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Modeling current and future species distribution of breeding birds as regional essential biodiversity variables (SD EBVs): A bird perspective in Swiss Alps

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ABSTRACT

Changes in distribution and abundance of species affect the entirety of biodiversity and monitoring these changes is critical for the efficient conservation of integrity and functions of species population. However, acquiring accurate information on biodiversity over large spatial scales poses a challenge since such data is patchy and incomplete, if not unavailable, in many areas. This study aims at examining the applicability of a novel approach based on Species Distribution Models (SDMs) to develop spatial predictions of Essential Biodiversity variables (EBVs; variables to be quantified at certain points in time and space to monitor variations in biodiversity) for birds based on bird diversity metrics such as the distributions of properties of key bird habitats. A major objective of this study is to build bird SDMs which can be used to derive spatial EBVs for bird species at a regional scale. We used as predictors 16 environmental variables that are known to be ecologically meaningful for birds, including two bioclimatic variables (Bio17 = precipitation of driest quarter and Bio7 = temperature annual range) for three periods of 'current', 'future 2050′, and 'future 2070′, eleven land-cover (land use) predictors, the normalized difference vegetation index, and two topographic variables (slope and topography). We used multiple modeling techniques to build presence-only SDMs relating bird presence to environmental features of each species. Here, we show that the suitability estimated according to the SDMs can be used as a spatial 'species distribution' EBV (SD EBV) and reflect the habitat quality and trends in land use and climatic impacts on populations of bird species. These developments could facilitate monitoring of bird species across space and time, ultimately helping to identify priority conservation areas, estimate habitat suitability and provide early warning signs regarding bird distribution trends. In general, bioclimatic variables, topography and forest structure were identified to have important ties to the species probability maps generated on the basis of the SDMs, signifying a dominant role of bioclimatic variable Bio17 in the development of habitat suitability patterns.

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1. Introduction

Several studies have reported a global decline or local loss of biodiversity around the world (Butchart et al., 2010; Tittensor et al., 2014; Geijzendorffer et al., 2016; Turak et al., 2017a), but the available data, tools, and methods have been inadequate to reliably quantify this decline (Green et al., 2005; Turak et al., 2017b; Flitcroft et al., 2019). In addition, obtaining good-quality information on biodiversity across whole spatial extents poses a challenge because in many regions, such information is patchy and incomplete, if not unavailable (Cabeza and Moilanen, 2001; Soberón and Peterson, 2004; Hortal et al., 2007; Turak et al., 2017a). Biodiversity comprises many dimensions such as distribution, abundance, and composition, thus the key to successful monitoring is to identify the most essential variables (Wilsey et al., 2005; Feld et al., 2009; Pereira et al., 2013; Proença et al., 2017). For this reason, the concept of essential biodiversity variables (EBVs) (Pereira et al., 2013) was introduced to represent biological state variables or a group of linked variables that can be measurable at particular points in time and space to document biodiversity changes (Geijzendorffer et al., 2016; Pettorelli et al., 2016a; Schmeller et al., 2017; Haase et al., 2018; Fernández et al., 2020).

EBV attempts to identify key elements to be monitored, determine the rate and direction of biodiversity changes at different spatial scales and time intervals (Pereira et al., 2013; Geijzendorffer et al., 2016; Pettorelli et al., 2016b; Turak et al., 2017a; Kissling et al., 2018b; Zilioli et al., 2019), and develop a manageable list of priority measurements for evaluating biodiversity (Brummitt et al., 2017; Latombe et al., 2017; Vihervaara et al., 2017). For example, in forests, variables representing genetic composition, species population attributes, community traits or habitat structure can be considered as essential biodiversity variables that can be used by forest managers and policymakers to make appropriate economic and environmental management decisions (De Groot et al., 2010; Harrington et al., 2010).

Changes in distribution and abundance of species have an impact on all aspects of biodiversity and it is crucial to track such changes to effectively protect population connectivity, its significant traits and functions, and address the potential extinction threats to species (Pereira et al., 2010; Kissling et al., 2018a; Jetz et al., 2019). We are able to obtain such significant information within the EBV class of species population which is defined as a “space-time-species-gram (cube)” (Jetz et al., 2019) and is identified according to the three subclasses of species distribution, population abundance, and population structure (Pereira et al., 2013; Brummitt et al., 2017; Hardisty et al., 2019). The ‘species distribution’ EBV (SD EBV), as an EBV that is more attainable (Kissling et al., 2018a; Jetz et al., 2019), allows the development of indicators that reflect population trends, the extinction of threatened species, the spread of invasive species, and biodiversity responses to land use and climate change (Butchart et al., 2010; Kissling et al., 2018a; Jetz et al., 2019).

SD EBV can be estimated by predictive modeling, through the use of species distribution models (SDMs) (Guisan et al., 2006; Elith and Leathwick, 2009; Pettorelli et al., 2016a; Turak et al., 2017b; Kissling et al., 2018a), since such models statistically relate to the distributions of populations (Guisan et al., 2017). These models are useful numerical tools employed to integrate the observed abundance or occurrence of species and environmental predictors to predict species distributions, environmental suitability, or the probability of species occurrence across a landscape and provide great opportunities to learn about the past, current, and future distributions of species (Elith and Leathwick, 2009; Guillera-Arroita et al., 2015; GEO BON, 2015; Vermeiren et al., 2020; Smeraldo et al., 2021). Therefore, SDMs can characterize ecological niches using environmental predictors to predict the presence/absence of a species in the study area (Hirzel and Le Lay, 2008; Vihervaara et al., 2017; Jetz et al., 2019). The spatial patterns of species distributions can provide information regarding the rarity and potential extinction risk of species, which is essential to effective monitoring (Elith and Burgman, 2002; Rushton et al., 2004; Wilson et al., 2004). The Red List Index, for example, is partly composed of data on two different EBV variables, abundance of species and their distributions, that can reflect changes in species abundance and distribution and be used to monitor species conservation status across space and time (Pereira et al., 2013; Pettorelli et al., 2016a; Turak et al., 2017b; Schmeller et al., 2018).

While the primary focus has been on global and supranational monitoring, recent studies have attempted to shift the current focus from global and international monitoring to national and even local geographical application of EBVs, arguing that biodiversity is better understood at national or regional level in terms of “local eco-evolutionary processes” (Navarro et al., 2017; Turak et al., 2017b; Vihervaara et al., 2017; Peterson and Soberón, 2018). EBVs can also become more practical and informative at a national monitoring level, as high-quality biodiversity data are an essential component of environmental models that attempt to describe the ecosystem (Michener and Jones, 2012; Kissling et al., 2015; Turak et al., 2017a; Vihervaara et al., 2017).

This study aims to evaluate and demonstrate the applicability of SDMs to establish spatial predictions of the EBV candidate ‘species distribution’ for bird species based on bird diversity metrics, such as the distribution and abundance of properties of key bird habitats. Here, bird SDMs can be used as a spectrum from national to regional scales in the development of a spatial EBV for bird species as a regional indicator, as EBVs are scalable and tend to change in size and scale (Vihervaara et al., 2017). EBVs occurring between the raw bird data (14 bird species) and indicators (indices derived from the SD EBV) are expected to map current and future species distributions to identify areas of optimal habitat suitability.

We used occurrence data of 14 bird species (11 near threatened (NT) and 3 vulnerable species (VU) in the category of the Red List status) because one of the targets of EBV class of species population is providing data for indicators such as Red List indices (Pereira et al., 2013; Pettorelli et al., 2016a; Turak et al., 2017b; Schmeller et al., 2018). These data are used as raw data in the first step of the ‘derived and modeled EBV data’ workflow (Brummitt et al., 2016; Kissling et al., 2018a; Jetz et al., 2019), to consider the SD EBV on a regional scale and build spatial SDMs with applying 16 environmental variables at 100 m spatial resolution including eleven land-cover (land use) predictors, the normalized difference vegetation index (NDVI), two topographic variables (slope and topography), and two bioclimatic variables for three periods of ‘current’, ‘future 2050′, and ‘future 2070′. The key

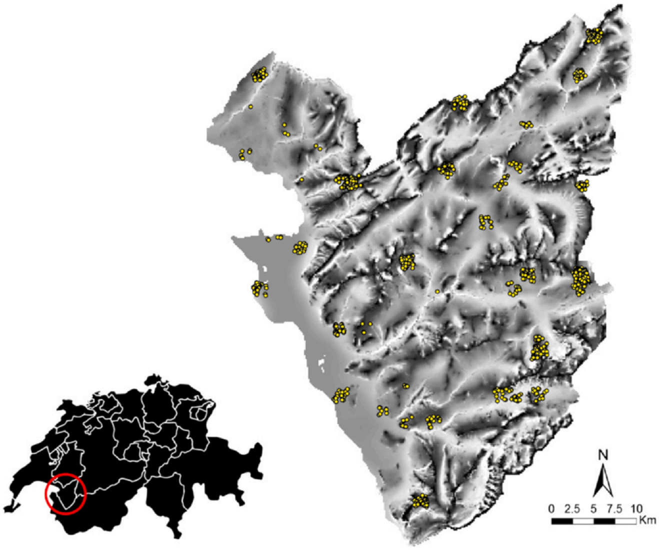

Fig. 1. Studied area and sampling points.

issues in this research are the following: (a) how to build bird SDMs in a mountain ecosystem that can be used to derive spatial SD EBVs for birds at a regional scale? (b) To provide potential distribution maps for three periods of 'current', 'future 2050′, and 'future 2070′ in response to land use and climate change. These developments could support the protection and management of bird species across space and time, ultimately help define bird protection and habitat suitability targets and provide early warning signs related to bird distribution patterns in the national red list.

