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ForestScope: Comprehensive tool for analysing soil, climate, and stand data in forest ecosystems

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ABSTRACT

In environmental conservation and management, analysing soil, climate, and stand data within forest ecosystems is crucial for understanding ecological dynamics, projecting changes, and developing sustainable forestry practices. Often, these data are scattered and unintegrated, complicating their use in modelling and analysis. Current tools lack modular integration of soil, climate, and stand data at large and diverse NFI datasets like International Co-operative Programme (ICP) scale (12,000+ sites). ForestScope bridges this gap by automating harmonization of ICP's Level I/II datasets, together with soil and climate data, which is essential for informed decision-making in forest management.

ForestScope introduces an open-source framework designed to systematically organize, extract, and harmonize fragmented soil, climate, and stand data from ICP datasets. It includes comparative analyses of International Soil Reference and Information Centre (ISRIC) and Harmonized World Soil Database (HWSD) soil datasets, and assessments of Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) climate models and Climatologies at High resolution for the Earth's Land Surface Areas (CHELSA) against observational data, selecting HWSD v2.0 and CHELSA as optimal for ICP data gaps.

Additionally, ForestScope integrates a vegetation model enhancing National Forest Inventory (NFI) data processing, thus improving forest ecosystem modelling. This advancement deepens our understanding of forest dynamics and supports more effective management strategies.

1. Introduction

Understanding and harmonizing the key datasets, specifically stand dynamics, soil and climatic variables, is crucial for accurate and efficient ecological modelling, informed land-use and land management decisions. Forests act as sinks and storage for carbon (C), mitigating climate change, and providing various other ecosystem services fundamental for humanity, while hosting a wide variety of species (Ali, 2023; Mori et al., 2017; Waring et al., 2020). The complexity of forest ecosystems needs a thorough understanding of a variety of components, such as forest stand characteristics and management, climate variability, and soil conditions, all of which are required for both empirical study and ecological modelling (Gonçalves, 2022; Jain et al., 2023; Schwarzwald and Lenssen, 2022; Vereecken et al., 2016).

To understand forest growth patterns, quantifying C stock, and developing sustainable harvesting and conservation strategies (Gonçalves, 2018; Jonsson et al., 2020; Pan et al., 2018), information of forests is needed. Such information includes tree density, age, biomass, and species composition, which provides insight into the dynamics of forest ecosystems. The ICP NFI data plays an important role in collecting such information, delivering a thorough overview of forest resources at the national level (Ferretti et al., 2020). However, analysing forest growth dynamics is less accurate without incorporating climate and soil information.

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Temperature, precipitation, and solar radiation are among the most crucial climate variables affecting forest growth, biodiversity, and overall forest condition (Itter et al., 2017; Martinez del Castillo et al., 2022; Yang et al., 2006). Climate change creates major challenges to forest ecosystems, including alterations to biodiversity and geographical spectrum shifts (Härkönen et al., 2019; Malhi et al., 2020). Accurate and reliable climatic data is therefore needed for predicting and mitigating these impacts, directing conservation measures, and affecting sustainable forest management methods (Fremout et al., 2020).

The soil in forest ecosystems plays an important role in nutrient cycling, water retention, and providing a foundation for plant growth (Nakhavali et al., 2022). Soil attributes such as texture, pH, organic content, and water-holding capacity have a direct impact on forest productivity (Cajander, 1949; Hatten and Liles, 2019; Shen et al., 2022; Van Sundert et al., 2018). Furthermore, the interaction of soil and other environmental elements such as climate and topography impact the distribution and composition of forest types (Mäkipää et al., 2023; Mayer et al., 2020; Tesha et al., 2023; Q. Yang et al., 2021). As a result, thorough soil data is required to fully understand and manage forest ecosystems (Page-Dumroese et al., 2021).

Therefore, organisation and integration of large-scale NFI data like ICP, which includes stand, climate, and soil information, is critical for improving empirical and modelling studies in forest ecology (Majasalmi et al., 2018; Vangi et al., 2023; Yamaura et al., 2020). Currently, these data sets are neither unified nor integrated, challenging their use in modelling work or analysis. The climate, soil, and other related data are scattered and disjointed. This fragmentation leads to inefficiencies in data processing and analysis, as there are no robust tools to handle large, diverse datasets effectively. Consequently, researchers struggle to process these disparate data sources into a cohesive and integrated dataset suitable for modelling and informed assessments. Developing such tools not only enhances the processing of these data for modelling and forest ecosystems analysis but also supports effective policymaking and management methods aimed at preserving these important natural resources (FAO, 2022).

