farm management road (Map generated in QGIS Desktop 3. 24.1., land cover maps obtained from an open access CC BY 4.0 licensed https://livingatlas.arcgis.com/ and base map from https://gadm.org/ data portal). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

occupancy and detection of the European wildcat (*Felis silvestris*) with respect to habitat fragmentation and anthropogenic factors (Anile et al., 2019). Scully et al. (2018) investigated the factors influencing habitat selection by the Canadian lynx (*Lynx canadensis*) and their spatial correlation with surrounding animals using single-species occupancy models (Richmond et al., 2010) and two-species occupancy models (Scully et al., 2018). Other groups have used multispecies hierarchical occupancy models (Dorazio and Royle, 2005) with a Bayesian approach to estimate occupancy and abundance at the species, community, and group levels (Rich et al., 2016). By analyzing the importance and significant implications, the current study investigated the impact of wind farm roads on wild animals using this broadly applied single-species, single-season occupancy model.

The generation of scientific data and the collection and mapping of species in wind farm areas support the implementation of science-informed practices to mitigate negative impacts on wildlife (Teff-Seker et al., 2022). Previous case studies have focused on the effects of wind turbines on the wildlife of large-plain landscapes and seashores; however, little is known about their effects on the wildlife of forested areas (Schöll and Nopp-Mayr, 2021). Many wind power plants in Korea are installed on mountain ridges because of the high wind speeds and multi-directional exposure (Kim et al., 2017). However, knowledge of the impact of wind farm management roads on wild animals in forested areas is still limited. Management in areas under the strong influence of human infrastructure requires appropriate planning of the method of obtaining research in the field, but also proper analysis of data (Teff-Seker et al., 2022, Bogdanović et al., 2023). Therefore, the current study aimed to present data of wild mammalian species using camera surveillance records and the occupancy model from the Yeongyang-gun wind farm in Korea.

2. Materials and methods

2.1. Study area

This study was conducted on a section of an established wind farm in Yeongyang-gun, Korea (Fig. 1). Yeongyang-gun is a county located in the eastern part of North Gyeongsang Province and has mountainous terrain (36°36′49″N, 129°13′21″E). The mountain is covered with a mixed forest dominated by coniferous plants such as Pine and Larch, followed by broad-leaved plants such as Oak and Walnut trees. The study area is a habitat of predators such as martens (*Martes flavigula*), leopard cats (*Prionailurus bengalensis*), and terrestrial mammals such as roe deer (*Capreolus pygargus*), water deer (*Hydropotes inermis*), and wild boars (*Sus scrofa*). This region is also a habitat for several small- to medium-sized terrestrial mammals, including raccoons (*Nyctereutes procyonoides*), badgers (*Meles leucurus*), hares (*Lepus*), chipmunks (*Eutamias sibiricus*), and squirrels (*Sciurus vulgaris*). A total of 18 wind turbines with a 3.3 MW nameplate capacity and an average tower height of 84 m were established (the project was commissioned in 2015) on a mountain ridge at an altitude of 520–665 m above sea level in the study area. The Yeongyang Wind Farm_GS (the GS wind farm) is equipped with

Fig. 2. Camera installation, orientation, and animal detection in survey area a) Camera installation and camera height, b) Cameras installed near to wind turbine positioning to capture forward and backward sites, c) Camera captured wide road in curve section, d) Wildlife (roe deer) captured on camera while moving along the road.

Vestas Wind Systems V112–3.3 MW wind turbines (GlobalData, 2023). Based on the resource availability, a camera trap survey was conducted along the dead-end management road section connecting the six turbines (Fig. 1).

2.2. Camera trap survey

Based on resource availability, a total of 52 CTs encompassing five different brands (Reconyx (#12), Browning (#17), Moultrie (#16), Bushnell (#5), and Spypoint (#2)) were randomly installed at approximately 25 m intervals along a 1.3 km segment of farm management road in the forest area, and these CTs monitored and captured animal images over three months from 1st October to 30th December 2021, in photo mode (Rovero and Zimmermann, 2016). Animals captured within half an hour of each photo at the same station that could not be differentiated individually were considered the same individual or observation otherwise different (Shannon et al., 2014). Camera brands contain important information in CT studies; however, their effects are difficult to interpret (Burton et al., 2015). A random installation was performed to eliminate the problems caused by the different CT scanners used in this study. All cameras were installed with identical initial settings and high infrared sensitivity, recovery time (0.5 s), trigger speed (0.3 s), and delay period (5 s) with an auto sensor and high night vision mode.

The CT installation covered a variety of road types, including paved and unpaved surfaces with and without guardrails and encompassed sloped areas. By adjusting the surrounding landmarks, CTs were installed at the height of approximately 50 cm above the ground, with cameras facing downhill, adjusting the line of sight about the range of 20 m that captured the object moving on the road (see camera orientation and capture range in Fig. 2). The battery and Secure Digital (SD) cards for the CT were replaced once a month. All CT-detected objects were classified according to the camera station, detection time, and species (identified as terrestrial mammals). CamtrapR (Niedballa et al., 2016) aggregated the appearance/non-appearance data.

