



Contents lists available at ScienceDirect

Data in Brief

journal homepage: www.elsevier.com/locate/dib

Data Article

A harmonized database of European forest simulations under climate change

Marc Grünig^{a,*}, Werner Rammer^a, Katharina Albrich^b,
 Frédéric André^c, Andrey L.D. Augustynczyk^d, Friedrich Bohn^e,
 Meike Bouwman^f, Harald Bugmann^g, Alessio Collalti^{h,i},
 Irina Cristal^j, Daniela Dalmonech^{h,i}, Miquel De Caceres^k,
 Francois De Coligny^l, Laura Dobor^m, Christina Dollinger^a,
 David I. Forresterⁿ, Jordi Garcia-Gonzalo^j, José Ramón González^j,
 Ulrike Hiltner^g, Tomáš Hlásny^m, Juha Honkaniemi^b, Nica Huber^{g,w},
 Mathieu Jonard^c, Anna Maria Jönsson^o, Fredrik Lagergren^o,
 Mats Nieberg^{p,q,r}, Marco Mina^s, Frits Mohren^f, Christine Moos^t,
 Xaxier Morin^u, Bart Muys^v, Mikko Peltoniemi^b,
 Christopher PO Reyer^d, Ilié Storms^v, Dominik Thom^a,
 Maude Toigo^{u,x}, Rupert Seidl^a

^aTUM School of Life Sciences, Ecosystem Dynamics and Forest Management, Technical University of Munich, Hans-Carl-von-Carlowitz-Platz 2, 85354 Freising, Germany

^bNatural Resources Institute Finland, Forest Health and Biodiversity Group, Latokartanonkaari 9, 00790 Helsinki, Finland

^cEarth and Life Institute, Université catholique de Louvain, Croix du S, 1348 Ottignies-Louvain-la-Neuve, Belgium

^dInternational Institute for Applied Systems Analysis, Integrated Biosphere Futures Research Group, Schlossplatz 1, A-2361 Laxenburg, Austria

^eHelmholtz Centre for Environmental Research UFZ, Permoserstraße 15, 04318 Leipzig, Germany

^fWageningen University & Research, Forest Ecology and Forest Management Group, Droevendaalsesteeg 3a, 6708 PB Wageningen, the Netherlands

^gETH Zürich, Forest Ecology, Institute of Terrestrial Ecosystems, Universitätsstrasse 16, 8006 Zürich, Switzerland

^hNational Research Council of Italy (CNR-ISAFOM), Institute for Agriculture and Forestry Systems in the Mediterranean, Forest Modelling Lab., Via Madonna Alta 128, 06128 Perugia, Italy

ⁱNational Biodiversity Future Center (NBFC), Piazza Marina, 61 90133 Palermo, Italy

^jForest Science and Technology Center of Catalonia (CTFC), Crta. de St. Llorenç de Morunys, 25280 Solsona, Spain

^kCREAF, E08193 Bellaterra (Cerdanyola del Vallès), Catalonia, Spain

^lAMAP, INRAE-CIRAD-CNRS-IRD-Univ Montpellier, 34398 Montpellier cedex 5, France

^mFaculty of Forestry and Wood Sciences, Czech University of Life Sciences Prague, 165 21 Prague 6, Kamýcká 129, Czech Republic

* Corresponding author.

E-mail address: marc.gruenig@tum.de (M. Grünig).

Social media: [@GruenigMarc](https://twitter.com/GruenigMarc) (M. Grünig)

<https://doi.org/10.1016/j.dib.2024.110384>

2352-3409/© 2024 The Authors. Published by Elsevier Inc. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>)

Please cite this article as: M. Grünig, W. Rammer and K. Albrich et al., A harmonized database of European forest simulations under climate change, Data in Brief, <https://doi.org/10.1016/j.dib.2024.110384>

ⁿ CSIRO Environment, GPO Box 1700, ACT 2601, Australia

^o Department of Physical Geography and Ecosystem Science, Lund University, Sölvegatan 12, 223 62 Lund, Sweden

^p Potsdam Institute for Climate Impact Research (PIK), Member of the Leibniz Association, Telegrafenberg A 31, Potsdam, Germany

^q European Forest Institute, Platz der Vereinten Nationen 7, 53113 Bonn, Germany

^r Technische Universität Dresden, Chair of Forest Growth and Woody Biomass Production, Piener Straße 8, 01737 Tharandt, Germany

^s Institute for Alpine Environment, Eurac Research, Via Alessandro Volta, 13A, 39100 Bolzano, BZ, Italy

^t Bern University of Applied Sciences, BFH-HAFL, Länggasse 85, 3052 Zollikofen, Switzerland

^u Université de Montpellier Université Paul-Valéry Montpellier – EPHE– IRD, CEFE UMR 5175, CNRS, 1919 Route de Mende, F-34293 Montpellier, France

^v KU Leuven, Department of Earth and Environmental Sciences, Celestijnenlaan 200E, 3001 Leuven, Belgium

^w Swiss Federal Research Institute WSL, Remote Sensing, Zürcherstrasse 111, CH-8903 Birmensdorf, Switzerland

^x Université Bordeaux, Bordeaux Sciences Agro, INRAE, Biogeco, 69 route d'Arcachon, F-33612 Cestas, France

ARTICLE INFO

Article history:

Received 1 March 2024

Revised 27 March 2024

Accepted 29 March 2024

Available online xxx

Dataset link: [Data for: A harmonized database of European forest simulations under climate change \(Original data\)](#)

Keywords:

Process-based models

Vegetation dynamics

Europe's forests

Forest development

Forest structure

Forest composition

Forest functioning

ABSTRACT

Process-based forest models combine biological, physical, and chemical process understanding to simulate forest dynamics as an emergent property of the system. As such, they are valuable tools to investigate the effects of climate change on forest ecosystems. Specifically, they allow testing of hypotheses regarding long-term ecosystem dynamics and provide means to assess the impacts of climate scenarios on future forest development. As a consequence, numerous local-scale simulation studies have been conducted over the past decades to assess the impacts of climate change on forests. These studies apply the best available models tailored to local conditions, parameterized and evaluated by local experts. However, this treasure trove of knowledge on climate change responses remains underexplored to date, as a consistent and harmonized dataset of local model simulations is missing.