This study presents the first tool to automate the extraction and harmonization of ICP's soil, climate, and stand data into structured formats (CSV files). Its nearest-neighbour algorithm spatially matches ICP sites to high-resolution soil (HWSD/ISRIC) and climate (CHELSA/ISIMIP) datasets, resolving data fragmentation. While we primarily use ISRIC and HWSD soil data, our methodology is designed to accommodate alternative input files of soil data, should they be more applicable to a specific analysis. Here we ask whether a unified, open-source platform that automatically integrates stand, soil and climate data can demonstrably streamline and improve forest-ecosystem modelling workflows. We hypothesise that such a platform will (i) reduce the time required to prepare model-ready inputs, (ii) minimise the propagation of data-handling errors and (iii) enable rapid testing of process-based models at large spatial scales. Additionally, to demonstrate direct ecological-modelling utility, rather than merely data stewardship, ForestScope embeds the process-based vegetation model 3PGmix as an application example. In our approach, we place a strong emphasis on the flexibility of data usage. ForestScope offers an integrated analysis platform that surpasses existing tools by providing real-time data harmonization, advanced analytical functionalities, and user-friendly interaction, essential for dynamic and precise forest ecosystem management.

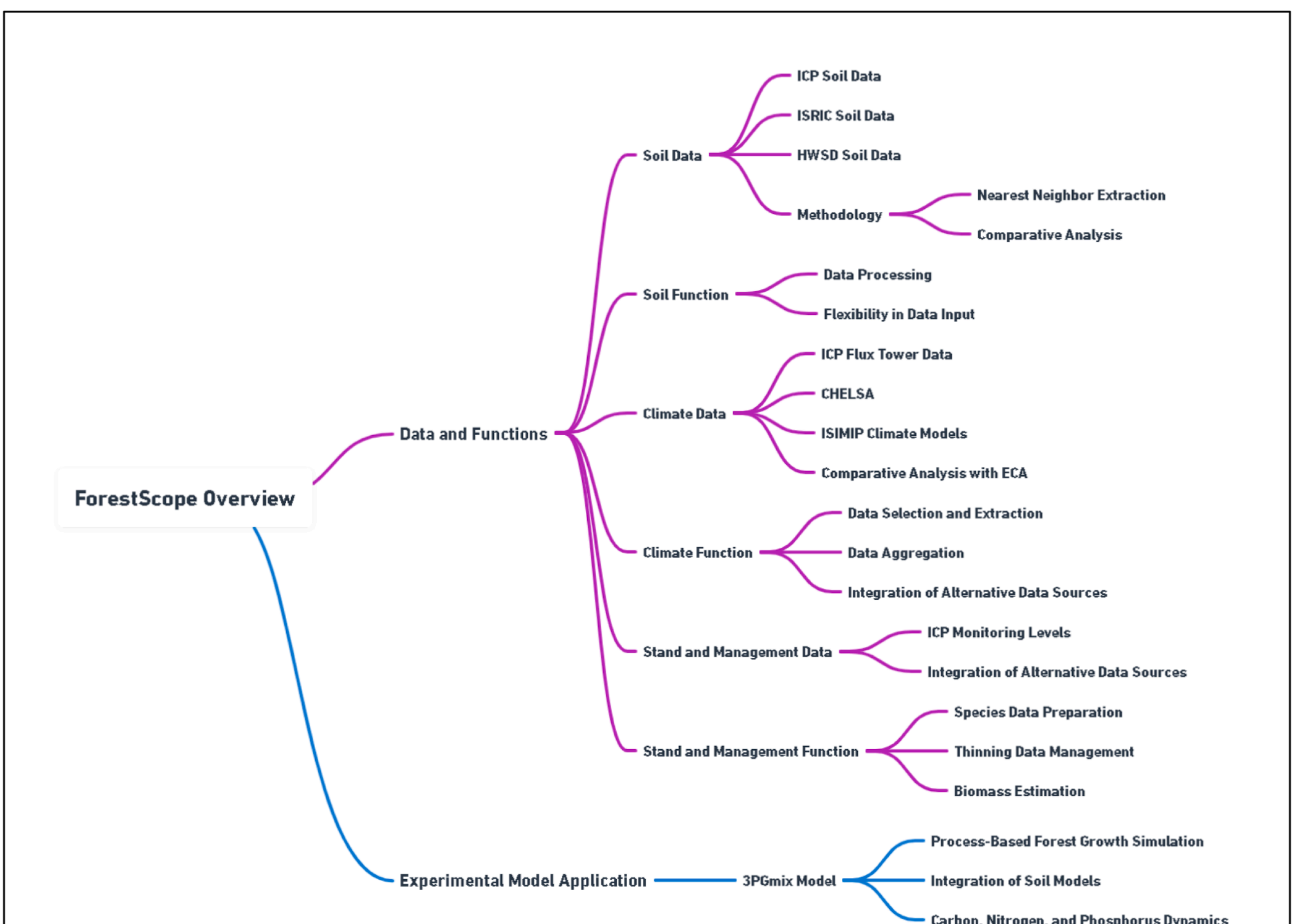

Fig. 1. Schematic Representation of ForestScope Structure, Components, and Functionalities.

2. Material and methods

2.1. Data processing and analysis framework

In this study, the methodologies are designed for handling three components: soil datasets, climate variables, and stand and management data (Fig. 1). The soil data component includes a detailed process of reading, processing, and analysing soil data, complemented by an evaluation of alternative data sources. The climate data section describes the assimilation and evaluation of climate variables from various sources against observational data. Lastly, it explains the functionalities for analysing stand and management information derived from ICP NFI data.

2.2. Data and functions

2.2.1. Soil data

Our methodology incorporates the use of three primary datasets, the ICP soil data (Fleck et al., 2016), ISRIC soil data (ISRIC, 2020) and the HWSD v1.2 (Nachtergaele et al., 2010) and v2.0 (Nachtergaele, van Velthuizen, et al., 2023), to organize and process soil data for specific points of the NFI data at ICP sites. These datasets were chosen for their comprehensive and diverse range of soil properties, sourced from various methods including soil surveys, remote sensing, and modelling.

The dataset from the ICP encompasses detailed physicochemical and hydraulic properties, enriched with extensive long-term observations of forest conditions across Europe. This includes key soil properties such as texture, pH, organic content, and plant-available water (Cools N and De Vos B, 2020). However, there are instances where this comprehensive soil information is not available for sites covered by the ICP NFI data (Ferretti et al., 2020). Additionally, when utilizing NFI data sources other than ICP, there is a possibility that such detailed soil information may be absent. To address this gap, we supplement our analysis with two alternative datasets:

- The ISRIC dataset is known for its detailed and wide-ranging information on soil properties. It is characterized by its high spatial resolution, providing soil property maps at resolutions up to 250 m (Poggio et al., 2021). This level of detail is obtained through a combination of diverse sources, making it a rich resource for understanding soil characteristics at a finer scale.
- The HWSD complements the ISRIC data by providing information on various soil properties as well. This database is compiled based on national soil databases, soil survey reports, and expert knowledge. The HWSD has a coarser spatial resolution of approximately 1 km, making it more suitable for broader, regional analyses(Nachtergaele, van Velthuizen Harrij, et al., 2023).

Both datasets include crucial information on soil attributes such as clay, silt, sand, soil organic C (SOC), nitrogen (N), and available water capacity (AWC), though they differ in their scale and resolution. While the ISRIC data provides a more detailed view at a finer scale, the HWSD offers a broader perspective. This distinction is vital in our methodology, as it allows us to tailor our analysis to the specific requirements of the ICP sites.

To integrate gridded soil information, each raster layer from ISRIC or HWSD was first resampled to the ICP plot footprint and re-projected to a common coordinate system. We then applied a depth- and area-matched procedure that (i) averages every resampled raster cell falling inside the circular plot buffer and (ii) re-weights the gridded depth intervals. Following the nearest-neighbour extraction method (Kramer, 2013) was used:

$$V(x,y) = V_{nn}(x_{nn}, y_{nn}) \quad (1)$$

where $V(x,y)$ is the estimated value of the data at the target location with coordinates (x,y); and $V_{nn}(x_{nn}, y_{nn})$ is the value at nearest neighbour data point with the coordinates (x_{nn}, y_{nn}). The target point (x,y) receives the value from its nearest neighbour data point in the dataset. The nearest neighbour is typically determined based on the shortest Euclidean distance from the target point. The Euclidean distance (d) between the target point and a potential nearest neighbour point can be calculated as:

$$d = \sqrt{(x - x_{nn})^2 + (y - y_{nn})^2} \quad (2)$$

A key component of our analysis involves comparing these two datasets against the soil data available from ICP sites. This comparison is crucial for understanding how global soil datasets align with site-specific data, which can reveal important insights about the local soil conditions at ICP sites. By examining the similarities and differences between these datasets and the ICP site data, we can enhance the accuracy and relevance of our environmental assessments and make more informed decisions regarding the most appropriate dataset to use for substituting missing data. Each record created by this procedure carries a provenance flag: “FIELD” when an ICP measurement exists, “DATABASE” when the value originates from HWSD or ISRIC, and stores the attribute-specific RMSE described below, so that the added uncertainty remains explicit throughout the workflow.