2.3. Covariates

Based on the suggestions of local ecologists and experts, we mined the environmental features surrounding the CT installation points for three scenarios: 10, 30, and 50 m raster grids to examine the grid effect on feature mapping and occupancy model. Information on the terrain, namely slope, topographic position index (TPI), terrain ruggedness index (TRI), roughness (Wilson et al., 2007), curvature types (plan curve, procurve, and tan curve) (Minár et al., 2020), and vegetation factors (forest, grassland, canopy height, and normalized difference vegetation index (NDVI)) were used to estimate the station use probability (Table 1). Similarly, the presence of man-made facilities on the management road, in addition to camera stations, guardrails, wind power turbines, and retaining walls, as well as camera specifications such as camera type (1 = Reconyx, 2 = Browning, 3 = Moultrie, 4 = Bushnell, 5 = Spypoint), camera effort (number of days the camera was in operation), and survey time covariates including temporary vegetation factor shrubs, were considered in analyzing the detection probability (Table 1). Station-use covariates were continuous variables, whereas detection was categorical. The shrub, guardrail, retaining wall, and wind power were the ordinal dummy variables assigned by surveyors as the absence around (0), the presence at the same roadside (1), and opposite (2) to the camera station within the camera capture range (average 20 m).

Table 1
Parameters used to estimate the station use and detection probabilities.

Station use parameters*					
Variable (Unit)	Mean	Range	Software	Data Source	Reference
Slope (°)	10.2	0–21.3	ArcGIS pro	DEM	Burrough et al. (2015)
TRI (m)	1.5	0–3.2	R (raster)	DEM	Wilson et al. (2007)
TPI (m)	0.5	-0.9–2.3	R (raster)	DEM	Wilson et al. (2007)
Roughness (m)	5.1	0–11.3	R (raster)	DEM	Wilson et al. (2007)
Plancurve (m^{-1})	0.1	-0.6–1.6	ArcGIS pro	DEM	Minár et al. (2020)
Procurve (m^{-1})	0.009	0–0.1	ArcGIS pro	DEM	Minár et al. (2020)
Tancurve (m^{-1})	0.003	-0.03–0.04	ArcGIS pro	DEM	Minár et al. (2020)
Forest (%)	0.02	0–0.4	-	LCLU	(https://egis.me.go.kr/intro/land.do)
Grass (%)	0.7	0.2–1	-	LCLU	(https://egis.me.go.kr/intro/land.do)
Canopy (m)	6.6	0–18	-	GLAD	Potapov et al. (2021)
NDVI (Dml)	0.5	0.3–0.7	ArcGIS pro	Sentinel-2	Trishchenko et al. (2002)

Detection parameter			
Variable	Mean	Range	description
Shrub	1.12	0–2	Camera station investigation
Guardrail	0.5	0–2	Camera station investigation
Retaining wall	0.65	0–2	Camera station investigation
Wind power	0.46	0–2	Camera station investigation
Cam_Effort			Number of camera operation days in the detection window (7 days)
Camtype	–	–	Type of camera (1 = Reconyx, 2 = Browning, 3 = Moultrie, 4 = Bushnell, 5 = Spypoint)
Survey time	–	–	Survey time (total no of detection time windows)

* Mean and ranges of parameters for 52 camera stations based on 10 m grid size; TRI: terrain ruggedness index; TPI: topographic position index; NDVI: normalized difference vegetation index.

2.4. Modeling framework

The effects of wind-farm roads on wildlife were examined using occupancy models and conditions. Errors in estimation due to the imperfect detection of species are a significant issue in ecological research, particularly when species are rare and low in number. Although occupancy models account for false negatives, in which an existing species is identified as non-existent because the investigator was unable to find it or because it was not captured by the camera, it is important to minimize these false negatives (MacKenzie et al., 2002; Kéry and Royle, 2015). The occupancy model can estimate probabilities, even at locations where no wild animals are present, by estimating the probability of detection; therefore, it is primarily used to explain incomplete detection (MacKenzie et al., 2002). In an occupancy model, the home range polygon of a species is typically applied. The current study used camera station points; however, because the cameras were located along roads, the home range of each species was not assumed. Therefore, we considered the station use probability instead of the occupancy probability (Ψ_i), as suggested by Tobler et al. (2015). The station use probability (Ψ_i) of station i, the station use rate (z) was calculated as follows:

$$z_i \sim Bernoulli(\Psi_i) \tag{1}$$

where Z_i represents the observed use level at station i.

$$y_{i,k}|z_i \sim Bernoulli(z_i \times p_{i,k}) \tag{2}$$

$p_{i,k}$ represents the probability of detection by a camera during the k^{th} survey period at station i and $y_{i,k}$ indicates the presence or absence of a species during the k^{th} survey period at station i. We used the dates on which all the cameras were monitored for 24 h per day. To reduce non-appearance and facilitate modeling, the appearance/non-appearance data for seven days were merged and defined as a single-detection-window dataset (Shannon, 2014).

The logistic regression equations below examined influencing the use status (Ψ_i) and detection probability ($p_{i,k}$).

$$\begin{aligned} logit(\Psi_i) = {} & \alpha_0 + w_1 \times \alpha_1 \times slope_i + w_2 \times \alpha_2 \times forest_i + w_3 \times \alpha_3 \times grass_i + w_4 \times \alpha_4 \times canopy_i + w_5 \times \alpha_5 \times NDVI_i + w_6 \times \alpha_6 \\ & \times TRI_i + w_7 \times \alpha_7 \times TPI_i + w_8 \times \alpha_8 \times roughness_i + w_9 \times \alpha_9 \times plancurv_i + w_{10} \times \alpha_{10} \times procurv_i + w_{11} \times \alpha_{11} \times tancurv_i \end{aligned} \tag{3}$$

$$\begin{aligned} logit(p_{i,k}) = {} & \beta_0 + w_{12} \times \beta_1 \times shrub_i + w_{13} \times \beta_2 \times guardrail_i + w_{14} \times \beta_3 \times steepslope_i + w_{15} \times \beta_4 \times windpower_i + w_{16} \times \beta_5 \\ & \times effort_{i,k} + w_{17} \times \beta_6 \times camtype_i + \beta_7 \times survey.t_{i,k} \end{aligned} \tag{4}$$