Here, our objectives were (i) to compile existing local simulations on forest development under climate change in Europe in a common database, (ii) to harmonize them to a common suite of output variables, and (iii) to provide a standardized vector of auxiliary environmental variables for each simulated location to aid subsequent investigations. Our dataset of European stand- and landscape-level forest simulations contains over 1.1 million simulation runs representing 135 million simulation years for more than 13,000 unique locations spread across Europe. The data were harmonized to consistently describe forest development in terms of stand structure (dominant height), composition (dominant species, admixed species), and functioning (leaf area index). Auxiliary variables provided include consistent daily climate information (temperature, precipitation, radiation, vapor pressure deficit) as well as information on local site conditions (soil depth, soil physical properties, soil water holding capacity, plant-available nitrogen). The present dataset facilitates analyses across models and locations, with the aim to better harness the valuable information contained in local simulations for large-scale policy support, and for fostering a deeper understanding of the effects of climate change on forest ecosystems in Europe.

© 2024 The Authors. Published by Elsevier Inc.
This is an open access article under the CC BY license
(<http://creativecommons.org/licenses/by/4.0/>)

1 Specifications Table

Subject	Environmental Sciences: Ecological modeling
Specific subject area	Harmonizing forest modeling simulations of climate change effects, process-based forest simulation models
Data format	Raw, harmonized
Type of data	Table, Database
Data collection	Data were contributed from the European forest modeling community. Each contributor uploaded simulation data files and a metadata file containing information on the design and drivers of the simulation as CSV files to an R Shiny application. Upon submission, the data were stored in a designated folder with a unique identifier assigned to each contributor. Contributions were required to follow specific criteria, including process-based simulations and annual output information on key vegetation development indicators (i.e. proportion of tree species, canopy height, and leaf area index). Other requirements were that simulation outputs were on the level of tree species, as well as in the absence of disturbances and management (or business-as-usual management).
Data source location	Technical University of Munich, TUM School of Life Sciences, Ecosystem Dynamics and Forest Management Group
Data accessibility	Repository name: <i>Data for: A harmonized database of European forest simulations under climate change</i> Data identification number: 10.5281/zenodo.10730807 Direct URL to data: https://zenodo.org/records/10.730.807

2 1. Value of the Data

- Forest simulation model outputs from 17 different models were collected and harmonized. The dataset contains 1.1 million individual simulation runs over 135 million simulation years across 13,599 unique locations in Europe, covering large proportions of the climate and soil conditions in Europe's forests.
- The database contains standardized output variables across all models. Specifically, harmonized simulation outputs are available for canopy height (structure), leaf area index (LAI; functioning) and tree species proportions (composition) at annual time step. To provide harmonized layers of context information for simulation results, we collated daily climate data for historic climate (1981–2005) and a set of climate change scenarios (2006–2100) and consistent soil properties for all simulations.
- This is the first harmonized dataset of local forest model simulations at continental scale. The data collected here will support synthetic analyses of climate change impact on Europe's forests, and will facilitate comparative analyses across locations and models. Further, our dataset also helps to identify regions that remain underrepresented in model-based climate impact assessments and should thus be the focus of future studies.

2. Background

The objective was to collate projections on forest development under climate change derived from simulation models. Specifically, we compiled existing simulation data from previously conducted analyses using published models at the stand- to landscape-scale. Contributions to the dataset were made by several experts of the European forest modeling community, and all contributors are co-authors of this paper. Model outputs were compiled for three common state variables describing complementary aspects of forest ecosystems. By harmonizing the output variables across different models and adding standardized climate and soil data we created a novel, bottom-up dataset for broad-scale, multi-model assessments of climate change impacts of Europe's forests.

Table 1

Structure of the harmonized simulation database including standardized auxiliary data for all simulations. Discrete vegetation states were created by combining the three state variables and binning the respective continuous variables – see methods for details. Note that each row in [Table 1](#) describes a column in the simulation database.

Section	Column name	Description
General	SourceID	ID to identify the source of the data (i.e. contributor).
	SimulationID	Unique numeric identifier of the simulation created by the contributor.
	Year	Year of the simulation starting with 1 or the calendar year (e.g., 2000).
Vegetation	Discrete vegetation state	Discrete state derived by combining the three state variables species composition, LAI class and dominant canopy height class (e.g. PIAB_3_20_22; see methods for details).
	Dominant height	In meters, harmonized (calculated from min, mean and max heights, details on the calculations are shown in the methods).
Soil	LAI	Leaf Area Index (one-sided or projected) in m ² /m ² .
	WHC	Water holding capacity of the site (mm).
	TextureSand	% sand content of the soil.
	TextureSilt	% silt content of the soil.
	TextureClay	% clay content of the soil.
Climate	SoilDepth	Depth of the plant-accessible soil (mm) without rocks (> 2 mm diameter).
	AvailableNitrogen	Plant available nitrogen (kg/ha/year).
	Scenario	Combination of GCM and RCP from which daily data was obtained.
	Temperature	Columns “tas_1” to “tas_365” with daily mean temperature [°C].
	Precipitation	Columns “prec_1” to “prec_365” with daily precipitation [mm].
	Radiation	Columns “rad_1” to “rad_365” with daily radiation [W/m ²].
	Vapor pressure deficit (VPD)	Columns “vpd_1” to “vpd_365” with daily vapor pressure deficit [kPa].

28 3. Data Description

29 The data are collected and stored in SQLite format. SQLite is a widely used open-source
 30 database format and can be accessed from all major data analysis platforms. One SQLite database
 31 contains the raw simulation outputs and a metadata table of all simulations including informa-
 32 tion about locations and harmonized soil conditions for those locations. This data follows the
 33 structure described in detail in the supplementary information (Tables S1 and S2). Simulation
 34 outputs with harmonized climate data are stored in one SQLite database per climate scenario.
 35 Tables in those databases follow the structure shown in [Table 1](#). Further, a metadata table of
 36 all simulations, including information about locations and soil conditions for those locations is
 37 provided ([Table S2](#)).

38 The database contains 11,17,453 simulation runs that together contain 135,375,583 simulation
 39 years. Simulations cover 13,599 unique locations across Europe and represent 92 tree species.
 40 Simulation data were provided from 19 research groups, using 17 different forest models. All
 41 simulations were created with locally tested and evaluated models that are well-documented
 42 and published in the peer-reviewed literature ([Table 2](#)). Note that as models are further devel-
 43 oped over time, model versions used for the simulations may vary from the cited references in
 44 some cases. While all models contributed to the coverage of climate and soil conditions across
 45 Europe, their individual contributions varied in terms of geographic range and number of sim-
 46 ulations provided. Likewise, for some models more data were available than for others. While
 47 the majority of simulations were run with iLand, MEDFATE simulations covered the largest cli-
 48 mate and soil gradient. The simulations in the database consist of 90.5% climate change runs and

Table 2

Models, number of simulations per model and their coverage of current climate and soil space of Europe. Percentage of climate and soil space refers to the area covered by the climate and soil space in which the model simulations are located. For this, we stratified the climate and soil space and checked which of the classes are covered by the simulations of each model. We then calculated the area covered by the classes that are represented by each model. Further details are described in the Experimental Design, Materials and Methods section. The Model type column distinguishes between stand-level (S) models and landscape-level (L) models.