The comparative analysis between the two alternative datasets and the ICP data was conducted with a focus on soil properties at various depths, specifically examining the topsoil layer (0–30 cm) and the bottom soil layer (30–100 cm) which are commonly utilized in soil data processing (Bachmann, 2006). The Root Mean Square Error (RMSE) was used as the primary metric for evaluation, allowing for a quantitative assessment of the alignment between the alternative datasets and the ICP soil data in terms of soil properties at these respective layers as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2}$$

where n is the number of observations at top or bottom soil layers, y_i is the actual observed value and $\widehat{y}_i$ is the corresponding point value from ISRIC or HWSD data. RMSE statistics for every property and horizon are compiled and attached to each record, enabling users to propagate or filter the associated uncertainty in subsequent analyses.

2.2.2. Soil function

The soil_data function within the ForestScope serves as a crucial component for the processing of HWSD and ISRIC soil data. The function extracts soil properties (e.g., clay, silt, sand, SOC, N, and AWC) for each ICP site using a nearest-neighbor algorithm. For a target ICP coordinate (x,y) the function computes the Euclidean distance (eq.2) to all HWSD/ISRIC raster cells. Following, the soil properties are extracted at 0–30 cm and 30–100 cm depths. Organizes results into a structured table with columns: site_id, latitude, longitude, soc_top (kg/m^2), clay_top (%), soc_bottom (kg/m^2), etc. A key feature of this function is its flexibility in data input; it allows users to either provide file paths for various soil attributes and AWC or choose files interactively through a GUI/R package interface. The function sets a predefined spatial extent for processing, ensuring that the soil data is cropped and handled within specific geographical boundaries. The nested process_isric_data and process_hwsd_data functions are the core component that reads and crops raster files according to the set extent, effectively converting raster data into accessible data frames.

In case that the AWC information is not provided, the function will apply the following equation to compute AWC based on soil attributes available in ISRIC/HWSD datasets:

$$AWC = (FC - WP) \times (1 - CRFVOL_{frac}) \times D_m$$

where FC is the field capacity, WP is the wilting point, $CRFVOL_{frac}$ is the coarse root-free volume expressed as a fraction, calculated as $\frac{CRFVOL}{100}$, and D_m is the depth of the soil layer in meters, converted from centimetres and limited to a maximum of 1 m, calculated as $\frac{\min(soil\_depth, 100)}{100}$.

2.2.3. Climate data

ForestScope, similar to its approach with soil data, also offers the flexibility to incorporate various climate data sources. While it primarily utilizes three data sources, it is designed to accommodate other alternative climate datasets for extended processing. The primary climate data sources include ICP flux tower data (Raspe et al., 2020), CHELSA (Karger et al., 2017), and the ISIMIP climate models (Büchner et al., 2023). Given that ICP climate data may not always be available for all corresponding NFI data locations, these alternative sources provide a means to supplement missing climate parameters.

The CHELSA dataset Integrates high-resolution global climate data from diverse sources, including satellite observations and terrestrial measurements. On the other hand, the ISIMIP models encompass an array of climate and socio-economic simulations, designed to project the effects of climate change across different dimensions. In this research, five climate models from the ISIMIP dataset (IPSL, GFDL, MPI, MRI, and UKESM) were utilized.

In terms of climate variables, ForestScope focuses on processing key parameters like air temperature (average, maximum, and minimum), precipitation, solar radiation, and atmospheric CO_2. These variables are recognized as some of the most critical in both empirical and modelling studies due to their significant influence on climate assessments and predictions (Baede et al., 2018).

To assess the robustness of the two alternative climate data sources, a comparative analysis was conducted against the European Climate Assessment & Dataset (ECA) (Cornes et al., 2018), which includes both historical and current climate data. The period chosen for this comparison spanned from 1980 to 2016, a timeframe for which data was available in both the observational records of the ECA and the CHELSA and ISIMIP datasets. This analysis encompassed a comprehensive range of data points: 15,086 for precipitation, 6455 for average temperature, 6345 for minimum temperature, 6236 for maximum temperature, and 2052 for solar radiation. The RMSE method was used to quantify the discrepancies, with a focus on identifying the least error in the predictions made by the ISIMIP models and the CHELSA climate data.