A Markov chain Monte Carlo (MCMC) trial was used to estimate the prior distribution for each dataset. The importance of covariates for station use and detection probabilities was assessed using the Bayesian inclusion parameter (w_c) coefficient for variable selection (Kuo and Mallick, 1998). The prior probability of a Bernoulli distribution with a success probability of 0.5 was used to calculate the w_c. This parameter was assigned a binary value of zero or one to indicate whether each covariate was included in the corresponding model. The final model was built by first selecting covariates through w_c ($w_c > 0.5$) in Eq. (3) and then through w_c ($w_c > 0.5$) in Eq. (4): Using the final model, we compared station usage and detection probabilities for each dataset.

To avoid dependence on the initial values in the MCMC chains, a uniform distribution ranging from 0 to 1 was used for all intercepts before the logit transformation. Additionally, a standard normal distribution with a mean of 0 and standard deviation of 10 (precision 0.01) was used for the slope of all variables to standardize the data. The model was run for 200,000 iterations for each MCMC chain at three thinning rates. A burn-in period of 50 000 iterations was used to analyze the model with Bayesian inclusion probabilities (w_c). Similarly, a model without w_c was run for 100,000 iterations with a burn-in period of 20 000. After the burn-in period, the tenth sample was collected and analyzed for each case. This thinning rate ensured that the posterior samples were sufficiently independent and reduced the correlation between samples. After obtaining the posterior samples, the results were analyzed using statistical techniques such as posterior means, medians, or credible intervals. Model convergence was evaluated using the Gelman-Rubin convergence statistic ($\widehat{R}$) (Gelman et al., 1995) and trace plots (Brooks and Gelman, 1998).

2.5. Data sampling and model selection

Because of the nature of CT, it was not possible to accurately identify the species in all images. Furthermore, the ability to obtain information about a species varies depending on camera performance and time (Kucera et al., 2011). Therefore, to the extent possible, species identified in all images were used in this study. We identified three large- and medium-sized mammals (roe deer, water deer, and wild boar) and four small- and medium-sized carnivores (badgers, raccoon dogs, leopard cats, and martens) from the CT images. The model was fitted considering station use and detection covariates, and the final model was selected based on the deviance information criteria (DIC) (Spiegelhalter et al., 2002).

2.6. Software

The GIS data used in this study were created using ArcGIS Pro 2.9.1 (Esri). All data analyses were performed using the R Studio (Team, 2020). MCMC analyses were performed using JAGS (version 4.3.0) (Plummer, 2003) and the R jagsUI package (version 1.5.2) (Kellner et al., 2019).

3. Results

We analyzed 52 CT records for seven investigation survey time windows (a total of 13 seven-day periods), and seven dominant mammal species were detected: badgers (three cameras; six detections), leopard cats (17 cameras; 32 detections), martens (two cameras; two detections), raccoon dogs (15 cameras; 34 detections), roe deer (45 cameras; 228 detections), water deer (18 cameras; 32 detections), and wild boar (33 cameras; 75 detections). The analysis was performed using the occupancy model, and successful convergence was observed for all datasets ($\widehat{R} < 1.1$).

3.1. Model performance and grid size effect

When the models for each species were compared based on DIC, roe deer (309.84), wild boar (312.68), badger (28.50), and raccoon dog (148.52) demonstrated a better fit to the occupancy model for the 10 m grid data set. The 30 m grid dataset was better fitted for water deer (179.18) and martens (4.13), whereas the 50 m grid dataset was a good fit for leopard cats (185.77). In most models of station use probability, forest area (a vegetation factor) and procurement (a terrain factor) were identified from the Bayesian inclusion parameters (W_c) (Table 2).

3.2. Station use parameters

We compared the station use probabilities of the species for the covariates and analyzed the parameters of the corresponding better-fitted model (Table 2). The median weight of parameters of the vegetation type 'forest' was observed as highly sensitive for water deer ($\alpha_{forest.30} = -10.71, CI = -22.30 \sim -1.90$) and the topography parameter TRI was sensitive for martens ($\alpha_{TRI.30} = 4.24, CI = 1.10 \sim 8.80$) (Table 3). With increasing vegetation and topography parameter values along the road, species occurrence decreased, except for roe deer in the forest, water deer on grass, badgers on Tancurve, and martens, based on TRI.

3.3. Detection parameters

Similarly, the covariates for the models of detection probabilities were compared for each detection window and significant model parameters (Table 2), and their detection probabilities were evaluated (Table 4). The highest influence but opposite relation was identified for badgers with camera type ($\beta_{cam2.10} = -8.76, CI = -24.0 \sim 9.30$) and shrub environments ($\beta_{shrub.10} = -8.05, CI = -18.40 \sim 5.50$). Guardrails were also identified as positive detection parameters for badgers ($\beta_{guardrail.10} = 6.85, CI = -6.80 \sim 17.0$). Camera types were observed as influencing parameters for detection probability but had mixed effects for each species and camera type.

3.4. Comparison of naïve occupancy with station use and detection probabilities

We calculated the influence of environmental variables on the probability of detecting wild animals based on road-related management factors, wild animal station use probabilities, and wind farm-related environmental factors. Each dataset's station use and detection probabilities were estimated using the better-suited model (Table 2). The results were compared with naïve occupancy

Table 2
Summary of models for each species by grid size. The model with the lowest DIC was chosen as the best and highlighted in bold font. A covariate with a Bayes inclusion probability (w_c) greater than 0.5 was chosen in the model, with a dot (.) indicates the absence of significant covariates.