MODEL OVERVIEW						
MODEL	Simulations	% of all	% clim	% soil	Model type	Model reference
ILAND	821,979	73.2	21.4	43.1	L	Seidl et al. 2012 [2]
4C	250,979	22.4	18.3	54.3	S	Lasch-Born et al., 2020 [3]
MEDFATE	22,464	2.0	40.8	64.5	S	De Cáceres et al., 2021 [4]
FORCLIM	9210	0.8	10.3	46.7	S	Bugmann, 1996 [5]; Huber et al., 2021 [6]
LPJ-GUESS2.1	6156	0.6	15.5	46.6	L	Smith et al., 2008 [7]
FORCEEPS	5040	0.5	4.8	6.7	S	Morin et al., 2021 [8]
TREEMIG	2820	0.3	0.6	0.3	L	Lischke et al., 2006 [9]
3PGN-BW	1428	0.1	40.0	59.8	S	Augustynczyk and Yousefpour, 2021 [10]
FORMIND	1008	0.1	24.2	6.0	S	Fischer et al., 2016 [11]
3D-CMCC-FEM	367	< 0.1	13.1	7.3	S	Collalti et al., 2018 [12]; Dalmonech et al., 2022 [13]
GOTILWA+	336	< 0.1	10.1	7.2	S	Nadal-Sala et al., 2013 [14]
SORTIE-ND	278	< 0.1	21.3	22.0	S	Canham et al., 2005 [15]
PREBAS	252	< 0.1	6.6	6.2	S	Minunno et al., 2019 [16]
3PGMIX	173	< 0.1	10.1	34.0	S	Forrester and Tang, 2016 [17]
LANDSCAPE	38	< 0.1	11.3	7.2	L	Haas et al., 2013 [18]
DNDC						
HETEROFOR	12	< 0.1	6.7	18.6	S	Jonard et al., 2020 [19]

49 9.5% of the simulations were run under baseline or observed climate conditions. The database
 50 contains simulations from 12 stand-level models and four landscape-level models (Table 2, see
 51 Bugmann & Seidl, 2022 [1] for a review on modeling approaches). For balance between stand-
 52 and landscape-level simulations, a subset of 1-ha stands from the full landscape was sampled
 53 and used as individual simulation runs.

54 In geographic space, the simulation runs cluster in Central Europe, Spain (Catalonia), Finland
 55 and Sweden, i.e. areas that were analyzed particularly intensively in previous modeling stud-
 56 ies (Fig. 1). To evaluate the proportion of the geographic area of Europe that was covered by
 57 the climate and soil conditions represented in the dataset, the climate and soil space (using the
 58 variables shown in Fig. 2) of the entire continent were stratified and strata in which simulations
 59 were located were obtained. As some of the strata cover more geographic area (i.e. climate and
 60 soil conditions that occur more often), a simulation in that strata could cover a larger percent-
 61 age of climate and soil space than other simulations. The climate space covered by all simula-
 62 tion data spans 79% of Europe's geographic area and the covered soil space spanned 75.4% of
 63 the geographic area (Fig. 2). Areas not covered are mostly unforested regions in highly conti-
 64 nental parts of eastern Europe (i.e. parts of Ukraine, western Romania), very warm regions in
 65 the Mediterranean (i.e. southern Spain, parts of Greece and Italy), and wet and very oceanic re-
 66 gions including large parts of the British Isles and southern Norway. For soil conditions, we find
 67 that mainly soils with very coarse or very fine texture, low nitrogen availability and low water
 68 holding capacity are not covered by simulations.

69 The database contains simulations for 92 species. While most species are represented in less
 70 than 1000 simulations (median 728), *Fagus sylvatica*, *Picea abies*, *Larix decidua*, and *Pinus sylvestris*
 71 are the most prevalent, each occurring in over 400,000 simulations (Fig. 3). Furthermore, the
 72 dataset contains simulations without forest management (39.2%) and simulations implementing
 73 common practices (60.8%).

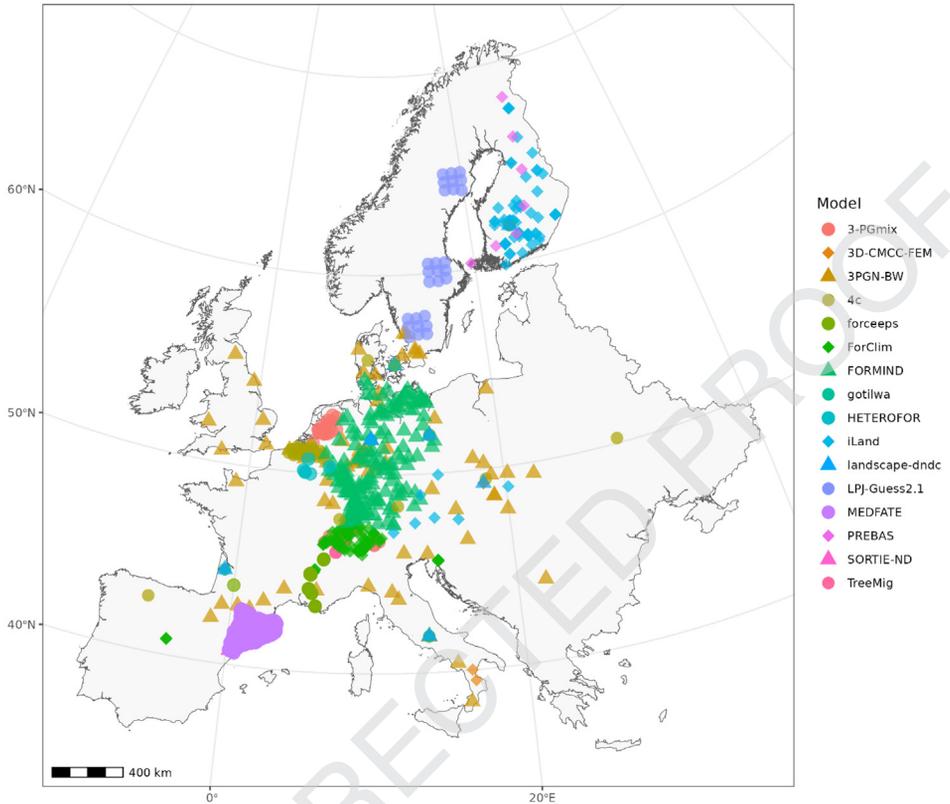


Fig. 1. Locations of the simulations in geographical space. Simulations from different models are displayed with different colors and symbols. Note that the projection of the map is Lambert Azimuthal Equal-Area (LAEA), the true north can be identified by following the longitudinal lines plotted in grey at 0° and 20° East.