2. Materials and methods

2.1. Study area and species data

The focus area of this study is a transdisciplinary research site in the western Swiss Alps in Vaud (46°10′ to 46°30′N; 6°50′ to 7°10′E; Fig. 1). It is a heterogeneous region that expands from Geneva Lake at 372 m above sea level to Pointe des Diablerets at 3210 m, with a total area of about 700 km^2 (Descombes et al., 2017; Scherrer et al., 2019). This region is exposed to human activities which includes the urbanization and intensive land use. It has been negatively affected by the development of tourism, sporting activities, and agriculture in the subalpine regions which are marked by a mosaic of meadows and forest patches (see http://rechalp.unil.ch; Randin et al., 2009; Scherrer et al., 2019; Amini Tehrani et al., 2020).

The bird data, obtained from the Swiss Institute of Ornithology, are collected from 1999 on an annual basis (Monitoring Häufige Brutvögel [MHB]; Schmid et al., 2004); for more information on the survey, see https://www.vogelwarte.ch/de/projekte/monitoring/monitoring-haeufige-brutvoegel). Systematic surveys, Swiss Breeding Bird Atlas 2013–2016 (Knaus et al., 2018) and Swiss Biodiversity Monitoring [BDM], an ongoing biodiversity monitoring program with annually updated information on bird species richness since 2001, provide data about the trends and changes in the population and range size of the most common species in their particular area. Surveys and monitoring programs follow the same methods employed by the Sempach's Common Breeding Bird Survey (MHB) of the Swiss Ornithological Institute (BDM Coordination Office, 2014). These data were collected using a systematic sampling design which involved 1263 sampling points in 267 quadrats each covering a grid cells of 1 km^2 across Switzerland. There are 39 quadrats located in our study area. Data were gathered three times from mid-April to mid-July (the breeding season) and twice for quadrats located above the timberline at an elevation of 2000 m. Surveys took about four hours and covered a transect of 4–6 kilometers along which several species of breeding birds were recorded according to visual observations or acoustic identification (Royle et al., 2007; Kéry and Royle, 2009).

A set of 14 bird species were used in this study, with 11 species known as near threatened (NT) and 3 vulnerable (VU) based on the national red list (Table S1). This classification allowed us to apply the research approach to a wide range of rare to poorly sampled bird species. Only species with greater than 20 occurrences have been considered, as species with fewer sample data are not regarded ideal for use in modeling due to errors associated with very limited sample size (Thuiller et al., 2005).

2.2. Environmental data

In our models, we used 16 environmental variables as predictors that are ecologically significant and affect birds as mobile species (Jaberg and Guisan, 2001). The data are collected from multiple sources at 100 m spatial resolution (Table 1; more

Table 1
Environmental variables. Description and name of each environmental variable used in the modeling process. The data were either provided by the OFS (Federal Office of Statistics) or OFT (Federal Office of Transports). For more detailed description of the variables, please refer to Supplementary.

Category	Name	Description – each layer is at a 100 M resolution	Source
Climatic	bio 17	Precipitation of Driest Quarter	Swisstopo OFT
	bio 7	Temperature Annual Range	Swisstopo OFT
Land cover	river	Binary map of river area	Swiss Federal Statistical Office, GEOSTAT, Swiss Land Use Statistics, DATASET, 2018
	arableland	Binary map of arable land area	Swiss Federal Statistical Office, GEOSTAT, Swiss Land Use Statistics, DATASET, 2018
	clearforest	Binary map of clear forest land area	Swiss Federal Statistical Office, GEOSTAT, Swiss Land Use Statistics, DATASET, 2018
	forestedge	Binary map of forest edge or tree line area	Swiss Federal Statistical Office, GEOSTAT, Swiss Land Use Statistics, DATASET, 2018
	lake	Binary map of lake area	Swiss Federal Statistical Office, GEOSTAT, Swiss Land Use Statistics, DATASET, 2018
	meadow	Binary map of meadow area	Swiss Federal Statistical Office, GEOSTAT, Swiss Land Use Statistics, DATASET, 2018
	swamp forest	Binary map of swamp forest area	Swiss Federal Statistical Office, GEOSTAT, Swiss Land Use Statistics, DATASET, 2018
	coniferous forest	Binary map of coniferous forest area	Swiss Federal Statistical Office, GEOSTAT, Swiss Land Use Statistics, DATASET, 2018
	vineyard	Binary map vineyard area	Swiss Federal Statistical Office, GEOSTAT, Swiss Land Use Statistics, DATASET, 2018
	broadleaves forest	Binary map of broad-leaved forest area	Swiss Federal Statistical Office, GEOSTAT, Swiss Land Use Statistics, DATASET, 2018
	building area	Binary map of building area	Swiss Federal Statistical Office, GEOSTAT, Swiss Land Use Statistics, DATASET, 2018
Others	NDVI	Normalized difference vegetation index at 100 m resolution. Aggregate from 10 m resolution	Swisstopo, SWISSIMAGE RS
Topographic	Slope	Slope inferred from a digital elevation model at a 25 m resolution. Aggregate to 100 m resolution	Swisstopo OFT
	Topo	Topography inferred from a digital elevation model at a 25 m resolution. Aggregate to 100 m resolution	Swisstopo OFT

information in Supplementary Information) and manipulated in ARCGIS 10.2 (Environmental System Research Institute, Inc.) or R 3.3 (R Core Team, 2016). These variables include two bioclimatic variables, Bio17 (precipitation of driest quarter) and Bio7 (temperature annual range) with data for the three periods of current, future 2050, and future 2070 derived from MeteoSwiss Grid-Data Products at 1 km resolution, eleven land-cover (land use) predictors including forest edge, arable land, coniferous forest, broadleaf forest, clear-cut forest, vineyard, building area, river, lake, meadow, and swamp forest, the proportion of each across the area is calculated with a land-cover layer (Swiss Federal Statistical Office, GEOSTAT, Swiss Land Use Statistics, DATASET, 2018) and reclassified into two classes of 1 or 0, and the normalized difference vegetation index (NDVI; Rouse et al., 1973) and two topographic variables: slope and topography. The variables were chosen as not to be too highly correlated (Spearman correlation < 0.7) (Dormann et al., 2013). For details regarding the environmental variables, see Table 1 and the Supplementary Methods.

2.3. Modeling

2.3.1. Species distribution models

The SDMs were constructed with modeling algorithms to explain the correlation between the bird occurrence data and geographically coincident environmental variables (Manel et al., 1999; Distler et al., 2015; Smeraldo et al., 2020; Zhu et al., 2020). We used multiple modeling techniques in the biomod2 package (Thuiller et al., 2016) to build presence-only SDMs for each species in R v3.3 (R Core Team, 2016) relating bird presence to the environmental variables (Brambilla and Ficetola, 2012; Guisan et al., 2017). Our choice of modeling techniques was aimed at capturing the variability in the different classes of algorithms (e.g., regression-based and regression-tree) and taking advantage of the use of different algorithms on the same platform (Meller et al., 2014). We combined the outputs from the different algorithms to obtain the best results (Guisan et al., 2017). SDMs include generalized linear models (GLMs), as an example of a parametric regression-based approach with a strong statistical foundation that is particularly useful for habitat suitability modeling (Austin, 2002; Guisan et al., 2002a, 2002b, 2017), multivariate adaptive regression splines (MARS; representing a regression technique providing an alternative regression-based method for fitting nonlinear responses using piecewise linear fits rather than smooth functions) (Elith et al., 2006; Leathwick et al., 2006), generalized boosting models (GBM; boosted regression trees, multivariate nonparametric regression and data-adaptive techniques) (McCaffrey et al., 2004), and random forest (RF; an ensemble learning technique based on combining a large set of decision trees) (Dobrowski et al., 2011; Vincenzi et al., 2011). All models were calibrated with presence-only data and 10,000 pseudo-absence records randomly selected (Wisz and Guisan, 2009; Breiner et al., 2015; Thuiller et al., 2016) with the disk parameter to prevent pseudo-absences selection within a radius of 1 km from a training presence (Scherrer et al., 2019).

As unbalanced prevalence reduces the accuracy of the models, the pseudo-absences were weighted equally to the presence (prevalence of 0.5; Ferrier et al., 2002; Thuiller et al., 2016; Guisan et al., 2017; Scherrer et al., 2019). Model accuracy was evaluated with a repeated split-sample procedure (10 times). An evaluation dataset was obtained by randomly drawing 30% of the records from the original dataset. The remaining 70% were used as training data to fit the models (Dube et al., 2014; Taleshi et al., 2019).

2.4. Projecting distributions

We used an ensemble of models fitted with different modeling techniques across the 14 bird species since the general predictions obtained from two or more models may show equal predictive performance, and also the combination of multiple modeling techniques' predictions could decrease uncertainty and perform generally better than individual modeling techniques (Araújo and New, 2007; Marmion et al., 2009; Engler et al., 2013).

To describe the current and future distributions of bird species, we projected the SDMs for all 14 species into a mean climate space (Hereford et al., 2017) for three time periods: the current time (1981–2010), future 2050 (2045–2074), and future 2070 (2070–2099). The models estimated the birds' distributions for the current time and projected them into the future given the bioclimatic predictors Bio7 and Bio17. This process resulted in three grid outputs (current, future 2050, and future 2070) for each species. To obtain the predicted species distribution maps for the current time, we stacked climatic suitability values across all SDMs and then averaged the suitability values (Distler et al., 2015; Fernandes et al., 2018). To generate probability maps (mean habitat suitability) for each time in the future (2050 and 2070), we considered the impact of climate change under the future emission scenario A2, which is commonly considered to be the worst-case scenario, describing a heterogeneous world with a continuously increasing global population. It is commonly seen as a scenario with four to five times more emission levels of CO_2 over 2000–99 when carbon emissions rise from around 350–850 ppm (Sheffield and Wood, 2008; Beaumont et al., 2008; Mokany et al., 2012). We then stacked the individual projected probabilities of all species predictions to yield the projected species distribution (Mateo et al., 2012).

