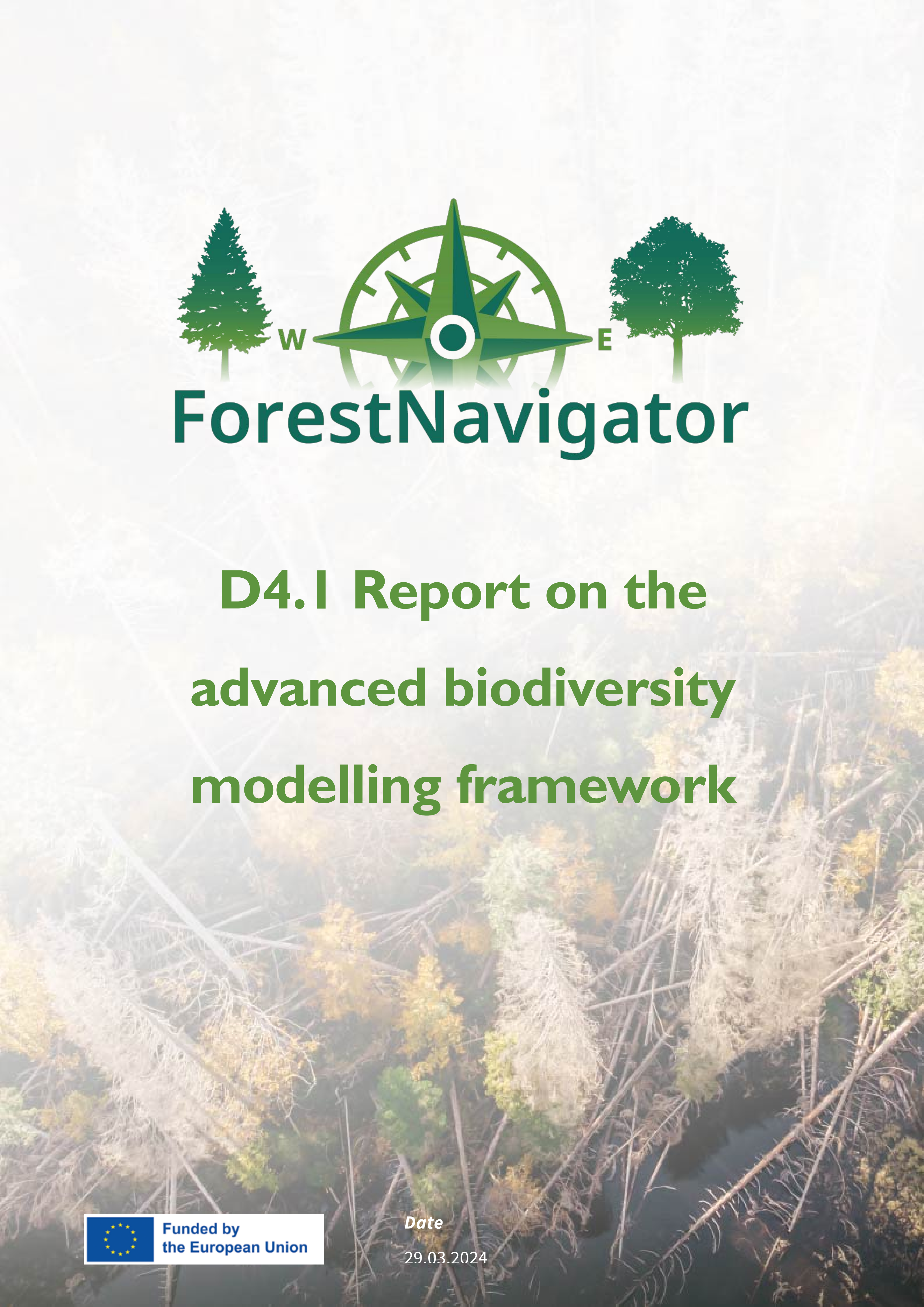


ForestNavigator

D4.1 Report on the advanced biodiversity modelling framework

Funded by the European Union

Date

29.03.2024

Grant Agreement	101056875
Call identifier	HORIZON-CL5-2021-D1-01
Project full title	ForestNavigator: Navigating European forests and forest bioeconomy sustainably to EU climate neutrality
Work package	WP4
Due date	31/03/2024
Deliverable lead	IIASA
Authors	Maximilian H.K. Hesselbarth, Martin Jung, Piero Visconti

Abstract

This report outlines the modelling framework to assess impacts of forest-based climate change mitigation pathways on forest biodiversity. It describes all included data sources, the data pre-processing, and outlines the individual modelling steps. Furthermore, it introduces the indicators used to quantify biodiversity.

Keywords

Forest biodiversity, species distribution modelling, ecological niche modelling, habitat suitability

Internal Technical Auditor	Name (Beneficiary short name)	Date of approval
Task leader	M.H.K. Hesselbarth (IIASA)	28/03/2024
WP leader	Julia Pongratz (LMU)	27/03/2024
Coordinator	Petr Havlík (IIASA)	27/03/2024
Project Office	Eleonora Tan (IIASA)	28/03/2024

Dissemination level

PU	Public, will be published on CORDIS	✓
SEN	Sensitive, limited under the conditions of the Grant Agreement	

Nature of the deliverable * **R**

Table of Contents

List of Figures

List of Tables

Abbreviations

BREG	Bayesian regularized regression
CHELSA	Climatologies at high resolution for the earth's land surface areas
EBD	eBird basic dataset
EEA	European Environment Agency
EU	European Union
DBH	Diameter at breast height
DEM	Digital elevation model
GARD	Global Assessment of Reptile Distributions
GBIF	Global Biodiversity Information Facility
GDB	Gradient descent boosting
GHS	Global Human Settlement
GISCO	Geographic Information System of the Commission
GLMNET	Regularized elastic net regression
GPP	Gross primary production
IGFS	Improved gridded forest structure data
ISRIC	International Soil Reference and Information Centre
IUCN	International Union for Conservation of Nature
LAI	Leaf area index
NPP	Net primary production
pHiHXO	pH measured in water solution
pHiKCl	pH measured in potassium chloride solution
RCP	Representative concentration pathway
SDM / iSDM	Species distribution model / integrated species distribution model
SEBI	Streamlining European Biodiversity Indicators
SEH	Societas Europaea Herpetologica
SSP	Shared socioeconomic pathways
WP	Work package

1. Introduction

Forest-based climate change mitigation pathways play a crucial role in reducing net greenhouse gas emissions and achieving the climate neutrality goals of the European Union (EU). However, reaching these goals is challenging due to interactions between climate change, natural disturbances, and management strategies. Moreover, conflicts might arise between socio-economic demands, biodiversity conservation, and various other ecosystem services as the aforementioned interactions also influence outcomes of the mitigation pathways. Thus, the *ForestNavigator* project aims to assess the potential and impacts of forest-based mitigation pathways using an integrated modelling framework.

The biodiversity assessment of Work Package 4 (WP4) develops a modelling framework to assess the biodiversity impacts of various climate change scenarios and forest management pathways. Global environmental changes are profoundly affecting forest ecosystems (Hisano et al., 2018; Sala et al., 2000). Among others, this includes direct and indirect effects on biodiversity. Direct effects include that climate change is projected to increase extinction risks for many European plants (Thuiller et al., 2005), alter forest tree species distributions (Dyderski et al., 2018), and enable range expansion of beetle species (Buse et al., 2013). Indirect effects include disturbances due to climate change (Schuldt et al., 2020; Seidl et al., 2017), but also adapted forest management strategies which both can have impacts on forest structure. Forest structure has been shown to be a driver of plant (De Frenne et al., 2013; Gao et al., 2014), beetle (Parisi et al., 2021) and overall (Thom et al., 2017) species diversity. Thus, climate change and the biodiversity crisis are deeply connected (Pettorelli et al., 2021; Pörtner et al., 2023). Furthermore, diversity often increases resilience of ecosystems (Chapin III et al., 2000) and is linked to ecosystem functioning (Ruiz-Benito et al., 2017). Consequently, additionally to carbon stocks and socioeconomic aspects, there is the need for mitigation pathways to consider conservation measures to counteract the biodiversity crisis and its consequences for ecosystem services and society (European Commission, 2020; IPBES, 2019). The modelling framework introduces in this report quantifies impacts of climate change scenarios and forest management pathways on biodiversity. Thus, we are able to identify scenarios and pathways that potentially support or reduce forest biodiversity and identify forest taxa that are extraordinarily resilient or vulnerable to the scenarios and pathways.

To model the response of multiple forest taxa with high conservation relevance to climate change scenarios and forest management pathways, we use integrated species distribution models (*iSDM*). More generally, *SDM*s allow to infer, predict, and project habitat suitability of species in space and time, usually in a raster grid cell context, using statistical relationships between environmental covariates (e.g., climatic conditions or forest characteristics) and species observations (Elith and Leathwick, 2009; Guisan and Thuiller, 2005). *iSDM*s specifically leverage information across various data types (such as multiple biodiversity data sources, priors, offsets, statistical frameworks; Isaac et al., 2020). By balancing and combining strengths across datasets and frameworks, they have the potential to mediate existing spatial and thematic biases present in most openly available biodiversity datasets. Thus, *SDM*s can be used to assess impacts of forestry on biodiversity (e.g., Leitão et al., 2022; Oettel and Lapin, 2021) or identify areas of high conservation value (e.g., Jung et al., 2021).

While *SDMs* have been applied frequently to support forest management (Pecchi et al., 2019), modelled species almost solely include forest tree species (e.g., Bonannella et al., 2022; Chakraborty et al., 2021; Mauri et al., 2022). Furthermore, environmental covariates often do not include information on land use and specifically detailed forest characteristics. Thus, we are modelling forest biodiversity using multiple forest taxa (e.g., mammals, birds, or arthropods), and including covariates describing environmental conditions as well as forest characteristics affected by forest management practices. Biodiversity indicators are often employed to quantify diversity, typically focusing on the presence of species or species groups that serve as proxies for other species or general habitat characteristics (Gao et al., 2015). The forest taxa included in the biodiversity assessment of WP4 are selected based on their conservation and community relevance and are in line with current biodiversity monitoring frameworks and strategies. Furthermore, they cover a wide range of habitat requirements, dispersal abilities, or general mobility.

This report introduces the modelling workflow in detail. First, we describe how biodiversity data is acquired and which climatic, environmental and forest characteristics covariates are included. Second, we outline all pre-processing steps such as data cleaning and harmonizing applied to both biodiversity data and covariates. Third, we present the *iSDM*s algorithms, and fourth, we present how model outputs are translated into biodiversity indicators.