74 4. Experimental Design, Materials and Methods

75 4.1. Data collection

76 A central database of forest simulations was created from existing model outputs from pre-
 77 vious simulation studies, collating information from a variety of stand- to landscape-scale for-
 78 est simulation models across Europe. The focus lay on models that were locally evaluated, thus
 79 encapsulating the best available bottom-up understanding of quantitative forest ecosystem dy-
 80 namics in Europe. Furthermore, the dataset was restricted to results from process-based models,
 81 as these are expected to be more robust under changing environmental conditions compared
 82 to purely empirical models [20]. Simulation outputs were provided by modeling groups in two
 83 files, a simulation data file and a metadata file containing information on the design and drivers
 84 of the simulation (Table S1 & S2). Forest simulations under climate change conditions were of
 85 particular interest, but simulation runs under baseline climate conditions were also included.
 86 The minimum requirements for contribution to the dataset were that the model conducting the
 87 simulation was process-based, and that simulation outputs provide annual information on basic
 88 indicators of vegetation development (i.e. proportion of tree species, canopy height, and leaf
 89 area index). While some models provide a broader range of output indicators, these three vari-
 90 ables were chosen as least common denominator for describing forest composition, structure,
 91 and functioning. Furthermore, the simulations had to provide information at the level of individ-

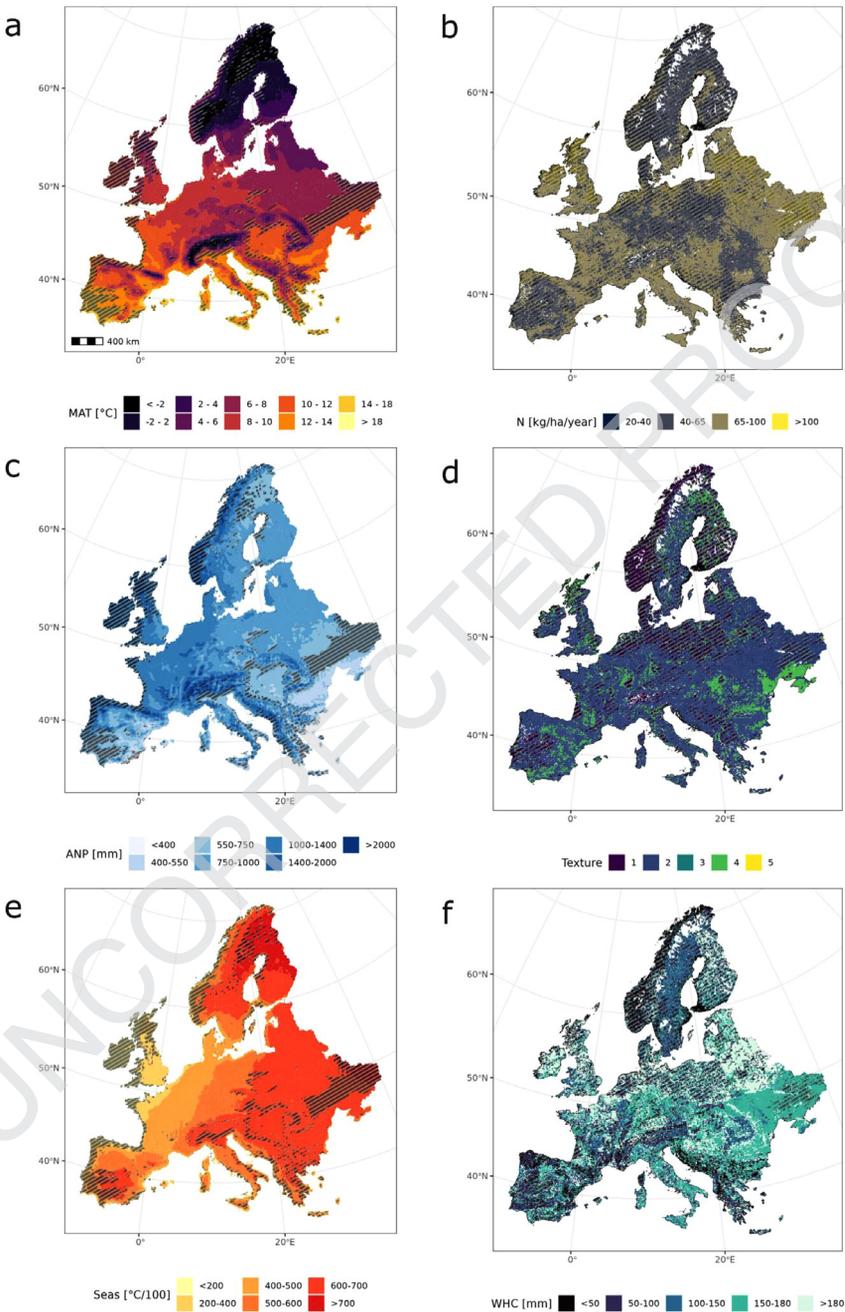


Fig. 2. Climate and soil space covered by simulations. Climate space was stratified into unique combinations of mean annual temperature (MAT; ten classes; panel a), annual precipitation (ANP; 7 classes; panel c) and temperature seasonality (Seas; seven classes; panel e). Soil space was stratified into unique combinations of plant-available nitrogen (N; five classes, but 0–20 kg/ha/year is not covered; panel b), soil texture (classes from coarse (=1) to very fine (=5) according to the European Soil Database classification scheme for soil texture; panel d) and water holding capacity (WHC; five classes; panel f). Areas not covered by the data in this database are hatched. For more details and data sources see section 3.2.1 Climate and 3.2.2 Soil.