2.4.1. Changes in species relative abundance

Predicted species abundance is related indirectly to how much habitat is maximally occupied by species and how much the probability of species occurrence is positively related to species abundance (Zurell et al., 2012; Van Couwenberghe et al., 2013; Ashcroft et al., 2017; Weber et al., 2017). Habitat suitability variations could be correlated with variations in the abundance of species, as species are more abundant in highly suitable habitats. Therefore, a positive indicator of habitat suitability could be the relative abundance of species and it could be used as an early warning indicator for population decreases and shrinkage in the species range (Ashcroft et al., 2017; Weber et al., 2017; Acevedo et al., 2017; Yu et al., 2020). The trends of the changes in species abundance can be used to monitor changes in the conservation status of species across time (Renwick et al., 2012; Thomas, 2005; Turak et al., 2017b). Predictions of the changes in species relative abundance were made for the current time, future 2050 and future 2070. Then, we used the criteria used for the identification of IUCN Red List categories (critical, endangered and vulnerable) for conservation purposes of species (Bibby et al., 2000).

2.5. Model performance

We used three statistics to evaluate the predictive performance of the models: the area under the receiver operating characteristic curve (AUC), which has been commonly used for measuring the performance of SDMs, the true skills statistic (TSS), and Cohen's kappa statistic (KAPPA) (Cohen, 1960; Allouche et al., 2006; Fernandes et al., 2019). These techniques were used to assess the agreement between the presence and pseudo-absence records and the predicted probability of occurrence (Elith et al., 2006) and analyze the uncertainty around the mean from different algorithms (ensemble models) (Barry and Elith, 2006; Van Niel and Austin, 2007; Guisan et al., 2017; Ancillotto et al., 2020; Sharma et al., 2021).

3. Result

3.1. Important predictors and model performance

When averaging the individual bird species distributions across all species, precipitation of driest quarter (Bio17), coniferous forest (coniferous), and topography (topo) were the variables showing the greatest relative contributions to the model fits (0.16, 0.14, and 0.13, respectively) (Fig. 2). For the near-threatened (NT) species, Bio17 (0.17), topo (0.10) and forest edge (0.10) showed a positive relationship with the species probability maps, while for vulnerable (VU) species, coniferous (0.20), topo (0.15), Bio17 (0.14) were the most important predictors. In the SDMs, bioclimatic variables generally had a significant relationship with the species probability maps, suggesting that Bio17 plays a dominant role in shaping patterns of habitat suitability.

The SDMs with ROC, KAPPA, and TSS scores of 0.71, 0.38, and 0.67, respectively, and a mean AUC score = 0.71 had good performance in predicting the distributions of bird species (Araújo et al., 2005) (Figs. 3, 4).

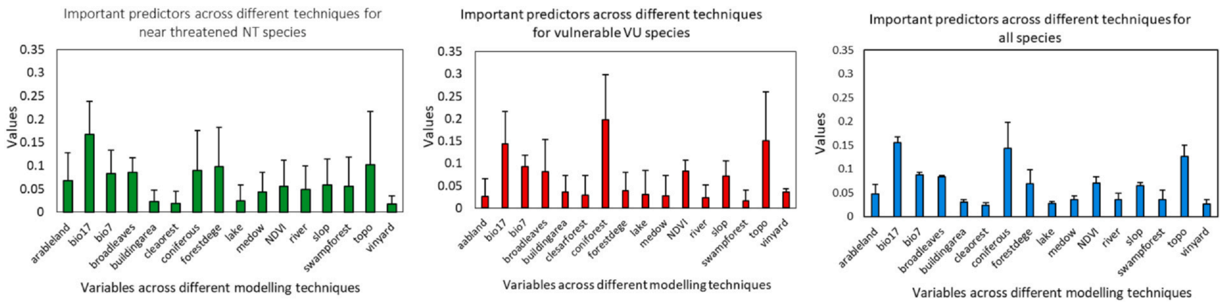

Fig. 2. Variable important across 14 bird species.

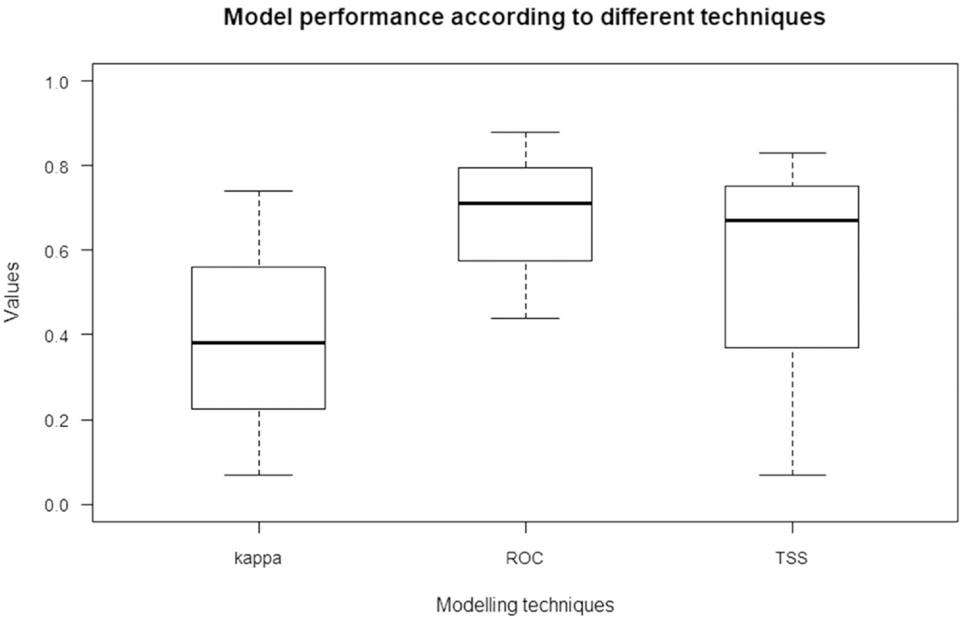

Fig. 3. Model performance across different modeling techniques.

3.2. Current and future patterns of species distributions

The SDMs provided relatively the same estimated patterns of current and future distributions across the two groups of species (near threatened (NT) and vulnerable (VU)) (Fig. 5). The estimated habitat suitability at the current time peaked in the eastern part of the study area, along the highland area, agricultural area and forest edge; conversely, lower latitudes and areas with lower elevations supported fewer species. In the future (2050), the species distributions are expected to increase across sections of the central, northern and southeastern parts of the study area according to the SDMs, and suitable habitat is projected to extend into these parts of the study area at high altitudes. In 2070, higher altitudes and areas with higher elevations are expected to support more species across most of the eastern and southern parts of the study area and into northern parts. These results suggest that in the future, higher altitudes in the study area will support more species, especially in the eastern part.

3.3. Changes in current and future species relative abundance

The results highlight that the relative abundance of all 14 evaluated species except for *Tetrao tetrix* (Black Grouse) and *Emberiza cirlus* (Cirl Bunting) will gradually increase from the current time to the future (2050 and 2070) (Fig. 6). *T. tetrix* showed a decline in relative abundance of 9.10% between 2050 and 2070 (20 years), and for *Emberiza cirlus*, there was a small decrease (0.17%) between the current and future times (2050), with a decrease of 1.41% between 2050 and 2070 (Fig. 6). These species could thus be in danger in 2070, especially *T. tetrix*, which could become vulnerable (VU) by 2070, as this species was predicted to lose 10% of its abundance over 20 years (IUCN, 2010). The abundances of *Alectoris graeca*, *Delichon urbicum*, and

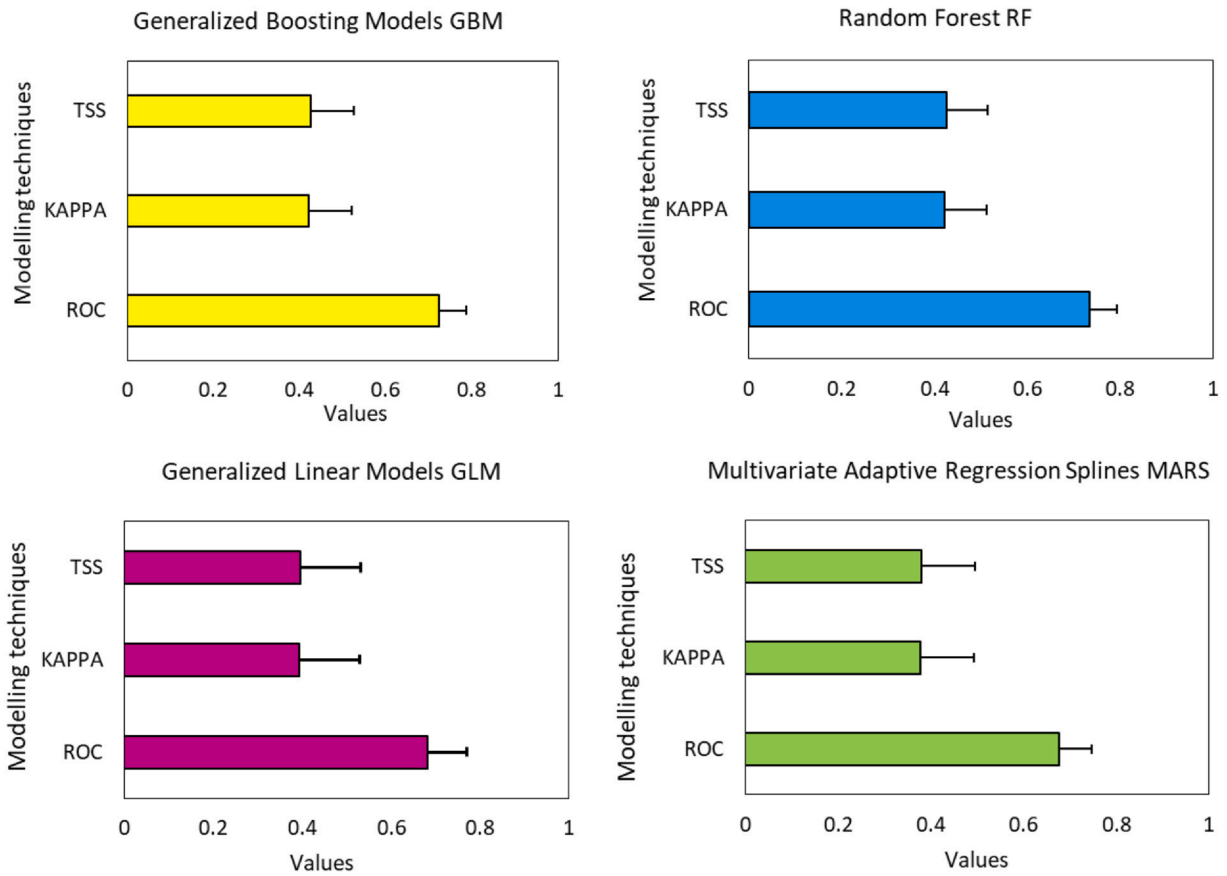

Fig. 4. Model performance across different modeling techniques.