2. Geographic and temporal extent and resolution

The spatial extent covers all 27 member countries of the EU (Figure 1). We focus on the continental part of the EU, thus excluding all overseas territories and outermost regions (such as French Polynesia or the Canary Islands). Because outcomes of *SDM*s are generally affected by the spatial resolution (e.g., Farashi and Alizadeh-Noughani, 2018; Guisan et al., 2007), this is an important choice. Based on data availability, if possible, we use a spatial resolution of 8 × 8 km for model parametrization and inference. For future projections we rely on a coarser spatial resolution that is constrained by the resolution of *G4M-X* model outputs, namely ~5 arcmins (equals about 10 × 10 km at the equator).

Overall, the temporal extent covers the years 2015 to 2100. For model training, we use data from the year 2015 – 2020 (or as close as possible). For model projections, the trained models are projected up to the year 2100. Range shifts of species due to changing environmental conditions and forest characteristics are rather long-term, even though rates increase (Renwick and Rocca, 2015; Williams and Blois, 2018). Thus, we are using a temporal resolution of 10-year intervals for all projections of species occurrence.

Figure 1: Spatial extent of the biodiversity modelling framework. All included countries colored green.

3. Included data sets

3.1. List of included species

To assess impacts of forest management on diverse forest taxa of conservation and policy relevance, we are using the Annexes I and II of the Article 12 Birds directive and Article 17 Habitats directive, respectively, as well as species listed in the *European Red Lists of Species*. However, only species associated with forests or woodlands are considered as specified in the corresponding habitat descriptions (Table 1). Last, we include species previously modelled by consortium members on national scales. In total, this includes 1,274 species that can be summarized to 13 species groups (Table 2). However, because some species are excluded during data acquisition or pre-processing, this species list only represents the potentially considered species. All species names were cleaned and harmonized using several databases with the help of the *taxize R* package (Chamberlain and Szöcs, 2013).

Table 1: Data sources of potentially included species of the biodiversity modelling workflow.

Data source	Habitat selection criterion	Number of species
Annexes I/II of Article 12/17	Including "*preferred*" association to "*woodlandForest*"	510
European Red Lists of Species	Habitat description includes: "*forest*", "*tree*", "*wood*", "*coniferous*", "*broadleaf*"	850
Species previously modelled on national scale (SI S1)	-	42

3.1.1. Species occurrence data

First, we use the *Global Biodiversity Information Facility* (*GBIF*), a database collecting biodiversity data from various sources (e.g., surveys, camera traps, remote sensing) and sampling methods (e.g., standardized protocols, opportunistic observations). We download observations for the years 2015 – 2020 including only those that have spatial coordinates and no flagged geospatial issues. Furthermore, we only include observations by humans or machines (e.g., camera traps). The *GBIF* data includes only where a species occurs, but not where the species does not occur, we are using it as presence-only data.

Second, for all bird species we are additionally using the *eBird* basic dataset (*EBD*; Fink et al., 2023; Sullivan et al., 2009). *eBird* is one of the largest citizen science projects and collects data about the presence and abundance of bird species using specified survey protocols. Additionally, the *EBD* includes so-called checklists that describe the corresponding birding activities (Sullivan et al., 2014). We downloaded all observations and checklists for the years 2015 – 2020.

Third, for all plant species we additionally use presence-absence data from the *sPlotOpen* database of vegetation plots. The *sPlotOpen* database consists of numerous regional, national, or continental vegetation-plot datasets that are located in natural or semi-natural vegetation

(Sabatini et al., 2021). We are including only sample plots that are located within forest vegetation as indicated in the database and that were sampled between the years 2015 – 2020.

3.1.2. Range maps and atlas data

Furthermore, we are using expert-derived range maps and atlas data in the modelling workflow. This includes data from the *IUCN Red Lists of Threatened Species* (IUCN, 2022), the *Birds and Habitats directives* atlas data, *BirdLife International* (BirdLife International and Handbook of the Birds of the World, 2022), the *Global Assessment of Reptile Distributions* (*GARD*; Roll et al., 2017), and the *Societas Europaea Herpetologica* atlas data (*SEH* Sillero et al., 2014). If several range maps are present for a single species, we summarize the them into a single map. However, while for some species groups range maps are available for most species (e.g., Mammals, Birds, Amphibians/Reptiles), for other species groups range maps are less or not available at all (e.g., Butterflies, Bees, Mollusca).

Table 2: Number of forest-associated species separated by species groups.

Species group	EEA Habitats and Birds directives	EU Red List of Species	Previously modelled on national scale
Amphibian	36	19	-
Bees	-	40	-
Beetles	26	181	-
Birds	179	37	-
Butterflies	17	47	-
Ferns	8	23	-
Fungi/Lichens	-	-	11
Mammals	108	14	-
Mollusca	10	97	-
Non-vascular Plants	16	-	21
Vascular Plants	77	160	-
Reptiles	23	17	-
Other Insects	5	102	-

3.2. List of explanatory covariates

To model and project species distributions, we are using several gridded datasets describing diverse aspects of climatic (e.g., precipitation) and environmental conditions (e.g., elevation), as well as forest characteristics (e.g., tree density or basal area). This includes both publicly available data (Figure 2, Table 3, 4) and data produced by other WPs and tasks in the *ForestNavigator* project (Figure 2, Table 4). Some of the data is static (or not projected in the future; e.g., the digital elevation model) and other is dynamic (or projected in the future). Dynamic covariates include climatic conditions and forest characteristics and are assumed to change in the future based on different climate change scenarios and forest management pathways. For all climatic covariates this includes the scenarios *i)* SSP1/RCP2.6, *ii)* SSP2/RCP7.0, and *iii)* SSP5/RCP8.5. For the forest characteristics, we use three forest stewardship storylines, developed by a different WPs and tasks in the *ForestNavigator* project, that reflect different forest management priorities, namely *i)* nature oriented, *ii)* multifunctionality oriented, and *iii)* wood-based economy oriented.

Table 3: Covariates describing climatic and environmental conditions used within the biodiversity modelling framework

Source	Covariate	Unit	Native resolution	Characteristic
CHELSA	Precipitation	kg m^{-2} $month^{-1}$	0.0083° (~700 m)	projected
	Temperature	Celsius		
	Temperature min/max	Celsius		
Copernicus DEM	Elevation	Meter	25 m	static
	Slope	Degree		
	Aspect	Degree		
ISRIC	Clay	g/kg	0.0083° (~700 m)	static
	Silt	g/kg		
	Sand	g/kg		
	Soil organic carbon	dg/kg		
	Available water capacity	Percentage		
	pHiHXO/ pHiKCl	pHx10		

We use two main data sources to describe forest characteristics. First, for current forest characteristics, we use the *Improved Gridded Forest Structure* data (*IGFS*; Pucher et al., 2022) which describes forest characteristics around the year 2015. To describe projected forest characteristics, we additionally use *G4M-X* model outputs created within different *WP*s and tasks of the *ForestNavigator* project.

Table 4: Covariates describing forest characteristics used within the biodiversity modelling framework

Covariates	***IGFS*[a]** **(static, 8 km)**	***G4M-X*[b]** **(projected, 5 arcmins)**
Tree age	age class	years
Tree height	m	m
Crown width	-	m
Crown length	-	m
Diameter at breast height	cm	cm
Basal area	m^2/ha	m^2/ha
Standing volume	m^3/ha	m^3/ha
Stem density	n/ha	n/ha
GPP/NPP	-	tC/ha/$year^{-1}$
LAI	-	m^2/m^2
Species composition	Dominant tree species group	Dominant tree species group
Litter	tC/ha (foliage)	tC/ha
Mortality	-	n/ha/$year^{-1}$
Deadwood	-	tC/ha

Sources: [a]Pucher et al. (2022); [b]ForestNavigator project

In general, many of the covariates are available in both data sources (Table 4) and values of the *IGFS* data are reasonably well correlated to the initial timestep of the *G4M-X* model data (Figure 2). Yet, there is also variation between the two data sources which can be explained by various reasons. Even though the *G4M-X* model runs are initialized with the *IGFS* data, some covariates in *G4M-X* are based on internal relationships, such as the tree volume per hectare. Additionally, the *IGFS* includes natural regeneration, which is not included in *G4M-X*. Moreover, the *IGFS* data is based on mixed species and age classes per cell, while *G4M-X* uses a simplified species and age class representation per grid cell.

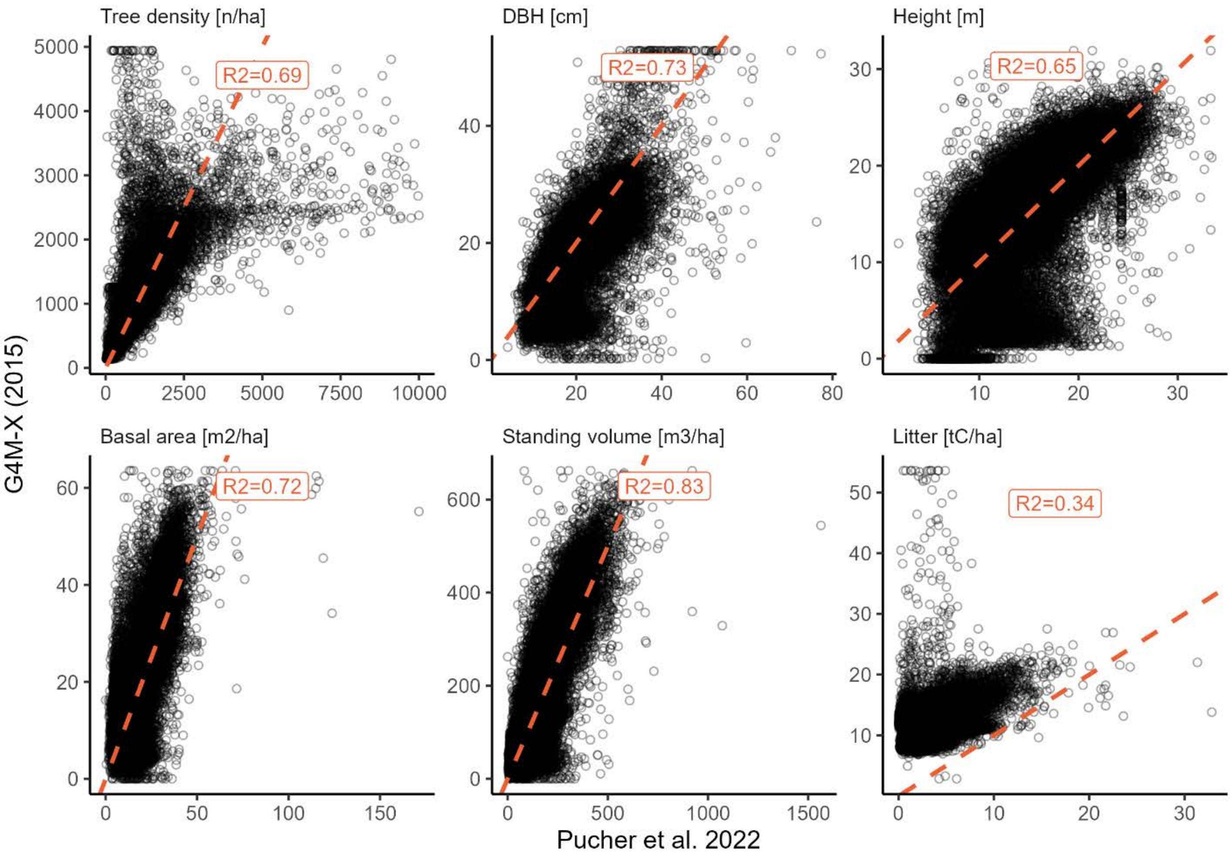


Figure 2: Comparison between continuous covariates describing forest characteristics based on the two used data sources, namely the Improved Gridded Forest Structure data (IGFS; Pucher et al., 2022) and the G4M-X model for the initial time step.