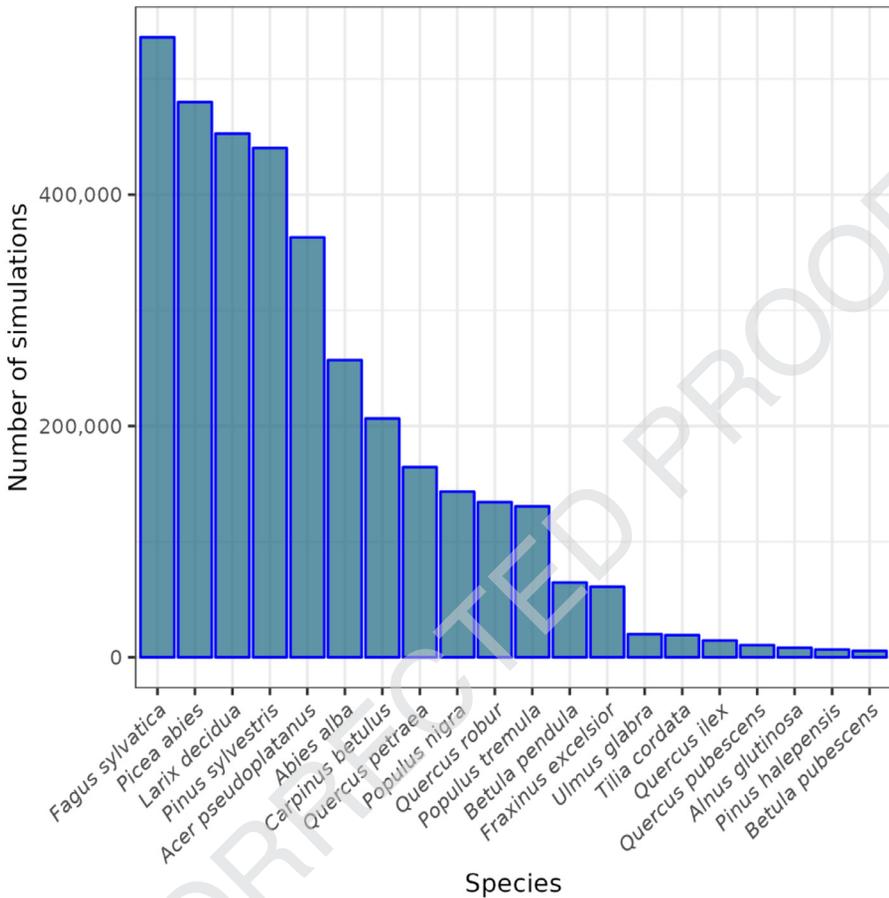


Fig. 3. Number of simulations in which the 20 most prevalent tree species in the dataset occur.

92 ual tree species, models simulating plant functional types were not included. With regard to the
 93 initial conditions of the simulation, both generic initial conditions (such as simulations starting
 94 from bare ground) and runs initialized with the current state of the vegetation were included.
 95 Further, simulation runs were conducted either in the absence of management interventions or
 96 assumed business-as-usual management for the area under study. Natural disturbances were not
 97 considered in the simulations. Simulation data were compiled and analyzed at stand level, hence
 98 information from landscape-scale simulation models were considered as unique data vectors at
 99 the level of simulated stands (i.e., areas of homogeneous climate and soil conditions) within a
 100 landscape. The temporal extent of simulations was variable, and both historical and future time
 101 series were included.

102 4.2. Data harmonization

103 Simulation data went through initial checks to ensure that the metadata for each simula-
 104 tion were complete and IDs in the metadata table (Table S2) were matching the simulation data
 105 (Table S1). To harmonize simulation outputs across the different models and simulation stud-
 106 ies we used discrete vegetation states as described by Rammer & Seidl (2019) [21]. Discrete

107 vegetation states condense the complexity of forest vegetation by describing the structure, com-
108 position, and function of vegetation as distinct states. To that end, continuous variables were
109 discretized, and a state was derived for every simulation year in the output of each model. With
110 regard to stand composition, a species was categorized as dominant if it held more than 66% of
111 a stand's basal area. Admixed species were explicitly considered if their share was $\geq 20\%$. Based
112 on these categories, a unique string was derived to describe species composition by concatenat-
113 ing the first two characters of the genus name and the first two characters of the species name
114 (e.g. *Pinus sylvestris* to PISY), and combining all dominant and admixed species occurring in a
115 stand. Letters for dominant species were capitalized, while admixed species were in lowercase
116 letters (e.g. PISYfasy means *Pinus sylvestris* is the dominant species and has a share of more than
117 66%, with *Fagus sylvatica* as an admixed species with more than 20% of the basal area). To cat-
118 egorize ecosystem functioning, LAI (as a key indicator for the exchange of carbon, water, and
119 energy of the system with the atmosphere) was grouped into three classes: class 1 for sparse
120 (LAI < 2), class 2 for moderate ($2 \leq \text{LAI} \leq 4$), and class 3 for dense forest canopies (LAI > 4).
121 For structure, the dominant height of the canopy was employed, as the vertical utilization of
122 space is a key element of forest structure. Canopy height can further indicate the development
123 stage of forest stands. The height information from different models (mean, minimum, maxi-
124 mum) was harmonized to dominant stand height. For stands dominated by *Pinus sylvestris*, *Abies*
125 *alba*, *Larix decidua*, *Picea abies*, *Fagus sylvatica* and *Quercus robur*, allometric factors calibrated by
126 Kahn (1994) [22] were applied to describe the relationship of stand dominant height to maxi-
127 mum tree height. For other species, a statistical model based on yield table data was derived to
128 estimate dominant height from mean and maximum tree height [22]. Specifically, for 14 species,
129 a linear mixed model with dominant height as dependent variable, mean and maximum height
130 as predictor variable, and random slopes for the different species was calibrated (conditional
131 $R^2 = 0.999$; marginal $R^2 = 0.996$). To make the analysis robust to individual outliers, domi-
132 nant height was limited to lie between 0.8 times maximum height (lower limit) and maximum
133 height (upper limit). Some models only provided information for mean height (but not maxi-
134 mum height), or for minimum and maximum height only (but not mean height). In the latter
135 case, mean height was calculated as the arithmetic mean of minimum and maximum height.
136 For simulations for which only mean height was available, maximum height was estimated us-
137 ing a linear mixed model. This model was calibrated on a random subsample of the dataset of
138 all simulation data across all models that contained both maximum and mean height. In the
139 linear mixed model, maximum height was used as the dependent variable, mean height as pre-
140 dictor variable and random effects for species were included (conditional $R^2 = 0.54$; marginal
141 $R^2 = 0.25$). Maximum height was then predicted from mean heights with this model and subse-
142 quently calculated dominant height from mean and maximum height as described before. Sub-
143 sequently, continuous information on dominant height was grouped into 2-m bins. Finally, the
144 individual states for forest composition, structure, and function were combined into a unique
145 string describing the state of the vegetation (e.g., PIABfasy_3_20_22 representing a stand domi-
146 nated by *Picea abies* (PIAB) with admixed *Fagus sylvatica* (fasy) that has a dense forest canopy
147 (LAI class 3) and a dominant height of between 20 and 22 m). This harmonization and dis-
148 cretization of the underlying simulation data resulted in a total of 18,598 distinct vegetation
149 states being recorded in our database.

150 4.3. Auxiliary data

151 In addition to the harmonized simulation data and the respective metadata, a common data
152 vector of auxiliary data was compiled. This vector contained standardized climate and soil data
153 for each simulation, in order to facilitate the analysis and interpretation of the dataset.