Species	Model					
	10 m		30 m		50 m	
	parameter	DIC	parameter	DIC	parameter	DIC
Roe deer	**Ψ(forest)** ***p*(camtype)**	**309.84**	Ψ(.) *p*(camtype)	310.18	Ψ(plancurve+tancurve) *p*(camtype)	311.71
Water deer	Ψ(forest+plancurve+procurve) *p*(shrub+camtype)	197.90	**Ψ(forest+grass+procurve)** ***p*(shrub+camtype)**	**179.18**	Ψ(forest+grass+plancurve +procurve+tancurve) *p*(camtype)	206.85
Wild boar	**Ψ(procurve)** ***p*(.)**	**312.68**	Ψ(.) *p*(.)	314.73	Ψ(procurve) *p*(.)	315.44
Badger	**Ψ(forest+procurve+tancurve)** ***p*(shrub+guardrail+camtype)**	**28.50**	Ψ(procurve) *p*(shrub+guardrail+camtype)	28.58	Ψ(grass+procurve) *p*(camtype)	30.11
Racoon dog	**Ψ(forest+procurve)** ***p*(camtype)**	**148.52**	Ψ(.) *p*(camtype)	155.91	Ψ(.) *p*(camtype)	155.16
Leopard cat	Ψ(TPI+plancurve+procurve) *p*(camtype)	234.65	Ψ(forest+procurve) *p*(camtype)	195.30	**Ψ(procurve)** ***p*(camtype)**	**185.77**
Marten	Ψ(grass+NDVI+procurve) *p*(shrub+windpower+effort +camtype)	12.07	**Ψ(forest+grass+NDVI+TRI +procurve)** ***p*(shrub+windpower+camtype)**	**4.13**	Ψ(grass+NDVI+TRI+procurve) *p*(windpower+camtype)	6.12

Note:- camtype: Camera type; TRI: terrain ruggedness index; TPI: topographic position index; NDVI: normalized difference vegetation index.

Table 3
Coefficients (median) of covariates for station use (for better-fitted model M#).

Parameter	Roe deer (M10)	Water deer (M30)	Wild boar (M10)	Badger (M10)	Raccoon dog (M10)	Leopard cat (M50)	Marten (M30)
Vegetation							
Forest	7.67 (−3.80 to 23.60)	-10.71 (−22.30 to −1.90)	–	-6.59 (−23.0 to 7.10)	-6.73 (−19.60 to 2.90)	–	-8.29 (−23.30 to 5.80)
Grass	–	5.21 (−0.20 ~ 12.40)	–	–	–	–	-10.61 (−24.60 to 0.80)
NDVI	–	–	–	–	–	–	-6.44 (−22.30 to 8.80)
Topography							
TRI	–	–	–	–	–	–	4.24 (1.10–8.80)
Procurve	–	-0.50 (−20.0 to 19.10)	-6.91 (−25.2 to 11.600)	-1.23 (−20.40 to 17.60)	-1.93 (−20.10 to 16.60)	-1.02 (−20.50 to −18.30)	-0.63 (−20.0 to 18.90)
Tancurve	–	–	–	1.84 (−17.50 to 21.30)	–	–	–

Note: - Values with 95 % credible intervals are in parentheses.

Table 4
Intercept estimates of the logit of covariates on the detection probability (in the best model).

Parameter	Roe deer (M10)	Water deer (M30)	Wild boar (M10)	Badger (M10)	Raccoon dog (M10)	Leopard cat (M50)	Marten (M30)
Shrub	–	1.50 (0.50 to 1.90)	–	−8.10 (−18.40 to 5.50)	–	–	−5.04 (−11.50 to 0.70)
Guardrail	–	–		6.85 (−6.8 to 17.0)	–	–	–
Wind power	–	–	–	–	–	–	−2.67 (−21.70 to 18.50)
Cam1	–	1.62 (0.60 to 2.80)	–	–	–	–	−2.26 (−22.0 to 18.80)
Cam2	–	–	–	−8.76 (−24.0 to 9.30)	−1.49 (−2.70 to −0.30)	–	–
Cam3	0.86 (0.20 to 1.60)	−1.34 (−3.40 to 0.30)	–	–	–	–	–
Cam4	–	2.20 (0.80 to 3.60)	–	−3.33 (−21.0 to 15.70)	–	–	–
Cam5	−2.02 (−3.40 to −0.80)	–	–	−1.23 (−20.0 to 17.70)	−4.79 (−21.40 to 17.30)	−4.81 (−21.40 to 16.90)	−0.19 (−20.0 to 19.50)

Note:– Values with 95 % credible intervals are in parentheses.

Table 5
Summary of results for each species Number of observations events (N), camera station with observations (station), naïve occupancy, estimated station use (Ψ), and detection probability (p).

Data set	N	Station	Naïve occupancy	Ψ	p
Roe deer	228	45	0.87	0.87	0.76
Water deer	32	18	0.35	0.72	0.14
Wild boar	75	33	0.64	0.72	0.30
Badger	6	3	0.06	0.21	0.12
Raccoon dog	34	15	0.29	0.36	0.27
Leopard cat	32	17	0.33	0.41	0.23
Marten	2	2	0.04	0.05	0.14

Note:- Number of observations events (N), camera station with observations (station), naïve occupancy, estimated station use (Ψ), and detection probability (p).