4. Biodiversity modelling workflow

The biodiversity modelling workflow (Figure 3) is implemented in the open-source *R* programming language (R Core Team, 2021). All steps of the workflow are separated into several modular *R* scripts that are hosted and available on the IIASA GitLab instance and will be updated during the project duration. Key software packages used for general data (pre-)processing include, besides others, *terra* (Hijmans, 2021), *sf* (Pebesma, 2018), and packages from the *tidyverse* (Wickham et al., 2019). To train and project all *iSDM*s, we are using the *ibis.iSDM* software package (Jung, 2023) and landscape metrics are calculated using the *landscapemetrics* software package (Hesselbarth et al., 2019). All packages are openly available on the *Comprehensive R Archive Network* or *GitHub*.

4.1. Pre-processing of data sets

4.1.1. Climatic, environmental and forest covariates

We crop and mask all covariate layers storing climatic and environmental conditions as well as forest characteristics to the same spatial extent using the *NUTS* regions provided by the *GISCO* statistical unit dataset (10 m scale spatial resolution). Within the spatial extent, all covariate layers are aggregated as close as possible to the same spatial resolution using cell arithmetic means or modal values for continuous and discrete layers, respectively, and resampled to the same background layer using bilinear interpolation for continuous values and nearest neighbor values for discrete values. We homogenize all NA cells across layers, remove correlated layers using Pearson’s $r \geq 0.7$ as cut-off and scale values using the mean and standard deviation. However in order to guarantee that climate change scenarios are included, specific covariate layers were not removed even if highly correlated, for example temperature and precipitation.

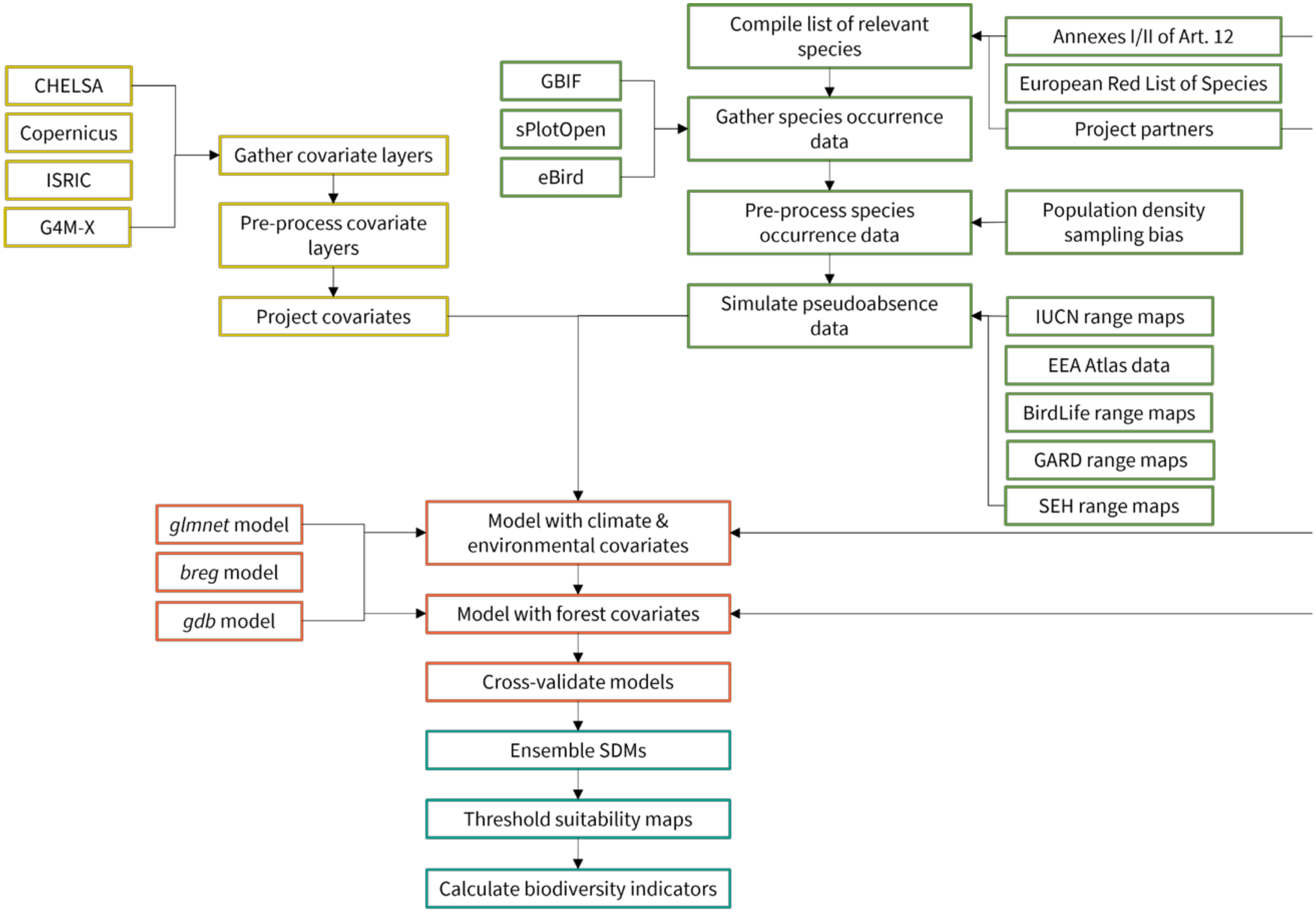


Figure 3: Overview of the biodiversity modelling workflow.

4.1.2. Preparation of species occurrence data

Because model accuracy of *SDM*s decreases with less than about 25 – 30 observations (Hernandez et al., 2006; Wisz et al., 2008), we include only species with at least 35 observations, thus limiting our list of species that can be reliably estimated.

The data quality on *GBIF* is frequently criticized, e.g., due to spatial biases based on sampling accessibility (Beck et al., 2014). Thus, before data can be used reliably, it needs to be pre-processed and cleaned. First, because the individual count value is not always provided or seems problematic (e.g., very high values), we set the individual count information to one for all *GBIF* occurrence data. Second, we remove all records with a coordinate uncertainty larger than 5 km or that do not report any coordinate uncertainty. Third, we use the *CoordinateCleaner R* package (Zizka et al., 2019) to further remove low-quality records from the data. Here we remove all coordinates located in capitals or urban areas, at country centroids, at the *GBIF* headquarters, at known biodiversity institutes, in the ocean, or general outliers and duplicates.

For the *eBird* data, we transform the presence-only to presence-absence data, one of the advantages of *eBird*. This can be done due to the checklists, and specifically including only checklists which reports all observed species. Then, based on the assumption that if a specific species is not listed in a specific checklist, it was truly absence (so-called zero filling). Yet, the effort across checklists differs, which is a potential source of bias (Johnston et al., 2021). Thus, for better homogeneity of observation probabilities following the “Best Practices for Using eBird Data” (Strimas-Mackey et al., 2023), we remove all observations that were collected during birding activities longer than 6 hours, with a travelled distance longer than 10 kilometer, or including more than 10 people.

Because *sPlotOpen* is based on traditional vegetation plots, the data can be used as presence-absence data (Sabatini et al., 2021). Similar to the *eBird* data, for all sample plots at which a specific species was not recorded, we assume that the species is absent.

Geographic sampling bias is a well-known issue for (citizen-generated) species occurrence data (Hijmans, 2012) and occurrence data might not reflect where species are present, but rather where they are observed. This can be quantified by extracting the climatic and environmental conditions at all species occurrences and within expert-derived range maps/atlas data. The overlap between the values can be described by the modified Hellinger metric (Warren et al., 2008). For all species with a small overlap (e.g., < 25%), we assume that the occurrence data does not reflect the true range of a species, i.e., there is a geographic sampling bias (Figure 4). Spatial thinning is an approach to mediate this bias (Aiello-Lammens et al., 2015; Steen et al., 2021) and previous to training *iSDMs* assuming that more observations are made closely to highly populated areas we thin occurrence data for each species using the *GHS*-population grid from the year 2015 as bias layer (Schiavina et al., 2023).