154 4.3.1. Climate

155 To derive common and coherent climate data for all simulation runs included in the database,
156 the simulation-specific climate time series (which was restricted to annual values for tempera-

157 ture and precipitation) provided by the modeling groups was matched with climate data from
158 a common climate dataset. This approach allowed to address problems of different data resolu-
159 tion and representation in the data used for individual simulations (e.g., some models operate
160 with monthly climate data while others use daily climate data, some models use maximum
161 and minimum temperature as drivers while others use mean temperature, some models in-
162 clude climatic drivers beyond temperature and precipitation such as vapor pressure deficit (VPD)
163 while others do not, some simulation runs were driven by detailed downscaled climate data
164 while others used coarser-resolution climate information as input). As common climate database
165 EURO-CORDEX climate data was harnessed for historical conditions as well as three RCP sce-
166 narios (RCP2.6, RCP4.5 and RCP8.5), each simulated with three global circulation models (MPI-
167 M-MPI-ESM-LR, ICHEC-EC-EARTH, NCC-NorESM1-M, all downscaled with the SMHI-RCA4 RCM),
168 resulting in 12 climate scenarios. The climate data was obtained in a $0.11^\circ \times 0.11^\circ$ spatial resolu-
169 tion and daily temporal resolution from the Copernicus Climate Data Store. (<https://cds.climate.copernicus.eu/cdsapp#!dataset/projections-cordex-domains-single-levels?tab=overview>). GCMs
170 were selected to cover a broad gradient of temperature and precipitation conditions [23] rep-
171 resentative for the current and future climatic conditions in Europe.

173 For the harmonized dataset, the goal was to obtain daily climate data from EURO-CORDEX
174 for all simulations. To achieve this, the best matching EURO-CORDEX trajectory was assigned to
175 each simulation and for each simulation year the daily data from the best matching year from
176 that scenario was extracted. In more detail, information on the type of climate trajectory used
177 for the simulation run (baseline run without climate change, SRES, or RCP scenario family) was
178 obtained from the metadata of each simulation. Baseline conditions refer to historical time se-
179 ries, while SRES and RCP scenarios refer to simulations under future climate scenarios. The best
180 matching EURO-CORDEX scenario was assigned to each simulation based on a comparison be-
181 tween slopes (i.e. temporal change) of temperature and precipitation used in the simulations
182 with those calculated from EURO-CORDEX scenarios for the simulation location. The difference
183 of the slope for temperature and precipitation was obtained and the overall difference was cal-
184 culated as $\Delta T + 0.1 * \Delta P$ to choose the trajectory with the smallest overall difference. Whenever
185 simulation metadata contained specific information on the GCM and/or RCP used for the cli-
186 mate forcing used in the simulation, this information was harnessed to limit selection options
187 from the EURO-CORDEX database. For instance, if the climate trajectory of a simulation was run
188 with an RCP2.6 scenario, the temperature and precipitation slopes were only compared with the
189 three RCP2.6 scenarios contained in our EURO-CORDEX selection. The best matching trajectory
190 was then adjusted to the mean temperature and precipitation level of the simulation. Specifi-
191 cally, the difference between mean temperatures of the simulation and climate scenario trajec-
192 tory and the multiplicative difference for precipitation was added. This was necessary to make
193 sure that the adjusted time series represented the climate used in the simulations, as they may
194 differ due to the relatively coarse resolution of the gridded climate data. Next, a time series
195 from the adjusted scenario data was constructed, matching the individual years to each year
196 in the simulation. For this, an index combining the additive difference between mean annual
197 temperatures and the multiplicative difference of annual precipitation (again with $\Delta T + 0.1 * \Delta P$)
198 was calculated for each pair of simulation data year and climate scenario year. To prevent mul-
199 tiple occurrences of the same year, one of the three best matching years was randomly sampled
200 with replacement. Finally, the thus constructed daily climate time series data for all variables
201 (temperature, precipitation, radiation and VPD) was stored along the simulation it represents.

202 4.3.2. Soil

203 Mirroring the approach taken with climate data, the simulation metadata provided by the
204 modelling groups was facilitated to derive a consistent and quantitative soil data set across all
205 simulations. While some simulation metadata contained exact numbers on all relevant soil vari-
206 ables considered (i.e. soil depth, soil texture (sand, silt, clay percentage), water holding capacity
207 (WHC) and available nitrogen), others provided more descriptive values for water and nutrient
208 conditions, such as soil water or fertility ratings (see Table S3). To complete missing data and
209 convert descriptive ratings to quantitative soil characteristics pan-European datasets on soil in-

210 formation were leveraged. For soil depth, soil texture and WHC gridded data (1 km resolution)
211 from the European Soil Data Center (ESDAC [24]) was obtained. Soil fertility was approximated
212 by means of plant-available nitrogen, considering that nitrogen is the most important macro-
213 nutrient for forests in Europe at the continental scale. Since data on plant-available nitrogen
214 (i.e., the annual flux of mineralized nitrogen) is not available for large scales, we used a sta-
215 tistical approach to estimate mineralization rates based on fertility and climate data and com-
216 bined them with data on nitrogen stocks. Specifically, the SQ1 nutrient availability map from
217 the harmonized European soil database [25] was reclassified from the four classes of soil ferti-
218 lity considered therein to values of 100, 65, 40 and 20 kg/ha/year of plant-available nitrogen. In
219 a next step, from the Soilgrids dataset [26] the nitrogen pool (in kg/m²) across Europe based on
220 relative nitrogen content (g/kg) and bulk density (kg/m³) for soil layers up to 30 cm soil depth
221 were obtained. The reclassified soil fertility map was divided by the nitrogen pool layer to ap-
222 proximate a coarse pseudo-mineralization rate. This pseudo-mineralization rate was then used
223 as a dependent variable to calibrate a generalized linear model (GLM) with mean annual tem-
224 perature, annual precipitation, temperature seasonality (obtained from CHELSA [27]; we used
225 CHELSA data instead of EURO-CORDEX to create a layer of 1 km spatial resolution, matching the
226 other soil layers) and soil pH (from Soilgrids) as predictor variables ($D^2 = 0.64$). The calibrated
227 model was used to project pseudo-mineralization rates for continental Europe at 1 × 1 km res-
228 olution providing more consistent estimates based on local soil and climate conditions. Finally,
229 the nitrogen pool was multiplied with the modeled pseudo-mineralization rate to get an ap-
230 proximation of plant-available nitrogen.