Sylvia borin were predicted to increase negligibly from the current time to the future (2050) and to experience a slight declining trend between 2050 and 2070. Thus, for these three species, a nonsignificant change from the beginning of the current time to 2070 is expected to occur, and the trend of species abundance during the three evaluated times will change approximately insignificantly.

4. Discussion

A major focus of this work was to consider EBVs at a regional scale (the western Swiss Alps) by building spatial SDMs, evaluate the response of bird species to land use and climate change, map current and future species distributions to identify areas of optimal habitat suitability (Elith and Leathwick, 2009; Riordan and Rundel, 2014; Alcaraz-Segura et al., 2017; Kissling et al., 2018a; Jetz et al., 2019), identify priority conservation areas for bird species (Elith et al., 2006; Gogol-Prokurat, 2011), and ultimately provide useful information for conservation planning (Brotons et al., 2004; Johnson and Gillingham, 2005). As a partial consideration of the SD EBV, it was also important to explore which barriers currently and, in the future, negatively affect regional species distributions (Hijmans and Graham, 2006; Jetz et al., 2012; Pereira et al., 2013). Therefore, these models and distribution maps involving the SD EBV on a regional scale can be used as comprehensive and practical tools for biodiversity conservation decisions (Geijzendorffer et al., 2016; Turak et al., 2017b).

4.1. Variable importance and species distribution maps

Our results are consistent with the finding that the most important variables are the bioclimatic variable of precipitation of driest quarter (Bio17), subalpine forest (coniferous forest), and topography. These variables are positively related to the occurrence probability of the species (Hatchwell et al., 1996; Chamberlain et al., 2013; Maggini et al., 2014), and most of the species considered in this study inhabit in alpine, subalpine, flower meadow, and montane forest edge habitat and brood on the ground in mown meadows in highland areas. Therefore, conservation efforts should be focused on these areas to optimize

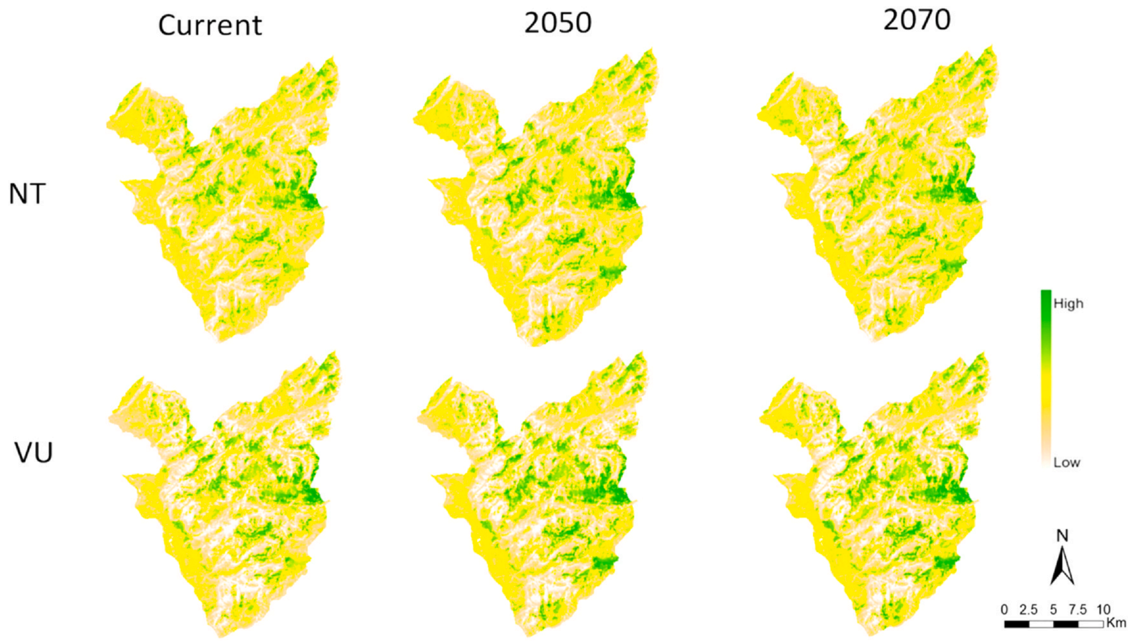

Fig. 5. Prediction maps of the two groups of bird species Vulnerable (VU) and Near Threatened (NT) across different times current, future 2050 and feature 2070.

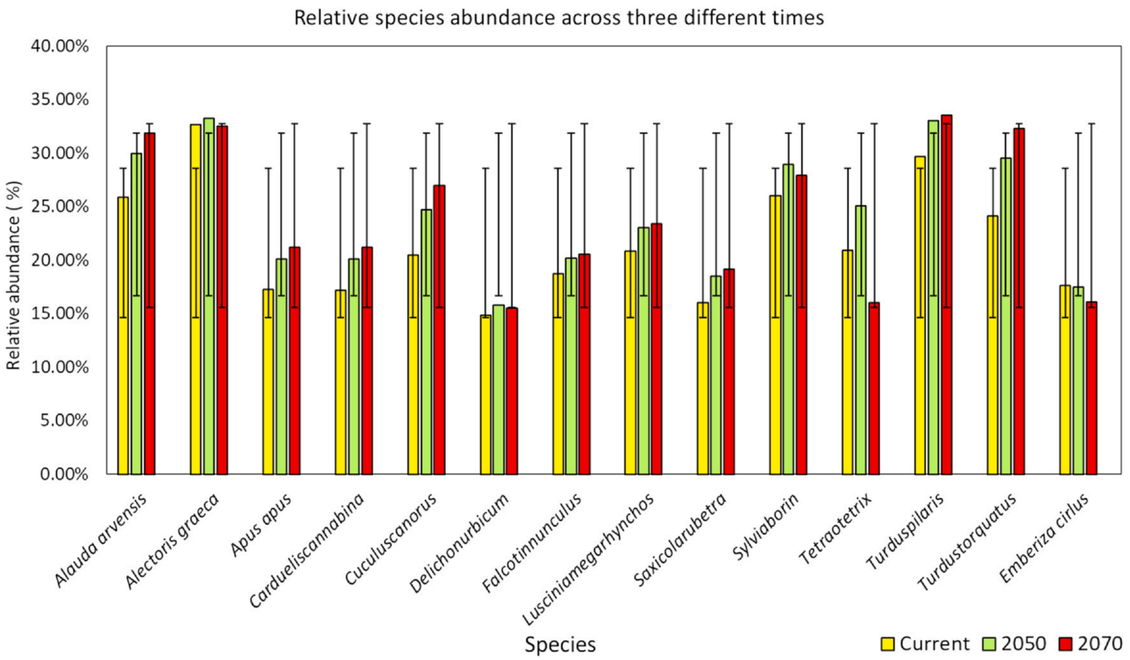

Fig. 6. Relative abundance of the two groups of bird species (vulnerable (VU)) and near threatened (NT)) at different times: current, future (2050) and future (2070).

habitat for the specie (Müller et al., 2005; Berger-Flückiger et al., 2008; Horch and Spaar, 2010, 2016; Liedvogel, 2018). Breeding birds in Switzerland's coniferous woodlands and alpine ecosystems are considerably more sensitive to changes in climate and land use than other species (Maggini et al., 2014). In May and June (breeding season), temperatures are high and little rainfall occurs, causing many alpine birds to temporarily move to higher altitudes (Maggini et al., 2011; Reif and Flousek, 2012; Chamberlain et al., 2013; Sattler et al., 2017). Therefore, species will benefit from warmer temperatures and eventually extend their habitat scale to higher elevations (Hughes, 2000; Parmesan and Yohe, 2003; von dem Bussche et al., 2008; Maggini et al., 2011). Thus, significant dependence on bioclimatic variables was identified, reflecting the altitudinal range and the corresponding forest structure favored by the species (von dem Bussche et al., 2008). These results are consistent with predictions from climate-based hypotheses, which suggest that upward shifts in bird distributions in the future are expected to result from climate warming and that these species track climate change (Maggini et al., 2011; Chen et al., 2011; Zbinden and Haller, 2013; Roth et al., 2014). The findings of this study reveal that bird populations would possibly be impacted by climate change during the breeding season due to the seasonal rise in temperature therefore we can say that in the western Swiss Alps, climate, specifically, temperature, is the key driver of bird distributions, such that slight variations in temperature can cause bird species to ascend in elevation during the breeding season.

4.2. Species abundance

By 2070, the population size and occupied area for most of the species were predicted to be primarily controlled by currently positive population growth and gradually increased from the beginning of the current time to the future (2050 and 2070) across climate scenario (A2) and SDM algorithms.