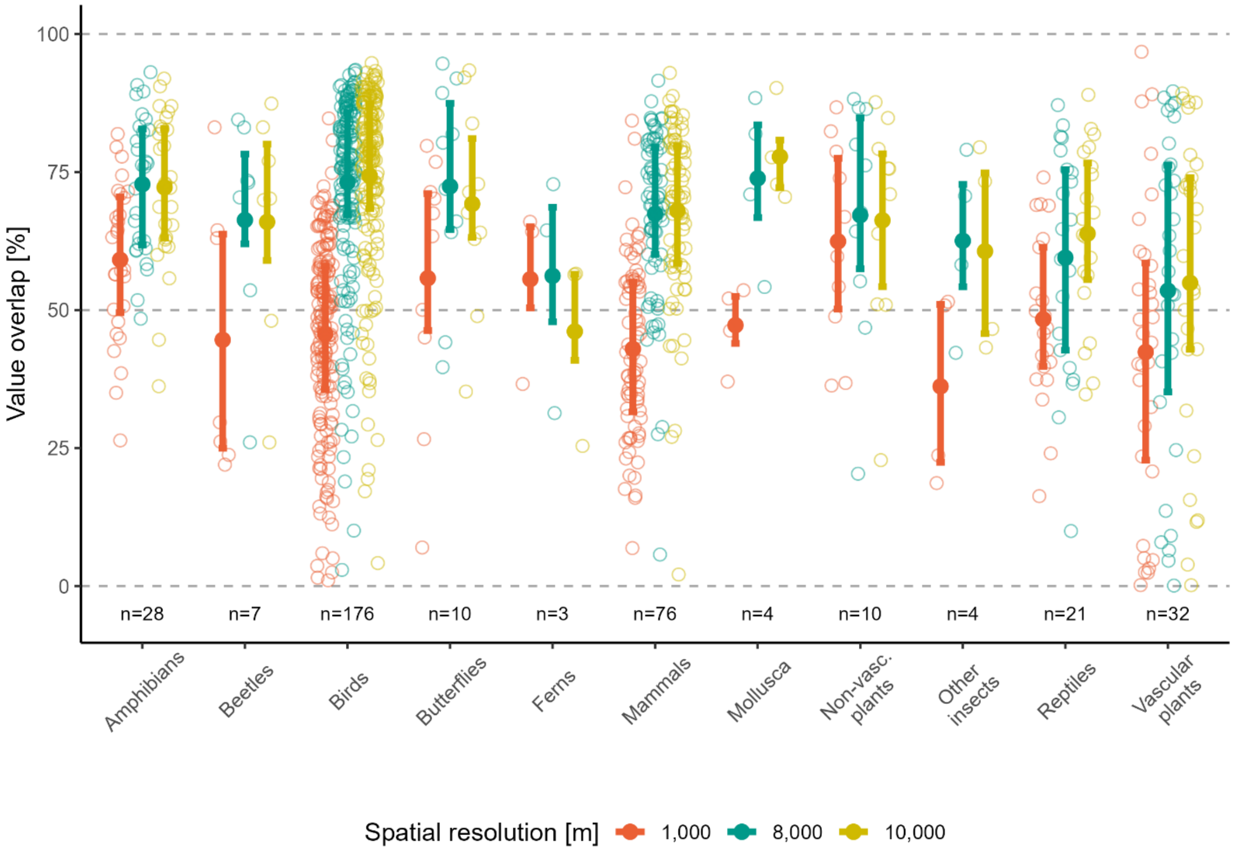


Figure 4: Value overlap of climatic and environmental covariates between species occurrence data and expert-derived range maps. The overlap is calculated for different spatial resolutions indicated by color. The error bars describes the 25 % –75 % quantiles for each resolution and species group, the solid point the mean value. Additionally, the number of species with an existing range map per group is included.

4.2. Species distribution modelling

4.2.1. Training species distribution models

We use covariates and species occurrence data for the years 2015 – 2020 (or as close as possible) to train the *iSDMs* using current climatic and environmental conditions as well as forest characteristics. For the parametrization, we used modelling approaches that requires presence-absence data (Barbet-Massin et al., 2012). Thus, for the presence-only datasets we simulate pseudo-absence data with a ratio of *r* = 2.5, i.e., creating just over twice as many absence points than presence points for each species. If a range map is available, all absence points are generated outside the species range, thus integrating this information into the prediction. If no range map is present, absence points are generated outside the minimum convex hull of all presence points. Similar, we subsampled all *eBird* and *splotOpen* absence data to the same presence-absence ratio.

We used a sequential (or step-wise) integration of two models using different sets of covariates. More specifically, the first model uses climatic and environmental covariates and the resulting habitat suitability is used as an additional covariate in the second model including all forest characteristic covariates. Furthermore, in order to keep the models as simple as possible, we include covariates depending on the species group based on assumptions on their typical biology and habitats (Figure 5). For example, we assume that soil conditions are mostly relevant for members of the kingdoms Plantae and Fungi, but not for members of the kingdom Animalia.

Additionally, we use priors for all species and forest characteristic covariates where such information is available. By using priors, we are able to influence the direction and/or magnitude of model parameters based on *a priori* ecological knowledge. We include priors for saproxylic species (i.e., species depending on deadwood) as well as for species that are characteristic of old-growth forests. This is based on published literature and databases (Blasi et al., 2010; Eckelt et al., 2018; Gao et al., 2015; Graf et al., 2022; Lachat et al., 2012; Oettel and Lapin, 2021; Stokland and Meyke, 2008) and certain terms in the "Habitats" column of the *European Red Lists of Species* (namely "deadwood", "woody debris", "saproxylic" or "old-growth", "primary forest", "primeval forest"). For all saproxylic species we use a prior for mortality and deadwood, for all old-growth forest species, we set a prior for forest age and diameter at breast height (*DBH*).

To model species distributions, we use different statistical frameworks (herein *engines*), such as elastic-net regularized generalized linear models (*glmnet*), Bayesian regularized regression (*breg*), or gradient descent boosting (*gdb*). For each engine, a habitat suitability projection and block validation via cross-validation is made. The output of the engines describe the probability of occurrence or relative habitat suitability in each raster grid cell. The projections of all engines can be combined (or ensembled) through a weighted mean using the cross-validation results. For further analysis of the results, the continuous habitat suitability maps are converted into binary presence-absence maps using threshold methods, such as a percentile threshold (e.g., $p = 15\%$) or the minimum predicted value of a known species occurrence.

4.2.2. Cross validation

We use cross-validation to verify the habitat suitability maps and get insights into the precision and extrapolation errors of the trained models (Roberts et al., 2017). We use the *blockCV R* package (Valavi et al., 2019) to split the species occurrence data in $k = 3$ folds. For each fold, we hold back a test subset of the data during model training. The test subset is then used to evaluate the trained model using appropriate metrics, such as Continuous Boyce Index (Hirzel et al., 2006). The evaluation metrics are used as weights for model ensembling by constructing a weighted average of all candidate models, whereas all with a remarkably low evaluation metric could be removed from the ensemble.

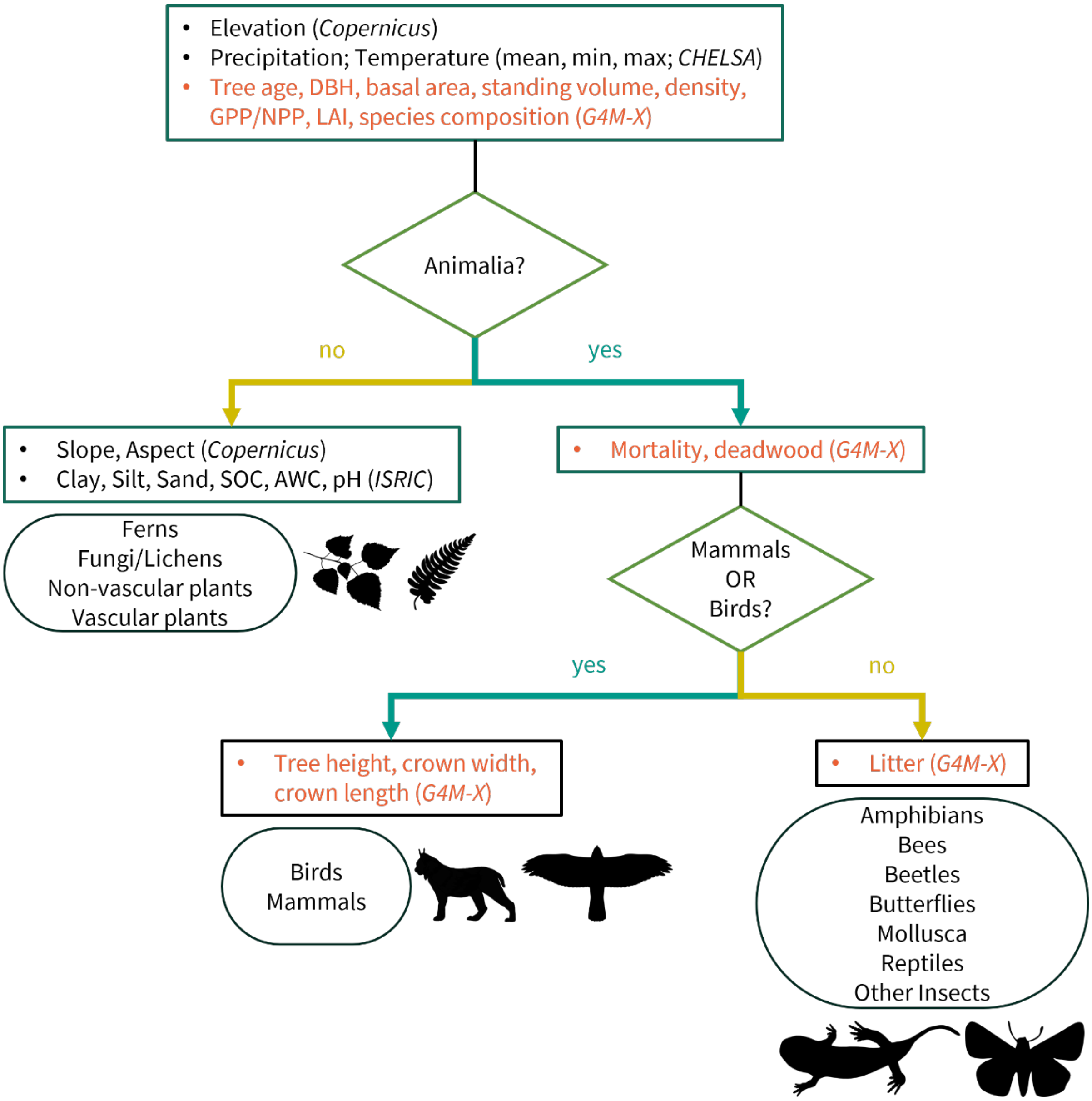


Figure 5: Selection of covariates describing climatic and environmental conditions as well as forest characteristics for species groups. Covariates related to forest characteristics are highlighted red.

4.2.3. Projecting species distributions

In general, projecting species distributions to future scenarios and pathways follows the same workflow as modelling present habitat suitability. However, there are a few differences. First, instead of using covariates for the year 2015 – 2020, projected climatic covariates based on the SSP1/RCP2.6, SSP2/RCP7.0, and SSP5/RCP8.5 scenarios and forest characteristics based on the nature oriented, multifunctionality oriented, and wood-based economy-oriented forest stewardship storylines are used. Second, instead of using the non-projected *IGFS* data covariates, outputs from the *G4M-X* model are used to describe future forest characteristics. The previously trained *iSDMs* can now be used to project species distributions to future climatic conditions and forest characteristics.