231 4.4. Coverage of simulated data

232 The coverage of the current climate and soil space of Europe's forests by simulation data
233 compiled here cover was investigated using the harmonized data (see Fig. 2). The historical
234 climate was categorized into ten stratified bins of mean annual temperature (< -2°C, -2 -
235 2°C, 2-4°C, 4 - 6°C, 6 - 8°C, 8 - 10°C, 10 - 12°C, 12-14°C, 14-18°C, > 18°C), seven strat-
236 ified bins of annual precipitation sum (< 400 mm, 400-550 mm, 550-750 mm, 750-1000 mm,
237 1000 - 1400 mm, 1400 - 2000 mm, > 2000 mm) and seven stratified bins of temperature sea-
238 sonality (calculated as standard deviation of monthly mean temperature* 100, binned to (< 200,
239 200-400, 400-500, 500-600, 600-700, 700-900, > 900). Simulations were assigned to their bins
240 based on the climate grid cell (0.11°) of the simulation's location, and the area that is covered
241 by the occupied bins was calculated. This approach likely underestimates the true climatic cov-
242 erage of the simulations, as individual simulations (both stand-level and landscape-level) of-
243 ten encompass climatic gradients within a single cell. Soil conditions were categorized into five
244 unique combinations of stratified values along the dimensions of soil texture (six classes from
245 fine to coarse calculated with sand, silt and clay content), water holding capacity (<50 mm, 50-
246 100 mm, 100-150 mm, 150 - 180 mm, >180 mm) and soil fertility (plant-available nitrogen of
247 < 20, 20-40, 40 -65, 65-100, >100 kg/ha/year). Again, each simulated location was located in
248 the three-dimensional space of soil conditions to assess how well the compiled simulation data
249 represented the soil conditions of Europe's forests.

250 Limitations

251 The majority of simulations were sourced from iLand model outputs (73.2%, as shown in
252 Table 2), totaling over 800,000 entries stored in large tables, which were unwieldy to manage. To
253 mitigate this, we divided the simulation data into smaller chunks with different unique identi-
254 fiers. Furthermore, the imbalance in the number of simulations from the various models creates
255 a bias that needs consideration during database utilization for analytical purposes.

256 Ethics Statement

257 We confirm to have read the ethical requirements for publication in Data in Brief and con-
258 firm that the current work does not involve human subjects, animal experiments, or any data
259 collected from social media platforms.

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

261 During the preparation of this work the authors used ChatGPT in order to improve readabil-
262 ity. After using this tool, the authors reviewed and edited the content as needed and take full
263 responsibility for the content of the publication.

Data Availability

Data for: [A harmonized database of European forest simulations under climate change](#)
(Original data) (Zenodo)

264 CRediT Author Statement

265 **Marc Grünig:** Conceptualization, Methodology, Software, Formal analysis, Data curation, Writ-
266 ing – original draft, Writing – review & editing, Visualization; **Werner Rammer:** Conceptualiza-
267 tion, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Writing –
268 review & editing, Funding acquisition; **Katharina Albrich:** Data curation, Writing – review &
269 editing; **Frédéric André:** Data curation, Writing – review & editing; **Andrey L.D. Augustynczik:**
270 Data curation, Writing – review & editing; **Friedrich Bohn:** Data curation, Writing – review &
271 editing; **Meike Bouwman:** Data curation, Writing – review & editing; **Harald Bugmann:** Data
272 curation, Writing – review & editing; **Alessio Collalti:** Data curation, Writing – review & edit-
273 ing; **Irina Cristal:** Data curation, Writing – review & editing; **Daniela Dalmonech:** Data cura-
274 tion, Writing – review & editing; **Miquel De Caceres:** Data curation, Writing – review & editing;
275 **Francois De Coligny:** Data curation, Writing – review & editing; **Laura Dobor:** Data curation,
276 Writing – review & editing; **Christina Dollinger:** Data curation, Writing – review & editing;
277 **David I. Forrester:** Data curation, Writing – review & editing; **Jordi Garcia-Gonzalo:** Data cu-
278 ration, Writing – review & editing; **José Ramón González:** Data curation, Writing – review &
279 editing; **Ulrike Hiltner:** Data curation, Writing – review & editing; **Tomáš Hlásny:** Data cura-
280 tion, Writing – review & editing; **Juha Honkaniemi:** Data curation, Writing – review & editing;
281 **Nica Huber:** Data curation, Writing – review & editing; **Mathieu Jonard:** Data curation, Writing
282 – review & editing; **Anna Maria Jönsson:** Data curation, Writing – review & editing; **Fredrik**
283 **Lagergren:** Data curation, Writing – review & editing; **Mats Nieberg:** Data curation, Writing –
284 review & editing; **Marco Mina:** Data curation, Writing – review & editing; **Frits Mohren:** Data
285 curation, Writing – review & editing; **Christine Moos:** Data curation, Writing – review & editing;
286 **Xaxier Morin:** Data curation, Writing – review & editing; **Bart Muys:** Data curation, Writing –
287 review & editing; **Mikko Peltoniemi:** Data curation, Writing – review & editing; **Christopher PO**
288 **Reyer:** Data curation, Writing – review & editing; **Ilié Storms:** Data curation, Writing – review &
289 editing; **Dominik Thom:** Data curation, Writing – review & editing; **Maude Toigo:** Data curation,
290 Writing – review & editing; **Rupert Seidl:** Conceptualization, Methodology, Writing – original
291 draft, Writing – review & editing, Funding acquisition.

292 Acknowledgments

293 We acknowledge funding received from the European Union's Horizon 2020 research and
294 innovation program under grant agreement no. [101000574](#) (RESONATE: Resilient forest value
295 chains – enhancing resilience through natural and socio-economic responses).

296 Declaration of Competing Interest

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

299 Supplementary Materials

300 Supplementary material associated with this article can be found, in the online version, at
301 [doi:10.1016/j.dib.2024.110384](https://doi.org/10.1016/j.dib.2024.110384).