Predictions of species abundance from the current time to the future show that all species except *T. tetrix* (Black Grouse) have no risk of extinction. The Black Grouse (*T. tetrix*) is an example of a species that sensitively reacts to the abandonment of alpine summer pastures and the subsequent intrusion of shrubs and trees (Signorell et al., 2010; Patthey et al., 2012; Zurell et al., 2012). Therefore, activities on timberline grasslands including excessive grazing of cattle and mowing of meadows lead to the invasion of shrubs and forest through traditional grazing which decreases the heterogeneity of habitat and impacts biodiversity adversely (Dullinger et al., 2003; Maurer et al., 2006; Patthey et al., 2012; Braunisch et al., 2016). It could be considered as indirect negative anthropogenic effects on species which perform through variation in habitat quality based on changes of vegetation. (Wegge and Kastdalen, 2008; Patthey et al., 2012). Therefore, Black Grouse need a mosaic of multiple and various vegetation types at a broad habitat matrix (Pearce-Higgins et al., 2007; Patthey et al., 2012; Braunisch et al., 2016).

The Black Grouse occupies the same narrow altitudinal belt around the timberline where snow-sports activities generally occur (Menoni and Magnani, 1998; Zeitler and Glanzer, 1998; Zeitler, 2000; Arlettaz et al., 2013). Winter sports bring species disruptions and stress, and species population may be significantly diminished by human activity. Therefore, in order to support the protection of the Black Grouse, monitoring and conservation programs should be established (Baltic et al., 2005; Formenti et al., 2015; Arlettaz et al., 2015).

The easiest and most promising approach to date has been the construction of winter refuges that mitigate encounters between snow-sport players and Black Grouse (Braunisch et al., 2011; Arlettaz et al., 2013, 2015). The development of wildlife refuges has considered being an important strategy by restricting human access to key areas for vulnerable or endangered species (Whitfield et al., 2008; Braunisch et al., 2011; Arlettaz et al., 2013). We could conclude that structural elements are important to the understanding of the occurrence of the species and the temperature and altitude factors for these species are less essential (Patthey et al., 2012; Braunisch et al., 2016).

5. Conclusion

This work ultimately allows us to consider the SD EBV at the regional scale in accordance with model-based evaluation (SDM) to predict and monitor ongoing and future changes in bird species distributions as a part of the Switzerland indicator assessment that is occurring in the study area and to measure bird responses to environmental changes for three periods of time. We now understand how and why species are distributed across space and time and the relationships between species and their environment in such a heterogeneous study area. Therefore, the patterns of the spatial distribution of species as a partial SD EBV or the path toward national implementation can inform us about rarity and potential extinction risk for species and are essential for effective monitoring (Walters et al., 2013; Pereira et al., 2017; Jetz et al., 2019). This study also demonstrates the importance of low temperatures at high elevations and forest structures for bird species in a mountainous area.

Despite years of coordination to address the loss of bird diversity, losses of species and their habitats continue to occur. Therefore, to successfully prevent species distribution loss, urgent progress on methods for tracking and reporting bird distribution changes is needed (Gaston et al., 2003; Jetz et al., 2007). As national and global information on bird species distributions could be essential, reporting and managing bird species providing an overview of bird distribution trends in different time periods can indicate whether suitability obtained through SDMs on a regional scale can be used as a small part or a spectrum of national to subnational indicators of a spatial 'species distribution' EBV (SD EBV) for bird species (Brummitt et al., 2017; Latombe et al., 2017; Jetz et al., 2019). Several challenges remain to be solved when building species distribution EBVs. For example, models and standards have been developed to predict the distributions of birds across species and scales through the remote sensing of habitat cover (satellite remote sensing), as such information plays a crucial role in building species distribution EBVs and is ideal for evaluating biodiversity changes (Vihervaara et al., 2017; Proença et al., 2017; Kissling et al., 2018a;

Dantas de Paula et al., 2019). EBV frameworks are applicable to a broad range of spatial, temporal and taxonomic scales (Zilioli et al., 2019), and we hope that our study contributes to fostering further research on EBVs.

Author Contributions

NAT designed the study, applied the methodology, and analyzed data with input from all authors. NAT led the writing of the manuscript. All authors contributed critically to the drafts and revised, read, and approved the final manuscript.

Data Availability Statement

The data that support the findings of this study are available from the Swiss Ornithological Institute but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available.

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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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.gecco.2021.e01596.

References

Acevedo, P., Ferreres, J., Escudero, M.A., Jimenez, J., Boadella, M., Marco, J., 2017. Population dynamics affect the capacity of species distribution models to predict species abundance on a local scale. Divers. Distrib. 23 (9), 1008–1017.
Alcaraz-Segura, D., Lomba, A., Sousa-Silva, R., Nieto-Lugilde, D., Alves, P., Georges, D., Honrado, J.P., 2017. Potential of satellite-derived ecosystem functional attributes to anticipate species range shifts. Int. J. Appl. Earth Obs. Geoinf. 57, 86–92.
Allouche, O., Tsoar, A., Kadmon, R., 2006. Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). J. Appl. Ecol. 43, 1223–1232. https://doi.org/10.1111/j.1365-2664.2006.01214. x
Amini Tehrani, N., Naimi, B., Jaboyedoff, M., 2020. Toward community predictions: multi-scale modelling of mountain breeding birds' habitat suitability, landscape preferences, and environmental drivers. Ecol. Evol.
Ancillotto, L., Bosso, L., Smeraldo, S., Mori, E., Mazza, G., Herkt, M., Russo, D., 2020. An African bat in Europe, Plecotus gaisleri: biogeographic and ecological insights from molecular taxonomy and Species Distribution Models. Ecol. Evol. 10 (12), 5785–5800.
Araújo, M.B., New, M., 2007. Ensemble forecasting of species distributions. Trends Ecol. Evol. 22 (1), 42–47. https://doi.org/10.1016/j.tree.2006.09.010
Araújo, M.B., Pearson, R.G., Thuiller, W., Erhard, M., 2005. Validation of species–climate impact models under climate change. Glob. Chang. Biol. 11 (9), 1504–1513.
Arlettaz, R., Patthey, P., Braunisch, V., 2013. Impacts of outdoor winter recreation on alpine wildlife and mitigation approaches: a case study of the Black Grouse. In: Rixen, C., Rolando, A. (Eds.), The Impacts of Skiing and Related Winter Recreational Activities on Mountain Environments, pp. 137–154.
Arlettaz, R., Nusslé, S., Baltic, M., Vogel, P., Palme, R., Jenni-Eiermann, S., Genoud, M., 2015. Disturbance of wildlife by outdoor recreation. Bull. Ecol. Soc. Am. 96 (3), 475–477.
Ashcroft, M.B., King, D.H., Raymond, B., Turnbull, J.D., Wasley, J., Robinson, S.A., 2017. Moving beyond presence and absence when examining changes in species distributions. Glob. Chang. Biol. 23 (8), 2929–2940.
Austin, M.P., 2002. Spatial prediction of species distribution: an interface between ecological theory and statistical modelling. Ecol. Model. 157, 101–118.
Baltic, M., Jenni-Eiermann, S.U.S.A.N.N.E., Arlettaz, R., Palme, R., 2005. A noninvasive technique to evaluate human-generated stress in the black grouse. Ann. N. Y. Acad. Sci. 1046 (1), 81–95.
Barry, S., Elith, J., 2006. Error and uncertainty in habitat models. J. Appl. Ecol. 43 (3), 413–423.
BDM Coordination Office, 2014. Swiss Biodiversity Monitoring BDM. Description of Methods and Indicators (Federal Office for the Environment, Bern, Switzerland), pp. 1–104.
Beaumont, L.J., Hughes, L., Pitman, A.J., 2008. Why is the choice of future climate scenarios for species distribution modelling important? Ecol. Lett. 11 (11), 1135–1146.
Berger-Flückiger, A.N.N.E., Horch, P., BIBER, O., 2008. Diesse (Jura Bernois, Suisse) between 1972 and 2007. Nos Oiseaux, 55, pp. 99–108.
Bibby, C., Jones, M., Marsden, S., 2000. Bird Surveys. Birdlife International, Cambridge, UK, pp. 137.
Brambilla, M., Ficetola, G.F., 2012. Species distribution models as a tool to estimate reproductive parameters: a case study with a passerine bird species. J. Anim. Ecol. 81 (4), 781–787.
Braunisch, V., Patthey, P., Arlettaz, R., 2011. Spatially explicit modeling of conflict zones between wildlife and snow sports: prioritizing areas for winter refuges. Ecol. Appl. 21 (3), 955–967.
Braunisch, V., Patthey, P., Arlettaz, R., 2016. Where to combat shrub encroachment in alpine timberline ecosystems: combining remotely-sensed vegetation information with species habitat modelling. PLoS One 11 (10), 0164318.
Breiner, F.T., Guisan, A., Bergamini, A., Nobis, M.P., Anderson, B., 2015. Overcoming limitations of modelling rare species by using ensembles of small models. Methods Ecol. Evol. 6, 1210–1218. https://doi.org/10.1111/2041-210X.12403
Brotons, L., Thuiller, W., Araújo, M.B., Hirzel, A.H., 2004. Presence-absence versus presence-only modelling methods for predicting bird habitat suitability. Ecography 27 (4), 437–448.
Brummitt, N., Aletrari, E., Syfert, M.M., Mulligan, M., 2016. Where are threatened ferns found? Global conservation priorities for pteridophytes. J. Syst. Evol. 54 (6), 604–616.