4.2.4. Biodiversity indicators

Many different biodiversity indicators were developed in the past and there is an ongoing discussion about their advantages and disadvantages (e.g., Heink and Kowarik, 2010; Santini et al., 2017). For example, the European Environment Agency (*EEA*) developed the Streamlining European Biodiversity Indicators (*SEBI*), however, they are not criticism-free (e.g. Feest, 2013). Generally, the most common species groups used as indicators in forest ecosystem studies are arthropods (including saproxylic species), birds (including woodpeckers), or plants (Oettel and Lapin, 2021). Furthermore, mammals, reptiles, vascular plants, bryophytes, lichens, and fungus can be found in the literature (Gao et al., 2015). To describe and capture biodiversity, usually more than just one indicator is recommended (Santini et al., 2017). Thus, we are applying several indicators simultaneously. Indicators are calculated for all climate change scenarios and forest management pathways. Importantly, this also includes a comparison of the indicator values to a reference values, i.e., before projecting species distributions temporally. This allows us to compare the indicator to the "reference" state and to evaluate impacts of the scenarios and pathway on biodiversity.

Habitat suitability and presence-absence maps: Habitat suitability maps for each species are the most unprocessed indicators that we produce. For each raster grid cell, the maps hold the probability of occurrence or (relative) habitat suitability. The maps allow to spatially highlight areas with biodiversity value. Furthermore, presence-absence maps based on thresholded habitat suitability values are produced for all species. These are closely related to the *SEBI* 01 indicator ("Abundance and distribution of selected species").

Area of suitable habitat: The presence-absence maps can be summarized to a single indicator by calculating the total area of all raster grid cells that indicate species presences, or in other words the total area of suitable habitat. While the total area of suitable habitat is an important indicator, also more detailed information about the suitable habitat patches (a patch being defined as connected habitat cells) are of interest. Thus, we are also including more detailed indicators such as the number of patches and the mean patch area.

Configuration of suitable habitat: Besides the area of suitable habitat, also the spatial configuration of the habitat in the landscape is crucial (Lucas et al., 2019). Thus, we are using several landscape metrics (e.g., Gustafson, 2019) to further quantify the presence-absence maps. For example, this includes the mean distance to the nearest patch, or the percentage of like adjacencies. While the first contains information about landscape connectivity, the later describes the fragmentation of the landscape.

Species richness: Species richness is one of the simplest biodiversity that can be computed by overlaying the presence-absence maps for several species or species groups. However, comparing species richness over a large spatial extent can be biased due to biogeographic patterns in biodiversity. Thus, we are also computing relative species richness, which controls for biases by expressing the potential species richness in relation to a local species pool (Vallecillo et al., 2016). We are using a moving window approach to determine the local species pool.

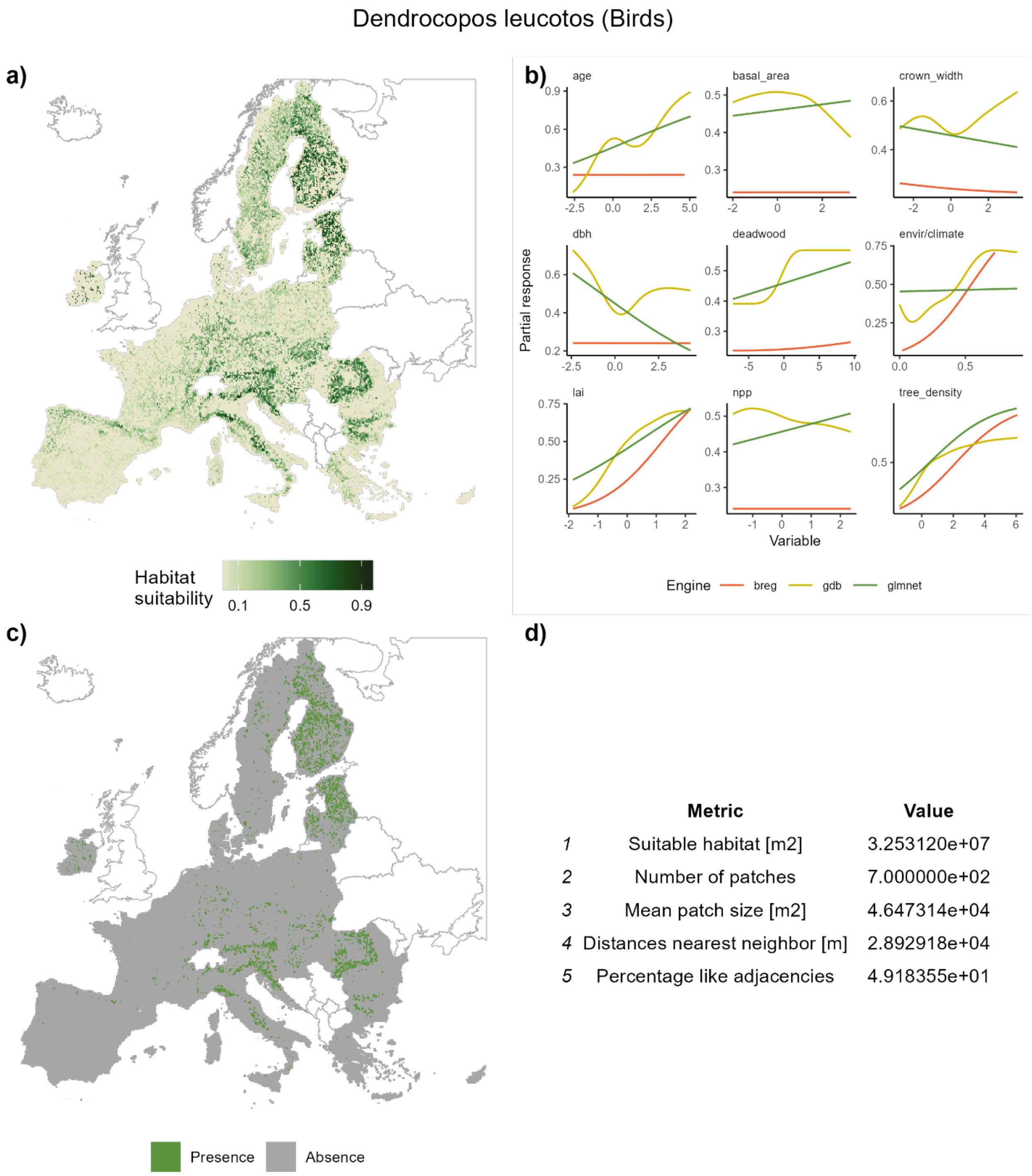
Sørensen similarity index: The Sørensen index is another important biodiversity indicator that describes the similarity (or dissimilarity) between species of two communities in space or time (e.g., Magurran, 2013). Using the species richness maps, we can use the index to describe how biodiversity changes across pathways. To do this, the index is calculated comparing two local communities using a moving window, whereas the communities include the same spatial extent but different scenarios and pathways.

We calculate all indicator values for the entire species pool, as well as for several subsets. This includes indicators separated by taxonomic ranks (e.g., families), different species groups (Table

2), or *IUCN* Red List status. Furthermore, we calculate all indicators only for species that are categorized as saproxylic species or characteristic of old-growth forest. This is based on the same published literature and databases as the priors of the model training.

4.3. Exemplary trained species distribution model

Figure 6 depicts an exemplary and preliminary trained *iSDM* for *Dendrocopos leucotos* (white-backed woodpecker). The trained model uses the current climatic and environmental conditions as well as current forest characteristics. Thus, the figure does not reflect any “final” results, but rather demonstrates how the reference state for some biodiversity indicators is constructed. The habitat suitability map shows the probability of species occurrence based on a model ensemble using three engines (Figure 6a). The corresponding partial response functions show how the covariates affect the fitted suitability (Figure 6b). The continuous values can be transformed to a presence-absence maps using a threshold approache (Figure 6c). Finally, the presence-absence map can be quantified using several landscape metrics (Figure 6d). The biodiversity indicators and their change will be evaluated in comparison to the reference state under the climate change scenarios and forest management pathways (Figure 7). This allows us to compare and evaluate the different scenario and pathways and their impact on biodiversity.



	Metric	Value
1	Suitable habitat [m2]	3.253120e+07
2	Number of patches	7.000000e+02
3	Mean patch size [m2]	4.647314e+04
4	Distances nearest neighbor [m]	2.892918e+04
5	Percentage like adjacencies	4.918355e+01

Figure 6: Exemplary trained iSDM using current climatic and environmental conditions and forest characteristics used as reference state. Results include a) the habitat suitability map, b) the partial response functions of the model fit, c) the occurrence of the species based on a threshold, and d) the composition and configuration of the suitable habitat.

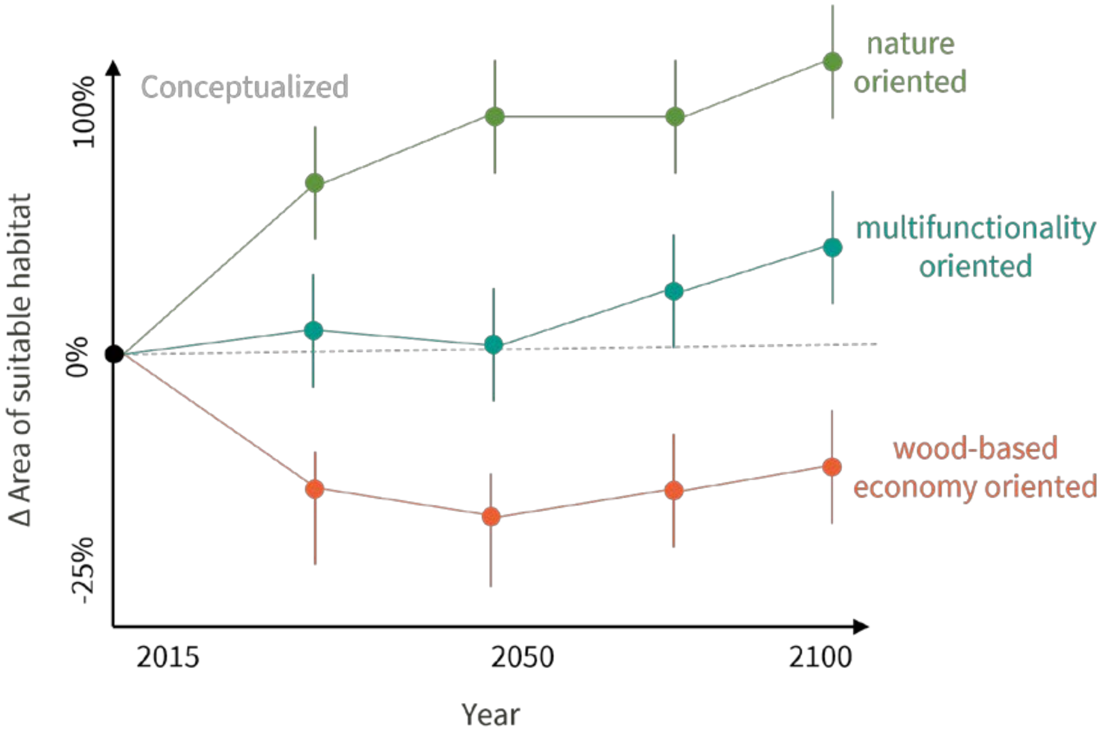


Figure 7: Conecptual figure of the projected area of suitable habitat. The figure shows a hypothesized reference state of the indicator and the relative changes under the three forest management pathways.