(detected stations/total stations) (Table 5).

In all datasets, we observed variations in the station use probability (Ψ) and detection probability (p), which provide insights into the factors influencing species presence. Notably, the estimates of Ψ and p revealed species-specific patterns. Among the studied species, roe deer exhibited the highest station use probability ($\Psi = 0.87$) and detection probability ($p = 0.76$), with a relatively small discrepancy compared to naïve occupancy (0.87). In contrast, water deer had a relatively low detection probability ($p = 0.14$) and a station use probability ($\Psi = 0.72$) significantly different from naïve occupancy. Wild boar demonstrated an intermediate detection probability ($p = 0.30$) and a station use probability ($\Psi = 0.72$). Conversely, badger displayed the lowest detection probability ($p = 0.21$) and station use probability ($\Psi = 0.12$). The raccoon dog and leopard cat had their respective detection probabilities (p) of 0.27 and 0.23, with station use probabilities (Ψ) of 0.36 and 0.41. In contrast, martens, while less frequently detected, had an estimated detection probability ($p = 0.23$) and station use probability ($\Psi = 0.05$), both differing notably from naïve occupancy (0.04). These findings highlight the species-specific variations in detection and station use probabilities, shedding light on the ecological factors that influence their presence in the studied areas.

4. Discussion

Numerous studies have demonstrated that wind turbines negatively affect wildlife populations. This study is significant because it assessed the impact of a wind farm established along the ridge of a mountain within a forest. Furthermore, previous studies have focused on flying species directly harmed by wind turbines (Kunz et al., 2007; Baerwald et al., 2008; Pearce-Higgins et al., 2009). We assessed the indirect effects of environmental changes on terrestrial mammals resulting from the construction and expansion of managed roads built to maintain wind farm operations.

The negative effects of wind turbines on wildlife are still being reported, and the destructive effects of wind farm construction on wildlife habitats are undeniable (Klich et al., 2020; Kumara et al., 2022). Our study examined this impact using CTs installed at 52 stations on wind-farm management roads. Very few badgers and martens were detected at three and two stations, respectively. Herbivores (roe deer, water deer) had a higher station use probability on the wind turbine management road than carnivores (leopard cats). Some studies have shown that wind farms do not adversely affect Artiodactyla, including roe deer (Flydal et al., 2004; Walter et al., 2006). According to our occupancy model findings, wild mammals are near the study area's wind farm management roads. Higher road use affects wildlife behavior and can increase roadkill probabilities; therefore, continuous research and conservation priorities must be directed toward minimizing the risks to wildlife (Grilo et al., 2021; Medrano-Vizcaíno et al., 2023).

The detection probabilities were low for all species except roe deer, with the lowest detection probability for water deer. Classifying CT images can vary greatly depending on the image quality. Identifying species with distinct phenotypes is relatively easy because they can typically be performed with the naked eye. In the case of wild boars or roe deer, identification can be performed based on images captured at night, from a distance, or when the face is not visible. Furthermore, the CT data-acquisition process results in false negatives (a feature of image collection when an object passes in front of the camera). This problem is exacerbated in small rare species (Burton et al., 2015; Findlay et al., 2020). We used the occupancy model to resolve this issue, as this model minimizes false negatives for species with low detection rates using the detection probability. Consequently, for all species, the estimated probability of station use was slightly higher than the probability of naïve occupancy. This occupancy model has significant advantages over other approaches for species that are rare or difficult to identify using images (Rich et al., 2016; Cordier et al., 2022).

We used five different types of cameras for detection covariates and observed the significance of all the studied species except for wild boar. However, among camera types, there are variations in sensitivity, performance, and viewing distance; therefore, it is critical to minimize these differences in equipment performance when conducting CT research (Burton et al., 2015). Understanding how wildlife reacts to the altered land cover and degraded forest topography resulting from wind farm construction is critical. When a wind farm is built within a forest, complex management roads are constructed, intensifying changes in the topography and land cover (Diffendorfer and Compton, 2014). Procurve emerged as a notable factor in our analyses for all species except for roe deer station use. Similarly, forest land cover features were crucial in most species, except wild boars, leopard cats, and martens. These alterations in land cover and forest landscapes are particularly meaningful for species that move between habitats and for those with limited migratory tendencies, ultimately leading to the loss of suitable habitats.

When the spatial scale of land cover features was examined at a grid scale, the 10 m grid size was optimal for all species except for water deer and leopard cats. A grid size of 10 m is thought to be better than 30 m and 50 m grids for understanding the topographical changes caused by road management, as we believe that the variation in topographical properties around this road is significant for wildlife. However, because the leopard cat is relatively small compared to large mammals, there are no restrictions on its activity, and its activity levels are high; therefore, a large grid of 50 m was identified as the best model (Mohamed et al., 2013). We only analyzed grids of 10, 30, and 50 m; varying grid sizes and impact analyses are warranted for future research.

Water deer have a high probability of station use in areas with low forest cover. Water deer prefer early successional vegetation, which may be explained by the preference for understory vegetation around managed roads after construction over old forests (where there is little understory vegetation). The plane curve was a significant parameter in the leopard cat model with a 10 m grid size. The plane curve represents the topological curvature along the contour line. A positive value represents a convex topography, whereas a negative value represents a concave topography (Minár et al., 2020). Leopard cats exhibited a low station use probability in concave terrains (Table S00), which can be attributed to movement patterns in search of areas with gentle slopes while avoiding spaces that are difficult to traverse owing to changes in topography caused by wind farm construction.