Brummitt, N., Regan, E.C., Weatherdon, L.V., Martin, C.S., Geijzendorffer, I.R., Rocchini, D., Schmeller, D.S., 2017. Taking stock of nature: essential biodiversity variables explained. Biol. Conserv. 213, 252–255.
Butchart, S.H., Walpole, M., Collen, B., Van Strien, A., Scharlemann, J.P., Almond, R.E., Carpenter, K.E., 2010. Global biodiversity: indicators of recent declines. Science 328 (5982), 1164–1168.
Cabeza, M., Moilanen, A., 2001. Design of reserve networks and the persistence of biodiversity. Trends Ecol. Evol. 16 (5), 242–248.
Chamberlain, D.E., Negro, M., Caprio, E., Rolando, A., 2013. Assessing the sensitivity of alpine birds to potential future changes in habitat and climate to inform management strategies. Biol. Conserv. 167, 127–135.
Chen, I.C., Hill, J.K., Ohlemüller, R., Roy, D.B., Thomas, C.D., 2011. Rapid range shifts of species associated with high levels of climate warming. Science 333 (6045), 1024–1026.
Cohen, J., 1960. A coefficient of agreement for nominal scales. Educ. Psychol. Meas. 20, 37–46. https://doi.org/10.1177/001316446002000104
Dantas de Paula, M., Gómez Giménez, M., Niamir, A., Thurner, M., Hickler, T., 2019. Combining European Earth Observation products with dynamic global vegetation models for estimating essential biodiversity variables. Int. J. Digit. Earth 1–16.
De Groot, R.S., Alkemade, R., Braat, L., Hein, L., Willemen, L., 2010. Challenges in integrating the concept of ecosystem services and values in landscape planning, management and decision making. Ecol. Complex. 7 (3), 260–272.
von dem Bussche, J., Spaar, R., Schmid, H., Schröder, B., 2008. Modelling the recent and potential future spatial distribution of the Ring Ouzel (Turdus torquatus) and Blackbird (T. merula) in Switzerland. J. Ornithol. 149 (4), 529–544.
Descombes, P., Vittoz, P., Guisan, A., Pellissier, L., 2017. Uneven rate of plant turnover along elevation in grasslands. Alp. Bot. 127 (1), 53–63.
Distler, T., Schuetz, J.G., Velásquez-Tibatá, J., Langham, G.M., 2015. Stacked species distribution models and macroecological models provide congruent projections of avian species richness under climate change. J. Biogeogr. 42 (5), 976–988.
Dobrowski, S.Z., Thorne, J.H., Greenberg, J.A., Safford, H.D., Mynsberge, A.R., Crimmins, S.M., Swanson, A.K., 2011. Modeling plant ranges over 75 years of climate change in California, USA: temporal transferability and species traits. Ecol. Monogr. 81 (2), 241–257.
Dormann, C.F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carre, G., Lautenbach, S., 2013. Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography 36, 27–46. https://doi.org/10.1111/j.1600–0587.2012. 07348.x
Dube, T., Mutanga, O., Elhadi, A., Ismail, R., 2014. Intra-and-inter species biomass prediction in a plantation forest: testing the utility of high spatial resolution spaceborne multispectral rapideye sensor and advanced machine learning algorithms. Sensors 14 (8), 15348–15370.
Dullinger, S., Dirnböck, T., Grabherr, G., 2003. Patterns of shrub invasion into high mountain grasslands of the Northern Calcareous Alps, Austria. Arct. Antarct. Alp. Res. 35 (4), 434–441.
Elith, J., Burgman, M.A., 2002. Predictions and their validation: rare plants in the Central Highlands, Victoria, Australia. In: Predicting Species Occurrences: Issues of Accuracy and Scale, pp. 303–314.
Elith, J., Leathwick, J.R., 2009. Species distribution models: ecological explanation and prediction across space and time. Annu. Rev. Ecol. Evol. Syst. 40, 677–697.
Elith H., J., Graham P., C., Anderson, R., Dudík, M., Ferrier, S., Guisan, A., Li, J., 2006. Novel methods improve prediction of species' distributions from occurrence data. Ecography 29 (2), 129–151.
Engler, R., Waser, L.T., Zimmermann, N.E., Schaub, M., Berdos, S., Ginzler, C., Psomas, A., 2013. Combining ensemble modeling and remote sensing for mapping individual tree species at high spatial resolution. For. Ecol. Manag. 310, 64–73.
Feld, C.K., Martins da Silva, P., Paulo Sousa, J., De Bello, F., Bugter, R., Grandin, U., Pärtel, M., 2009. Indicators of biodiversity and ecosystem services: a synthesis across ecosystems and spatial scales. Oikos 118 (12), 1862–1871.
Fernandes, R.F., Scherrer, D., Guisan, A., 2018. How much should one sample to accurately predict the distribution of species assemblages? A virtual community approach. Ecol. Inform. 48, 125–134.
Fernandes, R.F., Scherrer, D., Guisan, A., 2019. Effects of simulated observation errors on the performance of species distribution models. Divers. Distrib. 25 (3), 400–413.
Fernández, N., Ferrier, S., Navarro, L.M., Pereira, H.M., 2020. Essential biodiversity variables: integrating in-situ observations and remote sensing through modeling. Remote Sensing of Plant Biodiversity. Springer, Cham, pp. 485–501.
Ferrier, S., Drielsma, M., Manion, G., Watson, G., 2002. Extended statistical approaches to modelling spatial pattern in biodiversity in northeast New South Wales. II. Community-level modelling. Biodivers. Conserv. 11, 2309–2338. https://doi.org/10.1023/A:10213 02930424
Flitcroft, R., Cooperman, M.S., Harrison, I.J., Juffe-Bignoli, D., Boon, P.J., 2019. Theory and practice to conserve freshwater biodiversity in the Anthropocene. Aquat. Conserv. Mar. Freshw. Ecosyst. 29 (7), 1013–1021.
Formenti, N., Viganó, R., Bionda, R., Ferrari, N., Trogu, T., Lanfranchi, P., Palme, R., 2015. Increased hormonal stress reactions induced in an Alpine Black Grouse (Tetrao tetrix) population by winter sports. J. Ornithol. 156 (1), 317–321.
Gaston, K.J., Blackburn, T.M., Goldewijk, K.K., 2003. Habitat conversion and global avian biodiversity loss. Proc. R. Soc. Lond. Ser. B Biol. Sci. 270 (1521), 1293–1300.
Geijzendorffer, I.R., Regan, E.C., Pereira, H.M., Brotons, L., Brummitt, N., Gavish, Y., Schmeller, D.S., 2016. Bridging the gap between biodiversity data and policy reporting needs: an Essential Biodiversity Variables perspective. J. Appl. Ecol. 53 (5), 1341–1350.
GEO BON, 2015. Global Biodiversity Change Indicators. Version 1.2. Group on Earth Observations Biodiversity Observation Network Secretariat. Leipzig, 20 pages.
Gogol-Prokurat, M., 2011. Predicting habitat suitability for rare plants at local spatial scales using a species distribution model. Ecol. Appl. 21 (1), 33–47.
Green, R.E., Balmford, A., Crane, P.R., Mace, G.M., Reynolds, J.D., Turner, R.K., 2005. A framework for improved monitoring of biodiversity: responses to the World Summit on Sustainable Development. Conserv. Biol. 19 (1), 56–65.
Guillera-Arroita, G., Lahoz-Monfort, J.J., Elith, J., Gordon, A., Kujala, H., Lentini, P.E., Wintle, B.A., 2015. Is my species distribution model fit for purpose? Matching data and models to applications. Glob. Ecol. Biogeogr. 24 (3), 276–292.
Guisan, A., Edwards Jr., T.C., Hastie, T., 2002a. Generalized linear and generalized additive models in studies of species distributions: setting the scene. Ecol. Model. 157, 89–100. https://doi.org/10.1016/S0304-3800(02)00204-1
Guisan, A., Edwards Jr., T.C., Hastie, T., 2002b. Generalized linear and generalized additive models in studies of species distributions: setting the scene. Ecol. Model. 157 (2–3), 89–100.
Guisan, A., Lehmann, A., Ferrier, S., Austin, M., Overton, J.M.C., Aspinall, R., Hastie, T., 2006. Making better biogeographical predictions of species' distributions. J. Appl. Ecol. 43 (3), 386–392.
Guisan, A., Thuiller, W., Zimmermann, N.E., 2017. Habitat Suitability and Distribution Models: With Applications in R. Cambridge University Press.
Haase, P., Tonkin, J.D., Stoll, S., Burkhard, B., Frenzel, M., Geijzendorffer, I.R., Mirtl, M., 2018. The next generation of site-based long-term ecological monitoring: linking essential biodiversity variables and ecosystem integrity. Sci. Total Environ. 613, 1376–1384.
Hardisty, A.R., Michener, W.K., Agosti, D., García, E.A., Bastin, L., Belbin, L., De Giovanni, R., 2019. The Bari Manifesto: an interoperability framework for essential biodiversity variables. Ecol. Inform. 49, 22–31 (dimension).
Harrington, R., Anton, C., Dawson, T.P., de Bello, F., Feld, C.K., Haslett, J.R., Rounsevell, M.D., 2010. Ecosystem services and biodiversity conservation: concepts and a glossary. Biodivers. Conserv. 19 (10), 2773–2790.
Hatchwell, B.J., Chamberlain, D.E., Perrins, C.M., 1996. The demography of blackbirds Turdus merula in rural habitats: is farmland a sub-optimal habitat? J. Appl. Ecol. 33, 1114–1124.
Hereford, J., Schmitt, J., Ackerly, D.D., 2017. The seasonal climate niche predicts phenology and distribution of an ephemeral annual plant, Mollugo verticillata. J. Ecol. 105 (5), 1323–1334.
Hijmans, R.J., Graham, C.H., 2006. The ability of climate envelope models to predict the effect of climate change on species distributions. Glob. Chang. Biol. 12 (12), 2272–2281.
Hirzel, A.H., Le Lay, G., 2008. Habitat suitability modelling and niche theory. J. Appl. Ecol. 45 (5), 1372–1381.