5. Summary of next steps

So far, the focus has been on conceptualizing the modelling framework to assess impacts of climate change scenarios and forest-based mitigation pathways on biodiversity using *iSDM*s and biodiversity indicators. Additionally, covariates regarding climatic and environmental conditions as well as forest characteristics and species occurrence data were gathered and pre-processed.

The next steps include gathering and pre-processing of currently missing data, most importantly projected forest characteristics provided by other *WP*s and tasks of the *ForestNavigator* project. Once the data is fully available, the *iSDMs* can be trained, projected on the EU scale, and finally the biodiversity indicators can be calculated. This comprises the following tasks:

Training *iSDM*s based on current climatic/environmental conditions and forest characteristics: Once all covariates describing climatic and environmental conditions and forest characteristics are available and pre-processed, the *iSDM*s can be trained. This also includes the cross-validation of the models.

Project future species habitat suitability: Using the projected climatic and environmental conditions, as well as forest characteristics, species habitat suitabilities can be projected on an EU scale.

Compute biodiversity indicators: We will use the current and projected species habitat suitabilities to compute several biodiversity indicators and more importantly their change under the different climate change scenarios and forest management pathways. This will allow us to assess the impacts of different climate change scenarios and forest management pathways on biodiversity and contribute to informed decision-making in conservation and sustainable forest management.

6. References

Aiello-Lammens, M.E., Boria, R.A., Radosavljevic, A., Vilela, B., Anderson, R.P., 2015. spThin: an R package for spatial thinning of species occurrence records for use in ecological niche models. Ecography 38, 541–545. https://doi.org/10.1111/ecog.01132

Barbet-Massin, M., Jiguet, F., Albert, C.H., Thuiller, W., 2012. Selecting pseudo-absences for species distribution models: how, where and how many? Methods Ecol Evol 3, 327–338. https://doi.org/10.1111/j.2041-210X.2011.00172.x

BirdLife International and Handbook of the Birds of the World, 2022. Bird species distribution maps of the world.

Blasi, C., Marchetti, M., Chiavetta, U., Aleffi, M., Audisio, P., Azzella, M.M., Brunialti, G., Capotorti, G., Del Vico, E., Lattanzi, E., Persiani, A.M., Ravera, S., Tilia, A., Burrascano, S., 2010. Multi-taxon and forest structure sampling for identification of indicators and monitoring of old-growth forest. Plant Biosystems - An International Journal Dealing with all Aspects of Plant Biology 144, 160–170. https://doi.org/10.1080/11263500903560538

Bonannella, C., Hengl, T., Heisig, J., Parente, L., Wright, M.N., Herold, M., De Bruin, S., 2022. Forest tree species distribution for Europe 2000–2020: mapping potential and realized distributions using spatiotemporal machine learning. PeerJ 10, e13728. https://doi.org/10.7717/peerj.13728

Buse, J., Griebeler, E.M., Niehuis, M., 2013. Rising temperatures explain past immigration of the thermophilic oak-inhabiting beetle Coraebus florentinus (Coleoptera: Buprestidae) in south-west Germany. Biodivers Conserv 22, 1115–1131. https://doi.org/10.1007/s10531-012-0395-y

Chakraborty, D., Móricz, N., Rasztovits, E., Dobor, L., Schueler, S., 2021. Provisioning forest and conservation science with high-resolution maps of potential distribution of major European tree species under climate change. Annals of Forest Science 78, 26. https://doi.org/10.1007/s13595-021-01029-4

Chamberlain, S.A., Szöcs, E., 2013. taxize: taxonomic search and retrieval in R. F1000Res 2, 191. https://doi.org/10.12688/f1000research.2-191.v2

Chapin III, F.S., Zavaleta, E.S., Eviner, V.T., Naylor, R.L., Vitousek, P.M., Reynolds, H.L., Hooper, D.U., Lavorel, S., Sala, O.E., Hobbie, S.E., Mack, M.C., Díaz, S., 2000. Consequences of changing biodiversity. Nature 405, 234–242. https://doi.org/10.1038/35012241

De Frenne, P., Rodríguez-Sánchez, F., Coomes, D.A., Baeten, L., Verstraeten, G., Vellend, M., Bernhardt-Römermann, M., Brown, C.D., Brunet, J., Cornelis, J., Decocq, G.M., Dierschke, H., Eriksson, O., Gilliam, F.S., Hédl, R., Heinken, T., Hermy, M., Hommel, P., Jenkins, M.A., Kelly, D.L., Kirby, K.J., Mitchell, F.J.G., Naaf, T., Newman, M., Peterken, G., Petřík, P., Schultz, J., Sonnier, G., Van Calster, H., Waller, D.M., Walther, G.-R., White, P.S., Woods, K.D., Wulf, M., Graae, B.J., Verheyen, K., 2013. Microclimate moderates plant responses to macroclimate warming. Proc. Natl. Acad. Sci. U.S.A. 110, 18561–18565. https://doi.org/10.1073/pnas.1311190110

Dyderski, M.K., Paź, S., Frelich, L.E., Jagodziński, A.M., 2018. How much does climate change threaten European forest tree species distributions? Global Change Biology 24, 1150–1163. https://doi.org/10.1111/gcb.13925

Eckelt, A., Müller, J., Bense, U., Brustel, H., Bußler, H., Chittaro, Y., Cizek, L., Frei, A., Holzer, E., Kadej, M., Kahlen, M., Köhler, F., Möller, G., Mühle, H., Sanchez, A., Schaffrath, U., Schmidl, J., Smolis, A., Szallies, A., Németh, T., Wurst, C., Thorn, S., Christensen, R.H.B., Seibold, S., 2018. “Primeval forest relict beetles” of Central Europe: a set of 168 umbrella species for the protection of primeval forest remnants. J Insect Conserv 22, 15–28. https://doi.org/10.1007/s10841-017-0028-6

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. https://doi.org/10.1146/annurev.ecolsys.110308.120159

European Commission, 2020. Report on the status and trends in 2013 - 2018 of species and habitat types protected by the Birds and Habitats Directives. COM(2020) 635 final (No. 52020DC0635). Brussels.

Farashi, A., Alizadeh-Noughani, M., 2018. Effects of models and spatial resolutions on the species distribution model performance. Model. Earth Syst. Environ. 4, 263–268. https://doi.org/10.1007/s40808-018-0422-4

Feest, A., 2013. The utility of the Streamlining European Biodiversity Indicators 2010 (SEBI 2010). Ecological Indicators 28, 16–21. https://doi.org/10.1016/j.ecolind.2012.10.015

Fink, D., Auer, T., Johnston, A., Strimas-Mackey, M., Ligocki, S., Robinson, O., Hochachka, W., Jaromczyk, L., Crowley, C., Dunham, K., Stillman, A., Davies, I., Rodewald, A., Ruiz-Gutierrez, V., Wood, C., 2023. eBird Status and Trends. https://doi.org/10.2173/ebirdst.2022

Gao, T., Hedblom, M., Emilsson, T., Nielsen, A.B., 2014. The role of forest stand structure as biodiversity indicator. Forest Ecology and Management 330, 82–93. https://doi.org/10.1016/j.foreco.2014.07.007

Gao, T., Nielsen, A.B., Hedblom, M., 2015. Reviewing the strength of evidence of biodiversity indicators for forest ecosystems in Europe. Ecological Indicators 57, 420–434. https://doi.org/10.1016/j.ecolind.2015.05.028

Graf, M., Seibold, S., Gossner, M.M., Hagge, J., Weiß, I., Bässler, C., Müller, J., 2022. Coverage based diversity estimates of facultative saproxylic species highlight the importance of deadwood for biodiversity. Forest Ecology and Management 517, 120275. https://doi.org/10.1016/j.foreco.2022.120275

Guisan, A., Graham, C.H., Elith, J., Huettmann, F., NCEAS Species Distribution Modelling Group, 2007. Sensitivity of predictive species distribution models to change in grain size. Diversity and Distributions 13, 332–340. https://doi.org/10.1111/j.1472-4642.2007.00342.x

Guisan, A., Thuiller, W., 2005. Predicting species distribution: Offering more than simple habitat models. Ecology Letters 8, 993–1009. https://doi.org/10.1111/j.1461-0248.2005.00792.x

Gustafson, E.J., 2019. How has the state-of-the-art for quantification of landscape pattern advanced in the twenty-first century? Landscape Ecology 34, 1–8. https://doi.org/10.1007/s10980-018-0709-x

Heink, U., Kowarik, I., 2010. What criteria should be used to select biodiversity indicators? Biodivers Conserv 19, 3769–3797. https://doi.org/10.1007/s10531-010-9926-6

Hernandez, P.A., Graham, C.H., Master, L.L., Albert, D.L., 2006. The effect of sample size and species characteristics on performance of different species distribution modeling methods. Ecography 29, 773–785. https://doi.org/10.1111/j.0906-7590.2006.04700.x

Hesselbarth, M.H.K., Sciaini, M., With, K.A., Wiegand, K., Nowosad, J., 2019. landscapemetrics: An open-source R tool to calculate landscape metrics. Ecography 42, 1648–1657. https://doi.org/10.1111/ecog.04617

Hijmans, R.J., 2021. terra: Spatial Data Analysis. R package version 1.0-10. <https://CRAN.R-project.org/package=terra>.

Hijmans, R.J., 2012. Cross-validation of species distribution models: removing spatial sorting bias and calibration with a null model. Ecology 93, 679–688. https://doi.org/10.1890/11-0826.1

Hirzel, A.H., Le Lay, G., Helfer, V., Randin, C., Guisan, A., 2006. Evaluating the ability of habitat suitability models to predict species presences. Ecological Modelling 199, 142–152. https://doi.org/10.1016/j.ecolmodel.2006.05.017

Hisano, M., Searle, E.B., Chen, H.Y.H., 2018. Biodiversity as a solution to mitigate climate change impacts on the functioning of forest ecosystems. Biological Reviews 93, 439–456. https://doi.org/10.1111/brv.12351

IPBES, 2019. Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. Secretariat of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Service, Bonn, Germany. https://doi.org/10.5281/ZENODO.6417333

Isaac, N.J.B., Jarzyna, M.A., Keil, P., Dambly, L.I., Boersch-Supan, P.H., Browning, E., Freeman, S.N., Golding, N., Guillera-Arroita, G., Henrys, P.A., Jarvis, S., Lahoz-Monfort, J., Pagel, J., Pescott, O.L., Schmucki, R., Simmonds, E.G., O'Hara, R.B., 2020. Data integration for large-scale models of species distributions. Trends in Ecology & Evolution 35, 56–67. https://doi.org/10.1016/j.tree.2019.08.006

IUCN, 2022. International Union for Conservation of Nature (IUCN).