Shrub cover was a significant determinant of the probability of detecting deer. Water deer prefer scrublands to man-made features on roads. Wild animals are assumed to choose locations with few obstacles and easy movement; therefore, they enter roads and move along them. However, relating these findings to species ecology or environmental variation is difficult. Furthermore, because all camera settings were identical and the installation locations were chosen randomly, there was a difference in the camera performance that could not be controlled.

This study illustrates the application of the occupancy model for examining station use and detection probabilities in a wind farm management road using the example of a Yeongyang-gun wind farm in South Korea with varying grid size effects. However, data on biodiversity before wind farm construction were lacking in our study; thus, before-and-after comparisons were impossible. Furthermore, it should be noted that our data explain the probability of using wind farm management roads, which differs from the probability of using the entire wind farm. To comply with the closed assumption of the occupancy model, the monitoring period of three months between October and December was short (MacKenzie and Royle, 2005). This study captured only short-term data owing to resource availability and gained insights into its impact on wildlife. In addition to addressing the limitations of this study, the impact of forest management roads on habitat fragmentation and connectivity could be a topic for future research.

5. Conclusion

Wind turbines continue to proliferate worldwide, along with the destruction of wild animal and plant habitats. Understanding the responses of terrestrial mammals to the current wind-farm management systems is critical. Management roads impede wildlife movement, and wind turbines cannot always be avoided. This short survey found that terrestrial mammals use wind-farm management roads in the forest. It was deduced that some species prefer these forested routes and that changes in topography have an impact on wild animals. Ecological tunnels that provide safe passages for animals to cross roads should be designed to minimize road detection and diversity loss. We also recommend the development of an appropriate wind farm management plan by analyzing the return rate of wild animals through continuous monitoring.

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Declaration of Competing Interest

- All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version.
- This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue.
- The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript.

Data Availability

Data will be made available on request.

References

Agha, M., Lovich, J.E., Ennen, J.R., Augustine, B., Arundel, T.R., Murphy, M.O., Meyer-Wilkins, K., Bjurlin, C., Delaney, D., Briggs, J., Austin, M., 2015. Turbines and terrestrial vertebrates: variation in tortoise survivorship between a wind energy facility and an adjacent undisturbed wildland area in the desert southwest (USA). Environ. Manag. 56, 332–341.

Agha, M., Smith, A.L., Lovich, J.E., Delaney, D., Ennen, J.R., Briggs, J., Fleckenstein, L.J., Tennant, L.A., Puffer, S.R., Walde, A., Arundel, T.R., 2017. Mammalian mesocarnivore visitation at tortoise burrows in a wind farm. J. Wildl. Manag. 8, 11117–11124.

Anile, S., Devillard, S., Ragni, B., Rovero, F., Mattucci, F., Valvo, M.L., 2019. M.L., 2019. Habitat fragmentation and anthropogenic factors affect wildcat *Felis silvestris silvestris* occupancy and detectability on Mt Etna. Wildl. Biol. 1–13.

Baerwald, E.F., D'Amours, G.H., Klug, B.J., Barclay, R.M.R., 2008. Barotrauma is a significant cause of bat fatalities at wind turbines. Curr. Biol. 18, R695–R696.

Bogdanović, N., Zedrosser, A., Hertel, A.G., Zarzo-Arias, A., Ćirović, D., 2023. Where to go? Habitat preferences and connectivity at a crossroad of European brown bear metapopulations. Glob. Ecol. Conserv. 43, e02460.

Brooks, S.P., Gelman, A., 1998. General methods for monitoring convergence of iterative simulations. J. Comput. Graph. Stat. 7, 434–455.

Burrough, P.A., McDonnell, R.A., Lloyd, C.D., 2015. Principles of Geographical Information Systems. Oxford University Press.

Burton, A.C., Neilson, E., Moreira, D., Ladle, A., Steenweg, R., Fisher, J.T., Bayne, E., Boutin, S., 2015. Wildlife camera trapping: a review and recommendations for linking surveys to ecological processes. J. Appl. Ecol. 52, 675–685.

Carrete, M., Sánchez-Zapata, J.A., Benítez, J.R., Lobón, M., Montoya, F., Donázar, J.A., 2012. Mortality at wind-farms is positively related to large-scale distribution and aggregation in griffon vultures. Biol. Conserv. 145, 102–108.

Cordier, C.P., Smith, D.A.E., Smith, Y.E., Downs, C.T., 2022. Camera trap research in Africa: a systematic review to show trends in wildlife monitoring and its value as a research tool. Glob. Ecol. Conserv., e02326

De Lucas, M., Janss, G.F., Ferrer, M., 2005. A bird and small mammal BACI and IG design studies in a wind farm in Malpica (Spain). Biodivers. Conserv. 14, 3289–3303.

Diffendorfer, J.E., Compton, R.W., 2014. Land cover and topography affect the land transformation caused by wind facilities. PLoS One 9, e88914.

Dorazio, R.M., Royle, J.A., 2005. Estimating size and composition of biological communities by modeling the occurrence of species. J. Am. Stat. Assoc. 100, 389–398.