Horch, P., Spaar, R., 2010. Lo Stiaccino Saxicola rubetra, specie target per l′agricoltura estensiva. Ficedula 45, 20–27.
Horch, P., Spaar, R., 2016. Agriculture and nature conservation in Upper Goms: Joint commitment for the whinchat.
Hortal, J., Lobo, J.M., Jiménez-Valverde, A.L.B.E.R.T.O., 2007. Limitations of biodiversity databases: case study on seed-plant diversity in Tenerife, Canary Islands. Conserv. Biol. 21 (3), 853–863.
Hughes, L., 2000. Biological consequences of global warming: is the signal already apparent? Trends Ecol. Evol. 15 (2), 56–61.
IUCN, 2010. IUCN Standards and Petitions Subcommittee. 2010: Guidelines for Using the IUCN Red List Categories and Criteria. Version 8.1.
Jaberg, C., Guisan, A., 2001. Modelling the distribution of bats in relation to landscape structure in a temperate mountain environment. J. Appl. Ecol. 38, 1169–1181.
Jetz, W., Wilcove, D.S., Dobson, A.P., 2007. Projected impacts of climate and land-use change on the global diversity of birds. PLoS Biol. 5 (6), 157.
Jetz, W., McPherson, J.M., Guralnick, R.P., 2012. Integrating biodiversity distribution knowledge: toward a global map of life. Trends Ecol. Evol. 27 (3), 151–159.
Jetz, W., McGeoch, M.A., Guralnick, R., Ferrier, S., Beck, J., Costello, M.J., Meyer, C., 2019. Essential biodiversity variables for mapping and monitoring species populations. Nat. Ecol. Evol. 3 (4), 539–551.
Johnson, C.J., Gillingham, M.P., 2005. An evaluation of mapped species distribution models used for conservation planning. Environ. Conserv. 32, 117–128.
Kéry, M., Royle, J.A., 2009. Inference about species richness and community structure using species-specific occupancy models in the national Swiss breeding bird survey MHB. Modeling Demographic Processes in Marked Populations. Springer, Boston, MA, pp. 639–656.
Kissling, W.D., Hardisty, A., García, E.A., Santamaria, M., De Leo, F., Pesole, G., Los, W., 2015. Towards global interoperability for supporting biodiversity research on essential biodiversity variables (EBVs). Biodiversity 16 (2–3), 99–107.
Kissling, W.D., Ahumada, J.A., Bowser, A., Fernandez, M., Fernández, N., García, E.A., McRae, L., 2018a. Building essential biodiversity variables (EBV s) of species distribution and abundance at a global scale. Biol. Rev. 93 (1), 600–625.
Kissling, W.D., Walls, R., Bowser, A., Jones, M.O., Kattge, J., Agosti, D., Denny, E.G., 2018b. Towards global data products of Essential Biodiversity Variables on species traits. Nat. Ecol. Evol. 2 (10), 1531–1540.
Knaus, P., Antoniazza, S., Gu_elat, J., ery, M.K., Strebel, N., Wechsler, S., 2018. Schweizer brutvogelatlas 2013–2016. Schweizerische Vogelwarte, Sempach, Switzerland.
Latombe, G., Pyšek, P., Jeschke, J.M., Blackburn, T.M., Bacher, S., Capinha, C., Hui, C., 2017. A vision for global monitoring of biological invasions. Biol. Conserv. 213, 295–308.
Leathwick, J.R., Elith, J., Hastie, T., 2006. Comparative performance of generalized additive models and multivariate adaptive regression splines for statistical modelling of species distributions. Ecol. Model. 199 (2), 188–196.
Liedvogel, M., 2018. Molekulare Grundlagen und genetische Architektur des Vogelzugs. Vogelwarte Z. Vogelkd. 56 (4), 324–325.
Maggini, R., Lehmann, A., Kéry, M., Schmid, H., Beniston, M., Jenni, L., Zbinden, N., 2011. Are Swiss birds tracking climate change?: Detecting elevational shifts using response curve shapes. Ecol. Model. 222 (1), 21–32.
Maggini, R., Lehmann, A., Zbinden, N., Zimmermann, N.E., Bolliger, J., Schröder, B., Jenni, L., 2014. Assessing species vulnerability to climate and land use change: the case of the Swiss breeding birds. Divers. Distrib. 20 (6), 708–719.
Manel, S., Dias, J.M., Buckton, S.T., Ormerod, S.J., 1999. Alternative methods for predicting species distribution: an illustration with Himalayan river birds. J. Appl. Ecol. 36 (5), 734–747.
Marmion, M., Parviainen, M., Luoto, M., Heikkinen, R.K., Thuiller, W., 2009. Evaluation of consensus methods in predictive species distribution modelling. Divers. Distrib. 15 (1), 59–69.
Mateo, R.G., Felicísimo, Á.M., Pottier, J., Guisan, A., Muñoz, J., 2012. Do stacked species distribution models reflect altitudinal diversity patterns? PLoS One 7 (3), 32586.
Maurer, K., Weyand, A., Fischer, M., Stöcklin, J., 2006. Old cultural traditions, in addition to land use and topography, are shaping plant diversity of grasslands in the Alps. Biol. Conserv. 130 (3), 438–446.
McCaffrey, D.F., Ridgeway, G., Morral, A.R., 2004. Propensity score estimation with boosted regression for evaluating causal effects in observational studies. Psychol. Methods 9 (4) 403-25.
Meller, L., Cabeza, M., Pironon, S., Barbet-Massin, M., Maiorano, L., Georges, D., Thuiller, W., 2014. Ensemble distribution models in conservation prioritization: from consensus predictions to consensus reserve networks. Divers. Distrib. 20, 309–321.
Menoni, E., Magnani, Y., 1998. Human disturbance of grouse in France. Grouse News 15, 4–8.
Michener, W.K., Jones, M.B., 2012. Ecoinformatics: supporting ecology as a data-intensive science. Trends Ecol. Evol. 27 (2), 85–93.
Mokany, K., Harwood, T.D., Williams, K.J., Ferrier, S., 2012. Dynamic macroecology and the future for biodiversity. Glob. Chang. Biol. 18 (10), 3149–3159.
Müller, M., Spaar, R., Schifferli, L., Jenni, L., 2005. Effects of changes in farming of subalpine meadows on a grassland bird, the whinchat (Saxicola rubetra). J. Ornithol. 146 (1), 14–23.
Navarro, L.M., Fernández, N., Guerra, C., Guralnick, R., Kissling, W.D., Londoño, M.C., Delavaud, A., 2017. Monitoring biodiversity change through effective global coordination. Curr. Opin. Environ. Sustain. 29, 158–169.
Parmesan, C., Yohe, G., 2003. A globally coherent fingerprint of climate change impacts across natural systems. Nature 421 (6918), 37–42.
Patthey, P., Signorell, N., Rotelli, L., Arlettaz, R., 2012. Vegetation structural and compositional heterogeneity as a key feature in Alpine black grouse microhabitat selection: conservation management implications. Eur. J. Wildl. Res. 58 (1), 59–70.
Pearce-Higgins, J.W., Grant, M.C., Robinson, M.C., Haysom, S.L., 2007. The role of forest maturation in causing the decline of Black Grouse Tetrao tetrix. Ibis 149 (1), 143–155.
Pereira, H.M., Leadley, P.W., Proença, V., Alkemade, R., Scharlemann, J.P., Fernandez-Manjarrés, J.F., Chini, L., 2010. Scenarios for global biodiversity in the 21st century. Science 330 (6010), 1496–1501.
Pereira, H.M., Ferrier, S., Walters, M., Geller, G.N., Jongman, R.H.G., Scholes, R.J., Coops, N.C., 2013. Essential biodiversity variables. Science 339 (6117), 277–278.
Pereira, H.M., Belnap, J., Böhm, M., Brummitt, N., Garcia-Moreno, J., Gregory, R., van Swaay, C., 2017. Monitoring essential biodiversity variables at the species level. The GEO Handbook on Biodiversity Observation Networks. Springer, Cham, pp. 79–105.
Peterson, A.T., Soberón, J., 2018. Essential biodiversity variables are not global. Biodivers. Conserv. 27 (5), 1277–1288.
Pettorelli, N., Wegmann, M., Skidmore, A., Mücher, S., Dawson, T.P., Fernandez, M., Jongman, R.H., 2016a. Framing the concept of satellite remote sensing essential biodiversity variables: challenges and future directions. Remote Sens. Ecol. Conserv. 2 (3), 122–131.
Pettorelli, N., Owen, H.J.F., Duncan, C., 2016b. How do we want Satellite Remote Sensing to support biodiversity conservation globally? Methods Ecol. Evol. 7 (6), 656–665.
Proença, V., Martin, L.J., Pereira, H.M., Fernandez, M., McRae, L., Belnap, J., Honrado, J.P., 2017. Global biodiversity monitoring: from data sources to essential biodiversity variables. Biol. Conserv. 213, 256–263.
Randin, C.F., Jaccard, H., Vittoz, P., Yoccoz, N.G., Guisan, A., 2009. Land use improves spatial predictions of mountain plant abundance but not presence-absence. J. Veg. Sci. 20 (6), 996–1008.
Reif, J., Flousek, J., 2012. The role of species' ecological traits in climatically driven altitudinal range shifts of central European birds. Oikos 121 (7), 1053–1060.
Renwick, A.R., Massimino, D., Newson, S.E., Chamberlain, D.E., Pearce-Higgins, J.W., Johnston, A., 2012. Modelling changes in species' abundance in response to projected climate change. Divers. Distrib. 18 (2), 121–132.
Riordan, E.C., Rundel, P.W., 2014. Land use compounds habitat losses under projected climate change in a threatened California ecosystem. PLoS One 9 (1), 86487.
Roth, T., Plattner, M., Amrhein, V., 2014. Plants, birds and butterflies: short-term responses of species communities to climate warming vary by taxon and with altitude. PLoS One 9 (1), 82490.
Rouse, J.W.J., Haas, R.H., Schell, J.A., Deering, D.W., 1973. Monitoring vegetation systems in the Great Plains with ERTS. In: Third ERTS Symposium, NASA SP-351. US Government Printing office. Edited by S.C. Freden, E.P. Mercanti, and M.A. Becker. NASA.