Johnston, A., Hochachka, W.M., Strimas-Mackey, M.E., Ruiz Gutierrez, V., Robinson, O.J., Miller, E.T., Auer, T., Kelling, S.T., Fink, D., 2021. Analytical guidelines to increase the value of community science data: An example using eBird data to estimate species distributions. Diversity and Distributions 27, 1265–1277. https://doi.org/10.1111/ddi.13271

Jung, M., 2023. An integrated species distribution modelling framework for heterogeneous biodiversity data. Ecological Informatics 76, 102127. https://doi.org/10.1016/j.ecoinf.2023.102127

Jung, M., Arnell, A., De Lamo, X., García-Rangel, S., Lewis, M., Mark, J., Merow, C., Miles, L., Ondo, I., Pironon, S., Ravilious, C., Rivers, M., Schepaschenko, D., Tallowin, O., Van Soesbergen, A., Govaerts, R., Boyle, B.L., Enquist, B.J., Feng, X., Gallagher, R., Maitner, B., Meiri, S., Mulligan, M., Ofer, G., Roll, U., Hanson, J.O., Jetz, W., Di Marco, M., McGowan, J., Rinnan, D.S., Sachs, J.D., Lesiv, M., Adams, V.M., Andrew, S.C., Burger, J.R., Hannah, L., Marquet, P.A., McCarthy, J.K., Morueta-Holme, N., Newman, E.A., Park, D.S., Roehrdanz, P.R., Svenning, J.-C., Violle, C., Wieringa, J.J., Wynne, G., Fritz, S., Strassburg, B.B.N., Obersteiner, M., Kapos, V., Burgess, N., Schmidt-Traub, G., Visconti, P., 2021. Areas of global importance for conserving terrestrial biodiversity, carbon and water. Nat Ecol Evol 5, 1499–1509. https://doi.org/10.1038/s41559-021-01528-7

Lachat, T., Wermelinger, B., Gossner, M.M., Bussler, H., Isacsson, G., Müller, J., 2012. Saproxylic beetles as indicator species for dead-wood amount and temperature in European beech forests. Ecological Indicators 23, 323–331. https://doi.org/10.1016/j.ecolind.2012.04.013

Leitão, P.J., Toraño Caicoya, A., Dahlkamp, A., Guderjan, L., Griesser, M., Haverkamp, P.J., Nordén, J., Snäll, T., Schröder, B., 2022. Impacts of forest management on forest bird occurrence patterns - a case study in central Europe. Front. For. Glob. Change 5, 786556. https://doi.org/10.3389/ffgc.2022.786556

Lucas, P.M., González-Suárez, M., Revilla, E., 2019. Range area matters, and so does spatial configuration: predicting conservation status in vertebrates. Ecography 42, 1103–1114. https://doi.org/10.1111/ecog.03865

Magurran, A.E., 2013. Measuring biological diversity, 1., Auflage. ed. John Wiley & Sons, New York, NY.

Mauri, A., Girardello, M., Strona, G., Beck, P.S.A., Forzieri, G., Caudullo, G., Manca, F., Cescatti, A., 2022. EU-Trees4F, a dataset on the future distribution of European tree species. Sci Data 9, 37. https://doi.org/10.1038/s41597-022-01128-5

Oettel, J., Lapin, K., 2021. Linking forest management and biodiversity indicators to strengthen sustainable forest management in Europe. Ecological Indicators 122, 107275. https://doi.org/10.1016/j.ecolind.2020.107275

Parisi, F., Innangi, M., Tognetti, R., Lombardi, F., Chirici, G., Marchetti, M., 2021. Forest stand structure and coarse woody debris determine the biodiversity of beetle communities in Mediterranean mountain beech forests. Global Ecology and Conservation 28, e01637. https://doi.org/10.1016/j.gecco.2021.e01637

Pebesma, E.J., 2018. sf: Simple Features for R. <https://cran.r-project.org/package=sf>.

Pecchi, M., Marchi, M., Burton, V., Giannetti, F., Moriondo, M., Bernetti, I., Bindi, M., Chirici, G., 2019. Species distribution modelling to support forest management. A literature review. Ecological Modelling 411, 108817. https://doi.org/10.1016/j.ecolmodel.2019.108817

Pettorelli, N., Graham, N.A.J., Seddon, N., Maria Da Cunha Bustamante, M., Lowton, M.J., Sutherland, W.J., Koldewey, H.J., Prentice, H.C., Barlow, J., 2021. Time to integrate global climate change and biodiversity science-policy agendas. Journal of Applied Ecology 58, 2384–2393. https://doi.org/10.1111/1365-2664.13985

Pörtner, H.-O., Scholes, R.J., Arneth, A., Barnes, D.K.A., Burrows, M.T., Diamond, S.E., Duarte, C.M., Kiessling, W., Leadley, P., Managi, S., McElwee, P., Midgley, G., Ngo, H.T., Obura, D., Pascual, U., Sankaran, M., Shin, Y.J., Val, A.L., 2023. Overcoming the coupled climate and biodiversity crises and their societal impacts. Science 380, eabl4881. https://doi.org/10.1126/science.abl4881

Pucher, C., Neumann, M., Hasenauer, H., 2022. An Improved Forest Structure Data Set for Europe. Remote Sensing 14, 395. https://doi.org/10.3390/rs14020395

R Core Team, 2021. R: A language and environment for statistical computing.

Renwick, K.M., Rocca, M.E., 2015. Temporal context affects the observed rate of climate-driven range shifts in tree species: Importance of temporal context in tree range shifts. Global Ecology and Biogeography 24, 44–51. https://doi.org/10.1111/geb.12240

Roberts, D.R., Bahn, V., Ciuti, S., Boyce, M.S., Elith, J., Guillera-Arroita, G., Hauenstein, S., Lahoz-Monfort, J.J., Schröder, B., Thuiller, W., Warton, D.I., Wintle, B.A., Hartig, F., Dormann, C.F., 2017. Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. Ecography 40, 913–929. https://doi.org/10.1111/ecog.02881

Roll, U., Feldman, A., Novosolov, M., Allison, A., Bauer, A.M., Bernard, R., Böhm, M., Castro-Herrera, F., Chirio, L., Collen, B., Colli, G.R., Dabool, L., Das, I., Doan, T.M., Grismer, L.L., Hoogmoed, M., Itescu, Y., Kraus, F., LeBreton, M., Lewin, A., Martins, M., Maza, E., Meirte, D., Nagy, Z.T., De C. Nogueira, C., Pauwels, O.S.G., Pincheira-Donoso, D., Powney, G.D., Sindaco, R., Tallowin, O.J.S., Torres-Carvajal, O., Trape, J.-F., Vidan, E., Uetz, P., Wagner, P., Wang, Y., Orme, C.D.L., Grenyer, R., Meiri, S., 2017. The global distribution of tetrapods reveals a need for targeted reptile conservation. Nat Ecol Evol 1, 1677–1682. https://doi.org/10.1038/s41559-017-0332-2

Ruiz-Benito, P., Ratcliffe, S., Jump, A.S., Gómez-Aparicio, L., Madrigal-González, J., Wirth, C., Kändler, G., Lehtonen, A., Dahlgren, J., Kattge, J., Zavala, M.A., 2017. Functional diversity underlies demographic responses to environmental variation in European forests. Global Ecol. Biogeogr. 26, 128–141. https://doi.org/10.1111/geb.12515

Sabatini, F.M., Lenoir, J., Hattab, T., Arnst, E.A., Chytrý, M., Dengler, J., De Ruffray, P., Hennekens, S.M., Jandt, U., Jansen, F., Jiménez-Alfaro, B., Kattge, J., Levesley, A., Pillar, V.D., Purschke, O., Sandel, B., Sultana, F., Aavik, T., Aćić, S., Acosta, A.T.R., Agrillo, E., Alvarez, M., Apostolova, I., Arfin Khan, M.A.S., Arroyo, L., Attorre, F., Aubin, I., Banerjee, A., Bauters, M., Bergeron, Y., Bergmeier, E., Biurrun, I., Bjorkman, A.D., Bonari, G., Bondareva, V., Brunet, J., Čarni, A., Casella, L., Cayuela, L., Černý, T., Chepinoga, V., Csiky, J., Ćušterevska, R., De Bie, E., de Gasper, A.L., De Sanctis, M., Dimopoulos, P., Dolezal, J., Dziuba, T., El-Sheikh, M.A.E.-R.M., Enquist, B., Ewald, J., Fazayeli, F., Field, R., Finckh, M., Gachet, S., Galán-de-Mera, A., Garbolino, E., Gholizadeh, H., Giorgis, M., Golub, V., Alsos, I.G., Grytnes, J.-A., Guerin, G.R., Gutiérrez, A.G., Haider, S., Hatim, M.Z., Hérault, B., Hinojos Mendoza, G., Hölzel, N., Homeier, J., Hubau, W., Indreica, A., Janssen, J.A.M., Jedrzejek, B., Jentsch, A., Jürgens, N., Kącki, Z., Kapfer, J., Karger, D.N., Kavgacı, A., Kearsley, E., Kessler, M., Khanina, L., Killeen, T., Korolyuk, A., Kreft, H., Kühl, H.S., Kuzemko, A., Landucci, F., Lengyel, A., Lens, F., Lingner, D.V., Liu, H., Lysenko, T., Mahecha, M.D., Marcenò, C., Martynenko, V., Moeslund, J.E., Monteagudo Mendoza, A., Mucina, L., Müller, J.V., Munzinger, J., Naqinezhad, A., Noroozi, J., Nowak, A., Onyshchenko, V., Overbeck, G.E., Pärtel, M., Pauchard, A., Peet, R.K., Peñuelas, J., Pérez-Haase, A., Peterka, T., Petřík, P., Peyre, G., Phillips, O.L., Prokhorov, V., Rašomavičius, V., Revermann, R., Rivas-Torres, G., Rodwell, J.S., Ruprecht, E., Rūsiņa, S., Samimi, C., Schmidt, M., Schrodt, F., Shan, H., Shirokikh, P., Šibík, J., Šilc, U., Sklenář, P., Škvorc, Ž., Sparrow, B., Sperandii, M.G., Stančić, Z., Svenning, J.-C., Tang, Z., Tang, C.Q., Tsiripidis, I., Vanselow, K.A., Vásquez Martínez, R., Vassilev, K., Vélez-Martin, E., Venanzoni, R., Vibrans, A.C., Violle, C., Virtanen, R., von Wehrden, H., Wagner, V., Walker, D.A., Waller, D.M., Wang, H.-F., Wesche, K., Whitfeld, T.J.S., Willner, W., Wiser, S.K., Wohlgemuth, T., Yamalov, S., Zobel, M., Bruelheide, H., 2021. sPlotOpen – An environmentally balanced, open-access, global dataset of vegetation plots. Global Ecology and Biogeography 30, 1740–1764. https://doi.org/10.1111/geb.13346