Dormann, C.F., Calabrese, J.M., Guillera-Arroita, G., Matechou, E., Bahn, V., Bartoń, Hartig, F., 2018. Model averaging in ecology: a review of Bayesian, information-theoretic, and tactical approaches for predictive inference. Ecol. Monogr. 88, 485–504.
Findlay, M.A., Briers, R.A., White, P.J., 2020. Component processes of detection probability in camera-trap studies: understanding the occurrence of false-negatives. Mammal. Res. 65, 167–180.
Fiske, I., Chandler, R., 2011. Unmarked: An R package for fitting hierarchical models of wildlife occurrence and abundance. J. Stat. Soft 43, 1–23.
Flydal, K., Eftestøl, S., Reimers, E., Colman, J.E., 2004. Effects of wind turbines on area use and behaviour of semi-domestic reindeer in enclosures. Rangifer 24, 55–66.
Gelman, A., Carlin, J.B., Stern, H.S., Rubin, D.B., 1995. Bayesian Data Analysis. In: *Bayesian Data Anal.* Chapman Hall. /CRC. Hall/CRC, Chapman.
GlobalData, 2023, Power plant profile: Yeongyang Wind Farm_GS, South Korea. [WWW Document], URL https://www.power-technology.com/marketdata/power-plant-profile-yeongyang-wind-farmgs-south-korea/ (Accessed 8 November 2023).
Grilo, C., Borda-de-Água, L., Beja, P., Goolsby, E., Soanes, K., le Roux, A., Koroleva, E., Ferreira, F.Z., Gagné, S.A., Wang, Y., González-Suárez, M., 2021. Conservation threats from roadkill in the global road network. Glob. Ecol. Biogeogr. 30 (11), 2200–2210.
Hall, R., João, E., Knapp, C.W., 2020. Environmental impacts of decommissioning: Onshore versus offshore wind farms. Environ. Impact Assess. Rev. 83, 106404.
Husby, M., Pearson, M., 2022. Wind farms and power lines have negative effects on territory occupancy in Eurasian eagle owls (Bubo bubo). Animals 12, 1089.
Kellner, K., Meredith, M., Kellner, M.K., 2019. Package 'jagsUI.' A wrapper around Rjags" to streamline JAGS analyses R Package Version, 1.
Kéry, M., Royle, J.A., 2015. Applied Hierarchical Modeling in Ecology: Analysis of Distribution, Abundance and Species Richness in R and BUGS. Academic Press.
Kim, H.G., Kang, Y.H., Kim, J.Y., 2017. Evaluation of wind resource potential in mountainous region considering morphometric terrain characteristics. Wind Eng. 41, 114–123.
Klich, D., Łopucki, R., Ścibior, A., Gołębiowska, D., Wojciechowska, M., 2020. Roe deer stress response to a wind farms: methodological and practical implications. Ecol. Indic. 117, 106658.
Kucera, T.E., Barrett, R.H., O'Connell, A.F., Nichols, J.D., Karanth, K.U., 2011. Camera traps in animal ecology. In: Camera Traps in Animal Ecology: Methods and Analyses. Springer, New York City, pp. 9–26.
Kumara, H.N., Babu, S., Rao, G.B., Mahato, S., Bhattacharya, M., Rao, N.V.R., Tamiliniyan, D., Parengal, H., Deepak, D., Balakrishnan, A., 2022. Responses of birds and mammals to long-established wind farms in India. Sci. Rep. 12, 1–15.
Kunz, T.H., Arnett, E.P., Erickson, W.P., Hoar, A.R., Johnson, G.D., Larkin, R.P., Strickland, M.D., Thresher, R.W., Tuttle, M.D., 2007. Ecological impacts of wind energy development on bats: questions, research needs, and hypotheses. Front. Ecol. Environ. 5, 315–324.
Kuo, L., Mallick, B., 1998. Variable selection for regression models. Sankhyā: Indian J. Stat., Ser. B 65–81.
Łopucki, R., Klich, D., Gielarek, S., 2017. Do terrestrial animals avoid areas close to turbines in functioning wind farms in agricultural landscapes? Environ. Monit. Assess. 189, 1–11.
Lovich, J.E., Ennen, J.R., 2013. Assessing the state of knowledge of utility-scale wind energy development and operation on non-volant terrestrial and marine wildlife. Appl. Energy 103, 52–60.
MacKenzie, D.I., Nichols, J.D., 2004. Occupancy as a surrogate for abundance estimation Animal. Biodivers. Conserv. 27, 461–467.
MacKenzie, D.I., Royle, J.A., 2005. Designing occupancy studies: general advice and allocating survey effort. J. Appl. Ecol. 42, 1105–1114.
MacKenzie, D.I., Nichols, J.D., Lachman, G.B., Droege, S., Royle, J.A., Langtimm, C.A., 2002. Estimating site occupancy rates when detection probabilities are less than one. Ecology 83, 2248–2255.
MacKenzie, D.I., Nichols, J.D., Royle, J.A., Pollock, K.H., Bailey, L.L., Hines, J.E., 2017. Occupancy Estimation and Modeling: Inferring Patterns and Dynamics of Species Occurrence. Elsevier.
Masden, E.A., Cook, A.S., McCluskie, A., Bouten, W., Burton, N.H., Thaxter, C.B., 2021. When speed matters: the importance of flight speed in an avian collision risk model. Environ. Impact Assess. Rev.. 90, 106622.
Mazzamuto, M.V., Lo Valvo, M., Anile, S., 2019. The value of by-catch data: How species-specific surveys can serve non-target species. Eur. J. Wildl. Res. 65, 1–9.
Medrano-Vizcaíno, P., Grilo, C., Gonzalez-Suarez, M., 2023. Research and conservation priorities to protect wildlife from collisions with vehicles. Biol. Conserv. 280, 109952.