302 References

- 303 [1] H. Bugmann, R. Seidl, The evolution, complexity and diversity of models of long-term forest dynamics, *J. Ecol.* 110
304 (10) (2022) 2288–2307.
- 305 [2] R. Seidl, W. Rammer, R.M. Scheller, T.A. Spies, An individual-based process model to simulate landscape-scale forest
306 ecosystem dynamics, *Ecol. Modell.* 231 (2012) 87–100.
- 307 [3] P. Lasch-Born, F. Suckow, C.P. Reyser, M. Gutsch, C. Kollas, F.W. Badeck, H.K. Bugmann, R. Grote, C. Fürstenau, M. Lind-
308 ner, J. Schaber, Description and evaluation of the process-based forest model 4C v2. 2 at four European forest sites,
309 *Geosci. Model Dev.* 13 (11) (2020) 5311–5343.
- 310 [4] M. De Cáceres, M. Mencuccini, N. Martin-StPaul, J.M. Limousin, L. Coll, R. Poyatos, A. Cabon, V. Granda, A. Forner,
311 F. Valladares, J. Martínez-Vilalta, Unravelling the effect of species mixing on water use and drought stress in
312 Mediterranean forests: a modelling approach, *Agric. For. Meteorol.* 296 (2021) 108233.
- 313 [5] H.K. Bugmann, A simplified forest model to study species composition along climate gradients, *Ecology* 77 (7)
314 (1996) 2055–2074.
- 315 [6] N. Huber, H. Bugmann, M. Cailleret, N. Bircher, V. Lafond, Stand-scale climate change impacts on forests over large
316 areas: transient responses and projection uncertainties, *Ecol. Appl.* 31 (4) (2021) e02313.
- 317 [7] B. Smith, I.C. Prentice, M.T. Sykes, Representation of vegetation dynamics in the modelling of terrestrial ecosystems:
318 comparing two contrasting approaches within European climate space, *Glob. Ecol. Biogeogr.* (2001) 621–637.
- 319 [8] X. Morin, H. Bugmann, F. De Coligny, N. Martin-StPaul, M. Cailleret, J.M. Limousin, J.M. Ourcival, B. Prevosto,
320 G. Simioni, M. Toigo, M. Vennetier, E. Catteau, J. Guillemot, Beyond forest succession: a gap model to study ecosys-
321 tem functioning and tree community composition under climate change, *Funct. Ecol.* 35 (4) (2021) 955–975.
- 322 [9] H. Lischke, N.E. Zimmermann, J. Bolliger, S. Rickebusch, T.J. Löffler, TreeMig: a forest-landscape model for simulating
323 spatio-temporal patterns from stand to landscape scale, *Ecol. Modell.* 199 (4) (2006) 409–420.
- 324 [10] A.L.D. Augustynczyk, R. Yousefpour, Assessing the synergistic value of ecosystem services in European beech forests,
325 *Ecosyst. Serv.* 49 (2021) 101264.
- 326 [11] R. Fischer, F. Bohn, M.D. de Paula, C. Dislich, J. Groeneveld, A.G. Gutiérrez, ... A. Huth, Lessons learned from applying
327 a forest gap model to understand ecosystem and carbon dynamics of complex tropical forests, *Ecol. Modell.* 326
328 (2016) 124–133.
- 329 [12] A. Collalti, P.E. Thornton, A. Cescatti, A. Rita, M. Borghetti, A. Nolè, G. Matteucci, The sensitivity of the forest carbon
330 budget shifts across processes along with stand development and climate change, *Ecol. Appl.* 29 (2) (2019) e01837.
- 331 [13] D. Dalmonech, G. Marano, J.S. Amthor, A. Cescatti, M. Lindner, C. Trotta, A. Collalti, Feasibility of enhancing carbon
332 sequestration and stock capacity in temperate and boreal European forests via changes to management regimes,
333 *Agric. For. Meteorol.* 327 (2022) 109203.
- 334 [14] D. Nadal-Sala, S. Sabaté, C. Gracia, GOTILWA+: un modelo de procesos que evalúa efectos del cambio climático en
335 los bosques y explora alternativas de gestión para su mitigación, *Ecosistemas* 22 (3) (2013) 29–36.
- 336 [15] C.D. Canham, L.E. Murphy, M.J. Papaik, SORTIE-ND: software for spatially-explicit simulation of forest dynamics,
337 Institute of Ecosystem Studies, Millbrook, NY, 2005.
- 338 [16] F. Minunno, M. Peltoniemi, S. Härkönen, T. Kalliokoski, H. Makinen, A. Mäkelä, Bayesian calibration of a carbon
339 balance model PREBAS using data from permanent growth experiments and national forest inventory, *For. Ecol.*
340 *Manag.* 440 (2019) 208–257.
- 341 [17] D.I. Forrester, X. Tang, Analysing the spatial and temporal dynamics of species interactions in mixed-species forests
342 and the effects of stand density using the 3-PG model, *Ecol. Modell.* 319 (2016) 233–254.
- 343 [18] E. Haas, S. Klatt, A. Fröhlich, P. Kraft, C. Werner, R. Kiese, ... K. Butterbach-Bahl, LandscapeDNDC: a process model
344 for simulation of biosphere-atmosphere-hydrosphere exchange processes at site and regional scale, *Landsc. Ecol.*
345 28 (4) (2013) 615–636.
- 346 [19] M. Jonard, F. André, F. De Coligny, L. De Wergifosse, N. Beudez, H. Davi, ... C. Vincke, HETEROFOR 1.0: a spatially
347 explicit model for exploring the response of structurally complex forests to uncertain future conditions-Part 1:
348 carbon fluxes and tree dimensional growth, *Geosci. Model Dev.* 13 (3) (2020) 905–935.
- 349 [20] E.J. Gustafson, When relationships estimated in the past cannot be used to predict the future: using mechanistic
350 models to predict landscape ecological dynamics in a changing world, *Landsc. Ecol.* 28 (2013) 1429–1437.
- 351 [21] W. Rammer, R. Seidl, A scalable model of vegetation transitions using deep neural networks, *Methods Ecol. Evol.* 10
352 (6) (2019) 879–890.
- 353 [22] M. Kahn, Modellierung der Höhenentwicklung ausgewählter Baumarten in Abhängigkeit vom Standort,
354 Forstwissenschaftliche Fakultät der Universität der Universität München und Bayerische forstliche Versuchs-und
355 Forschungsanstalt (1994).

- 356 [23] K.M. Parding, A. Dobler, C.F. McSweeney, O.A. Landgren, R. Benestad, H.B. Erlandsen, ... H. Loukos, GCMeval-An
357 interactive tool for evaluation and selection of climate model ensembles, *Clim. Serv.* 18 (2020) 100167.
- 358 [24] R. Hiederer, Mapping Soil Properties for Europe - Spatial Representation of Soil Database Attributes, Luxembourg:
359 Publications Office of the European Union -2013 -47pp. - EUR26082EN Scientific and Technical Research series,
360 2013 ISSN 1831-9424, doi:[10.2788/94128](https://doi.org/10.2788/94128).
- 361 [25] G. Fischer, F. Nachtergaele, S. Prieler, H.T. van Velthuizen, L. Verelst, D. Wiberg, Global Agro-ecological Zones As-
362 sessment for Agriculture (GAEZ 2008), 2008.
- 363 [26] T. Hengl, J. Mendes de Jesus, G.B. Heuvelink, M. Ruiperez Gonzalez, M. Kilibarda, A. Blagotić, ... B. Kempen, Soil-
364 Grids250m: global gridded soil information based on machine learning, *PLoS One* 12 (2) (2017) e0169748.
- 365 [27] D.N. Karger, O. Conrad, J. Böhner, T. Kawohl, H. Kreft, R.W. Soria-Auza, ... M. Kessler, Climatologies at high resolution
366 for the earth's land surface areas, *Sci. Data* 4 (1) (2017) 1–20.