Sala, O.E., Chapin III, F.S., Armesto, J.J., Berlow, E., Bloomfield, J., Dirzo, R., Huber-Sanwald, E., Huenneke, L.F., Jackson, R.B., Kinzig, A., Leemans, R., Lodge, D.M., Mooney, H.A., Oesterheld, M., Poff, N.L., Sykes, M.T., Walker, B.H., Walker, M., Wall, D.H., 2000. Global Biodiversity Scenarios for the Year 2100. Science 287, 1770–1774. https://doi.org/10.1126/science.287.5459.1770

Santini, L., Belmaker, J., Costello, M.J., Pereira, H.M., Rossberg, A.G., Schipper, A.M., Ceaușu, S., Dornelas, M., Hilbers, J.P., Hortal, J., Huijbregts, M.A.J., Navarro, L.M., Schiffers, K.H., Visconti, P., Rondinini, C., 2017. Assessing the suitability of diversity metrics to detect biodiversity change. Biological Conservation 213, 341–350. https://doi.org/10.1016/j.biocon.2016.08.024

Schiavina, M., Freire, S., MacManus, K., 2023. GHS-POP R2023A - GHS population grid multitemporal (1975-2030). https://doi.org/10.2905/2FF68A52-5B5B-4A22-8F40-C41DA8332CFE

Schuldt, B., Buras, A., Arend, M., Vitasse, Y., Beierkuhnlein, C., Damm, A., Gharun, M., Grams, T.E.E., Hauck, M., Hajek, P., Hartmann, H., Hiltbrunner, E., Hoch, G., Holloway-Phillips, M., Körner, C., Larysch, E., Lübbe, T., Nelson, D.B., Rammig, A., Rigling, A., Rose, L., Ruehr, N.K., Schumann, K., Weiser, F., Werner, C., Wohlgemuth, T., Zang, C.S., Kahmen, A., 2020. A first assessment of the impact of the extreme 2018 summer drought on Central European forests. Basic and Applied Ecology 45, 86–103. https://doi.org/10.1016/j.baae.2020.04.003

Seidl, R., Thom, D., Kautz, M., Martin-Benito, D., Peltoniemi, M., Vacchiano, G., Wild, J., Ascoli, D., Petr, M., Honkaniemi, J., Lexer, M.J., Trotsiuk, V., Mairota, P., Svoboda, M., Fabrika, M., Nagel, T.A., Reyer, C.P.O., 2017. Forest disturbances under climate change. Nature Clim Change 7, 395–402. https://doi.org/10.1038/nclimate3303

Sillero, N., Campos, J., Bonardi, A., Corti, C., Creemers, R., Crochet, P.-A., Crnobrnja Isailović, J., Denoël, M., Ficetola, G.F., Gonçalves, J., Kuzmin, S., Lymberakis, P., De Pous, P., Rodríguez, A., Sindaco, R., Speybroeck, J., Toxopeus, B., Vieites, D.R., Vences, M., 2014. Updated distribution and biogeography of amphibians and reptiles of Europe. Amphib Reptilia 35, 1–31. https://doi.org/10.1163/15685381-00002935

Steen, V.A., Tingley, M.W., Paton, P.W.C., Elphick, C.S., 2021. Spatial thinning and class balancing: Key choices lead to variation in the performance of species distribution models with citizen science data. Methods Ecol Evol 12, 216–226. https://doi.org/10.1111/2041-210X.13525

Stokland, J.N., Meyke, E., 2008. The saproxylic database: an emerging overview of the biological diversity in dead wood. revec 10, 37–48. https://doi.org/10.3406/revec.2008.1459

Strimas-Mackey, M.E., Hochachka, W.M., Ruiz-Gutierrez, V., Robinson, O.J., Miller, E.T., Auer, T., Kelling, S., Fink, D., Johnston, A., 2023. Best practices for using eBird data. Version 2.0. Cornell Lab of Ornithology, Ithaca, New York.

Sullivan, B.L., Aycrigg, J.L., Barry, J.H., Bonney, R.E., Bruns, N., Cooper, C.B., Damoulas, T., Dhondt, A.A., Dietterich, T., Farnsworth, A., Fink, D., Fitzpatrick, J.W., Fredericks, T., Gerbracht, J., Gomes, C., Hochachka, W.M., Iliff, M.J., Lagoze, C., La Sorte, F.A., Merrifield, M., Morris, W., Phillips, T.B., Reynolds, M., Rodewald, A.D., Rosenberg, K.V., Trautmann, N.M., Wiggins, A., Winkler, D.W., Wong, W.-K., Wood, C.L., Yu, J., Kelling, S., 2014. The eBird enterprise: An integrated approach to development and application of citizen science. Biological Conservation 169, 31–40. https://doi.org/10.1016/j.biocon.2013.11.003

Sullivan, B.L., Wood, C.L., Iliff, M.J., Bonney, R.E., Fink, D., Kelling, S., 2009. eBird: A citizen-based bird observation network in the biological sciences. Biological Conservation 142, 2282–2292. https://doi.org/10.1016/j.biocon.2009.05.006

Thom, D., Rammer, W., Dirnböck, T., Müller, J., Kobler, J., Katzensteiner, K., Helm, N., Seidl, R., 2017. The impacts of climate change and disturbance on spatio-temporal trajectories of biodiversity in a temperate forest landscape. Journal of Applied Ecology 54, 28–38. https://doi.org/10.1111/1365-2664.12644

Thuiller, W., Lavorel, S., Araújo, M.B., Sykes, M.T., Prentice, I.C., 2005. Climate change threats to plant diversity in Europe. Proc. Natl. Acad. Sci. U.S.A. 102, 8245–8250. https://doi.org/10.1073/pnas.0409902102

Valavi, R., Elith, J., Lahoz-Monfort, J.J., Guillera-Arroita, G., 2019. blockCV: An R package for generating spatially or environmentally separated folds for k -fold cross-validation of species distribution models. Methods Ecol Evol 10, 225–232. https://doi.org/10.1111/2041-210X.13107

Vallecillo, S., Maes, J., Polce, C., Lavalle, C., 2016. A habitat quality indicator for common birds in Europe based on species distribution models. Ecological Indicators 69, 488–499. https://doi.org/10.1016/j.ecolind.2016.05.008

Warren, D.L., Glor, R.E., Turelli, M., 2008. Environmental niche equivalency versus conservatism: quantitative approaches to niche evolution. Evolution 62, 2868–2883. https://doi.org/10.1111/j.1558-5646.2008.00482.x

Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T., Miller, E., Bache, S., Müller, K., Ooms, J., Robinson, D., Seidel, D., Spinu, V., Takahashi, K., Vaughan, D., Wilke, C., Woo, K., Yutani, H., 2019. Welcome to the tidyverse. Journal of Open Source Software 4, 1686. https://doi.org/10.21105/joss.01686

Williams, J.E., Blois, J.L., 2018. Range shifts in response to past and future climate change: Can climate velocities and species' dispersal capabilities explain variation in mammalian range shifts? J Biogeogr 45, 2175–2189. https://doi.org/10.1111/jbi.13395

Wisz, M.S., Hijmans, R.J., Li, J., Peterson, A.T., Graham, C.H., Guisan, A., NCEAS Predicting Species Distributions Working Group, 2008. Effects of sample size on the performance of species distribution models. Diversity and Distributions 14, 763–773. https://doi.org/10.1111/j.1472-4642.2008.00482.x

Zizka, A., Silvestro, D., Andermann, T., Azevedo, J., Duarte Ritter, C., Edler, D., Farooq, H., Herdean, A., Ariza, M., Scharn, R., Svantesson, S., Wengström, N., Zizka, V., Antonelli, A., 2019. CoordinateCleaner: Standardized cleaning of occurrence records from biological collection databases. Methods Ecol Evol 10, 744–751. https://doi.org/10.1111/2041-210X.13152

Supporting information

S1: Species previously modelled on national scale

The following species were previously modelled on a national scale by consortium members of the *ForestNavigator* project. Thus, we are also included these species in our biodiversity modelling workflow to compare results across the EU scale modelling and the national scale modelling.

Species	Species group
Trichaptum abietinum	Fungus
Fomitopsis pinicola	Fungus
Gloeophyllum sepiarium	Fungus
Antrodia serialis	Fungus
Phellinus viticola	Fungus
Phellinus ferrugineofuscus	Fungus
Phellinus nigrolimitatus	Fungus
Phlebia centrifuga	Fungus
Fomitopsis rosea	Fungus
Amylocystis lapponica	Fungus
Tetrastes bonasia	Birds
Perisoreus infaustus	Birds
Poecile cinctus	Birds
Aegithalos caudatus	Birds
Ficedula parva	Birds
Picus canus	Birds
Dendrocopos minor	Birds
Picoides tridactylus	Birds
Lobaria pulmonaria	Lichens
Anastrophyllum hellerianum	Non-vascular plants
Anastrophyllum michauxii	Non-vascular plants

Buxbaumia viridis	Non-vascular plants
Callicladium haldanianum	Non-vascular plants
Calypogeia suecica	Non-vascular plants
Campylophyllum sommerfeltii	Non-vascular plants
Cephalozia catenulata	Non-vascular plants
Dicranodontium denudatum	Non-vascular plants
Dicranum flagellare	Non-vascular plants
Dicranum fragilifolium	Non-vascular plants
Geocalyx graveolens	Non-vascular plants
Herzogiella seligeri	Non-vascular plants
Herzogiella turfacea	Non-vascular plants
Jamesoniella autumnalis	Non-vascular plants
Jungermannia leiantha	Non-vascular plants
Lophozia ascendens	Non-vascular plants
Lophozia ciliata	Non-vascular plants
Lophozia longiflora	Non-vascular plants
Mylia taylorii	Non-vascular plants
Nowellia curvifolia	Non-vascular plants
Odontoschisma denudatum	Non-vascular plants
Scapania apiculata	Non-vascular plants
Scapania carinthiaca	Non-vascular plants