Royle, J.A., Kéry, M., Gautier, R., Schmid, H., 2007. Hierarchical spatial models of abundance and occurrence from imperfect survey data. Ecol. Monogr. 77 (3), 465–481.
Rushton, S.P., Ormerod, S.J., Kerby, G., 2004. New paradigms for modelling species distributions? J. Appl. Ecol. 41 (2), 193–200.
Sattler, T., Knaus, P., Schmid, H., Volet, B., 2017. The State of Birds in Switzerland. Report 2017. Swiss Ornithological Institute, Sempach.
Scherrer, D., Christe, P., Guisan, A., 2019. Modelling bat distributions and diversity in a mountain landscape using focal predictors in ensemble of small models. Divers. Distrib. 25 (5), 770–782.
Schmeller, D.S., Mihoub, J.B., Bowser, A., Arvanitidis, C., Costello, M.J., Fernandez, M., Saarenmaa, H., 2017. An operational definition of essential biodiversity variables. Biodivers. Conserv. 26 (12), 2967–2972.
Schmeller, D.S., Weatherdon, L.V., Loyau, A., Bondeau, A., Brotons, L., Brummitt, N., Mihoub, J.B., 2018. A suite of essential biodiversity variables for detecting critical biodiversity change. Biol. Rev. 93 (1), 55–71.
Schmid, H., Zbinden, N., Keller, V., 2004. Überwachung der bestandsentwicklung häufiger brutvögel in der schweiz. Swiss Ornithological Institute, Sempach, Switzerland.
Sharma, A., Dubey, V.K., Johnson, J.A., Rawal, Y.K., Sivakumar, K., 2021. Is there always space at the top? Ensemble modeling reveals climate-driven high-altitude squeeze for the vulnerable snow trout Schizothorax richardsonii in Himalaya. Ecol. Indic. 120, 106900.
Sheffield, J., Wood, E.F., 2008. Projected changes in drought occurrence under future global warming from multi-model, multi-scenario, IPCC AR4 simulations. Clim. Dyn. 31 (1), 79–105.
Signorell, N., Wirthner, S., Patthey, P., Schranz, R., Rotelli, L., Arlettaz, R., 2010. Concealment from predators drives foraging habitat selection in brood-rearing Alpine black grouse Tetrao tetrix hens: habitat management implications. Wildl. Biol. 16 (3), 249–257.
Smeraldo, S., Bosso, L., Fraissinet, M., Bordignon, L., Brunelli, M., Ancillotto, L., Russo, D., 2020. Modelling risks posed by wind turbines and power lines to soaring birds: the black stork (Ciconia nigra) in Italy as a case study. Biodivers. Conserv. 29, 1959–1976.
Smeraldo, S., Bosso, L., Salinas-Ramos, V.B., Ancillotto, L., Sánchez-Cordero, V., Gazaryan, S., Russo, D., 2021. Generalists yet different: distributional responses to climate change may vary in opportunistic bat species sharing similar ecological traits. Mamm. Rev. mam.12247. https://doi.org/10.1111/mam.12247
Soberón, J., Peterson, T., 2004. Biodiversity informatics: managing and applying primary biodiversity data. Philos. Trans. R Soc. Lond. Ser. B Biol. Sci. 359 (1444), 689–698.
Taleshi, H., Jalali, S.G., Alavi, S.J., Hosseini, S.M., Naimi, B., Zimmermann, N.E., 2019. Climate change impacts on the distribution and diversity of major tree species in the temperate forests of Northern Iran. Reg. Environ. Chang. 19 (8), 2711–2728.
Team, R.C., 2016. R: a language and environment for statistical computing vv 3.3. 1.
Thomas, J.A., 2005. Monitoring change in the abundance and distribution of insects using butterflies and other indicator groups. Philos. Trans. R Soc. B Biol. Sci. 360 (1454), 339–357.
Thuiller, W., Lavorel, S., Araújo, M.B., 2005. Niche properties and geographical extent as predictors of species sensitivity to climate change. Glob. Ecol. Biogeogr. 14 (4), 347–357.
Thuiller, W., Georges, D., Engler, R., Breiner, F., Georges, M.D., Thuiller, C.W., 2016. Package 'biomod2′. Species distribution modeling within an ensemble forecasting framework. Software.
Tittensor, D.P., Walpole, M., Hill, S.L., Boyce, D.G., Britten, G.L., Burgess, N.D., Baumung, R., 2014. A mid-term analysis of progress toward international biodiversity targets. Science 346 (6206), 241–244.
Turak, E., Brazill-Boast, J., Cooney, T., Drielsma, M., DelaCruz, J., Dunkerley, G., Koen, T., 2017a. Using the essential biodiversity variables framework to measure biodiversity change at national scale. Biol. Conserv. 213, 264–271.
Turak, E., Harrison, I., Dudgeon, D., Abell, R., Bush, A., Darwall, W., Juffe-Bignoli, D., 2017b. Essential Biodiversity Variables for measuring change in global freshwater biodiversity. Biol. Conserv. 213, 272–279.
Van Couwenberghe, R., Collet, C., Pierrat, J.C., Verheyen, K., Gégout, J.C., 2013. Can species distribution models be used to describe plant abundance patterns? Ecography 36 (6), 665–674.
Van Niel, K.P., Austin, M.P., 2007. Predictive vegetation modeling for conservation: impact of error propagation from digital elevation data. Ecol. Appl. 17 (1), 266–280.
Vermeiren, P., Reichert, P., Schuwirth, N., 2020. Integrating uncertain prior knowledge regarding ecological preferences into multi-species distribution models: effects of model complexity on predictive performance. Ecol. Model. 420, 108956.
Vihervaara, P., Auvinen, A.P., Mononen, L., Törmä, M., Ahlroth, P., Anttila, S., Koskelainen, M., 2017. How essential biodiversity variables and remote sensing can help national biodiversity monitoring. Glob. Ecol. Conserv. 10, 43–59.
Vincenzi, S., Zucchetta, M., Franzoi, P., Pellizzato, M., Pranovi, F., De Leo, G.A., Torricelli, P., 2011. Application of a Random Forest algorithm to predict spatial distribution of the potential yield of Ruditapes philippinarum in the Venice lagoon, Italy. Ecol. Model. 222 (8), 1471–1478.
Walters, M., Pereira, H.M., Ferrier, S., Geller, G.N., Jongman, R., Scholes, R.J., Reyers, B., 2013, October. Essential Biodiversity Variables. In: Convention on Biological Diversity, Subsidiary Body on Scientific, Technical, and Technological Advice.
Weber, M.M., Stevens, R.D., Diniz-Filho, J.A.F., Grelle, C.E.V., 2017. Is there a correlation between abundance and environmental suitability derived from ecological niche modelling? A meta-analysis. Ecography 40 (7), 817–828.
Wegge, P., Kastdalen, L., 2008. Habitat and diet of young grouse broods: resource partitioning between Capercaillie (Tetrao urogallus) and Black Grouse (Tetrao tetrix) in boreal forests. J. Ornithol. 149 (2), 237.
Whitfield, D.P., Ruddock, M., Bullman, R., 2008. Expert opinion as a tool for quantifying bird tolerance to human disturbance. Biol. Conserv. 141 (11), 2708–2717.
Wilsey, B.J., Chalcraft, D.R., Bowles, C.M., Willig, M.R., 2005. Relationships among indices suggest that richness is an incomplete surrogate for grassland biodiversity. Ecology 86 (5), 1178–1184.
Wilson, R.J., Thomas, C.D., Fox, R., Roy, D.B., Kunin, W.E., 2004. Spatial patterns in species distributions reveal biodiversity change. Nature 432 (7015), 393–396.
Wisz, M.S., Guisan, A., 2009. Do pseudo-absence selection strategies influence species distribution models and their predictions? An information-theoretic approach based on simulated data. BMC Ecol. 9 (1), 8.
Yu, H., Cooper, A.R., Infante, D.M., 2020. Improving species distribution model predictive accuracy using species abundance: application with boosted regression trees. Ecol. Model. 432, 109202.
Zbinden, N., Haller, H., 2013. The Alps, their birds and what we know about them. Ornithol. Beob. 110, 249–256.
Zeitler, A., 2000. Human disturbance, behaviour and spatial distribution of black grouse in skiing areas in the Bavarian Alps. Cah. d′Ethologie 20, 381–400.
Zeitler, A., Glanzer, U., 1998. Skiing and grouse in the Bavarian Alps. Grouse News 15, 8–12.
Zhu, Q., Hobson, K.A., Zhao, Q., Zhou, Y., Damba, I., Batbayar, N., David Fox, A., 2020. Migratory connectivity of Swan Geese based on species' distribution models, feather stable isotope assignment and satellite tracking. Divers. Distrib. 26 (8), 944–957.
Zilioli, M., Oggioni, A., Tagliolato, P., Pugnetti, A., Carrara, P., 2019. Feeding Essential Biodiversity Variables (EBVs): actual and potential contributions from LTER-Italy. Nat. Conserv. 34, 477.
Zurell, D., Grimm, V., Rossmanith, E., Zbinden, N., Zimmermann, N.E., Schröder, B., 2012. Uncertainty in predictions of range dynamics: black grouse climbing the Swiss Alps. Ecography 35 (7), 590–603.