Minár, J., Evans, I.S., Jenčo, M., 2020. A comprehensive system of definitions of land surface (topographic) curvatures, with implications for their application in geoscience modelling and prediction. Earth Sci. Rev. 211, 103414.
Mohamed, A., Sollmann, R., Bernard, H., Ambu, L.N., Lagan, P., Mannan, S., Hofer, H., Wilting, A., 2013. Density and habitat use of the leopard cat (*Prionailurus bengalensis*) in three commercial forest reserves in Sabah, Malaysian Borneo. J. Mammal. 94, 82–89.
Mohankumar, N.M., Hefley, T.J., 2022. Using machine learning to model nontraditional spatial dependence in occupancy data. Ecology 103, e03563.
Murphy, A.J., Goodman, S.M., Farris, Z.J., Karpanty, S.M., Andrianjakarivelo, V., Kelly, M.J., 2017. Landscape trends in small mammal occupancy in the Makira–Masoala protected areas, northeastern Madagascar. J. Mammal. 98, 272–282.
Nazir, M.S., Bilal, M., Sohail, H., Liu, M., Chen, B.W., Iqbal, H.M., 2020. Impacts of renewable energy atlas: reaping the benefits of renewables and biodiversity threats. Int. J. Hydrog. Energy 45, 22113–22124.
Niedballa, J., Sollmann, R., Courtiol, A., Wilting, A., 2016. camtrapR: an R package for efficient camera trap data management. Methods Ecol. Evol. 7, 1457–1462.
Park, K.J., Turner, A., Minderman, J., 2013. Integrating applied ecology and planning policy: the case of micro-turbines and wildlife conservation. J. Appl. Ecol. 50, 199–204.
Pearce-Higgins, J.W., Stephen, L., Langston, R.H., Bainbridge, I.P., Bullman, R., 2009. The distribution of breeding birds around upland wind farms. J. Appl. Ecol. 46, 1323–1331.
Plummer, M., 2003. JAGS: a program for analysis of Bayesian graphical models using Gibbs sampling. 124, 1–10.
Potapov, P., Li, X., Hernandez-Serna, A., Tyukavina, A., Hansen, M.C., Kommareddy, A., Pickens, A., Turubanova, S., Tang, H., Silva, C.E., 2021. Mapping global forest canopy height through integration of GEDI and landsat data. Remote Sens. Environ. 253, 112165.
Rich, L.N., Miller, D.A., Robinson, H.S., McNutt, J.W., Kelly, M.J., 2016. Using camera trapping and hierarchical occupancy modelling to evaluate the spatial ecology of an African mammal community. J. Appl. Ecol. 53, 1225–1235.
Richmond, O.M., Hines, J.E., Beissinger, S.R., 2010. Two-species occupancy models: a new parameterization applied to co-occurrence of secretive rails. Ecol. Appl. 20, 2036–2046.
Rovero, F., Zimmermann, F., 2016. Camera Trapping for Wildlife Research. Pelagic Publishing.
Rowcliffe, J.M., Field, J., Turvey, S.T., Carbone, C., 2008. Estimating animal density using camera traps without the need for individual recognition. J. Appl. Ecol. 45, 1228–1236.
Schöll, E.M., Nopp-Mayr, U., 2021. Impact of wind power plants on mammalian and avian wildlife species in shrub-and woodlands. Biol. Conserv. 256, 109037.
Scully, A.E., Fisher, S., Miller, D.A., Thornton, D.H., 2018. Influence of biotic interactions on the distribution of Canada lynx (*Lynx canadensis*) at the southern edge of their range. J. Mammal. 99, 760–772.
Shannon, G., Lewis, J.S., Gerber, B.D., 2014. Recommended survey designs for occupancy modelling using motion-activated cameras: Insights from empirical wildlife data. PeerJ 2, e532.
Smith, K.T., Taylor, K.L., Albeke, S.E., Beck, J.L., 2020. Pronghorn winter resource selection before and after wind energy development in south-central Wyoming. Rangel. Ecol. Manag. 73, 227–233.
Spiegelhalter, D.J., Best, N.G., Carlin, B.P., van der Linde, A., 2002. Bayesian measures of model complexity and fit. J. R. Stat. Soc. B (Stat. Methodol.) 64, 583–639.
Team, R.C., 2020. R: A language and environment for statistical computing.
Teff-Seker, Y., Berger-Tal, O., Lehnardt, Y., Teschner, N., 2022. Noise pollution from wind turbines and its effects on wildlife: a cross-national analysis of current policies and planning regulations. Renew. Sustain. Energy Rev. 168, 112801.
Tobler, M.W., Carrillo-Percastegui, S.E., Leite Pitman, R., Mares, R., Powell, G., 2008. An evaluation of camera traps for inventorying large-and medium-sized terrestrial rainforest mammals. Anim. Conserv. 11, 169–178.

Tobler, M.W., Hartley, Z.úñiga, Carrillo-Percastegui, A., Powell, G.V, S.E., 2015. Spatiotemporal hierarchical modelling of species richness and occupancy using camera trap data. J. Appl. Ecol. 52, 413–421.

Trishchenko, A.P., Cihlar, J., Li, Z., 2002. Effects of spectral response function on surface reflectance and NDVI measured with moderate resolution satellite sensors. Remote Sens. Environ. 81, 1–18.

Walter, W.D., Leslie, D.M., Jenks, J.A., 2006. Response of rocky mountain elk (*Cervus elaphus*) to wind-power development. Am. Midl. Nat. 156, 363–375.

Wilson, M.F., O'Connell, B., Brown, C., Guinan, J.C., Grehan, A.J., 2007. Multiscale terrain analysis of multibeam bathymetry data for habitat mapping on the continental slope. Mar. Geod. 30, 3–35.