2.2.4. Climate function

The climate function in the ForestScope framework is designed to systematically organize and analyze climate data from multiple sources. It starts by pinpointing and extracting site-specific climate information (e.g., temperature, precipitation, solar radiation) from a broader ICP dataset. For each selected forest site, the function gathers key metrics—such as minimum, maximum, and average temperatures, total rainfall, and solar radiation levels.

Next, it standardizes the dates linked to these climate variables by converting them into a uniform format (e.g., year, month, day) to ensure consistency. This step is critical for aligning the climate data's timeframe with the forest's growth period (stand age), management activities (e.g., logging or planting schedules), and the study's target duration. For example, if a study focuses on 2005–2020 but the ICP dataset only spans 1995–2015, the function adjusts the analysis to the overlapping period (2005–2015).

Furthermore, the function performs aggregations to create meaningful climate summaries. For temperature, it computes monthly and yearly averages, while for precipitation, it sums up the values. In cases where direct climate measurements are not available, the function has a mechanism to integrate alternative data sources like CHELSA and ISIMIP. It matches these alternative sources to the site's geographic coordinates, ensuring that the supplementary data is as relevant and accurate as possible.

The climate function also includes a calculation for frost days, an important variable in many ecological and agricultural models. It processes CO_2 data from sources like ISIMIP and aligns it with the climate data by year (Lange and Büchner, 2020). Furthermore, it considers N deposition data from ISIMIP data, which is vital for understanding nutrient cycles and their impact on ecosystems (Yang and Tian, 2020).

2.2.5. Stand and management data

The third level of data processed and analysed by ForestScope is stand and site management data (Fig. 2). The ICP monitoring program is structured in two primary levels: the first, known as Level I, often represents a subset of NFI and is characterized by broad-scale monitoring across various countries. Level II, on the other hand, involves more intensive monitoring with a focus on specific plots, entailing detailed data collection on forest conditions and variables (Dobbertin et al., 2020). However, it is crucial to recognize that Level I monitoring typically provides limited detail, predominantly offering general stand metrics such as total basal area or aggregated tree counts, without mandatory collection of finer-scale individual-tree attributes. Hence, ForestScope's capability for detailed stand-level analyses, particularly those focused on structural dynamics and management practices, is substantially enhanced by the availability of comprehensive Level II data. In cases where only Level I data are accessible, users should consider supplementing their analyses with alternative data sources to obtain the necessary granularity and precision for rigorous site-specific investigations.

In its current version, ForestScope integrates and processes data from these ICP levels, focusing on stand-level data, including number of trees, diameter, height, volume, and litter information. This allows for a comprehensive understanding of forest stand dynamics. Additionally, the application sources management-related data, such as thinning volume and periods, basal area, number of removed trees, and stem removal/remained volume directly from ICP sites. This approach enables ForestScope to capture a holistic view of forest stand structure and management practices, which are crucial for assessing forest health and planning sustainable forest management strategies (Borghi et al., 2023).

However, should detailed NFI and management data be available from alternative sources, ForestScope is designed to integrate these additional datasets. It can then perform the necessary analyses, as previously described, to align climate and soil data with the specific stand and management data points.

2.2.6. Stand and management function

The stand data function in ForestScope is a complex and multifaceted process, designed to handle species data preparation. The function creates a comprehensive list of species names and codes, which is utilized to generate a subset of data relevant to the stand history. This subset data includes the stand and management-related information, including plantation dates, rotation periods, and other time-sensitive features found within the observational data. Moreover, the function calculates various parameters crucial for modelling the stand dynamics. These include the number of trees, C and N content in deadwood and litter. Additionally, it processes sapling data, including number, weight fraction, root ratio, and stem size, providing a detailed picture of the younger trees in the stand (Meyer et al., 2018).

The function also incorporates above ground biomass estimation across various species and regions, using equations from the comprehensive dataset by Zianis et al. (2005). These equations are chosen for their wide applicability and robustness in modelling the relationship between tree dimensions and different biomass components. The most frequent models from Zianis et al. (2005) include:

1- Logarithmic Equations:
   ○ $Biomass = a \cdot \log(D) + b$ where D represents the diameter at breast height, and a and b are coefficients that have been empirically derived for specific tree components, species, and countries.

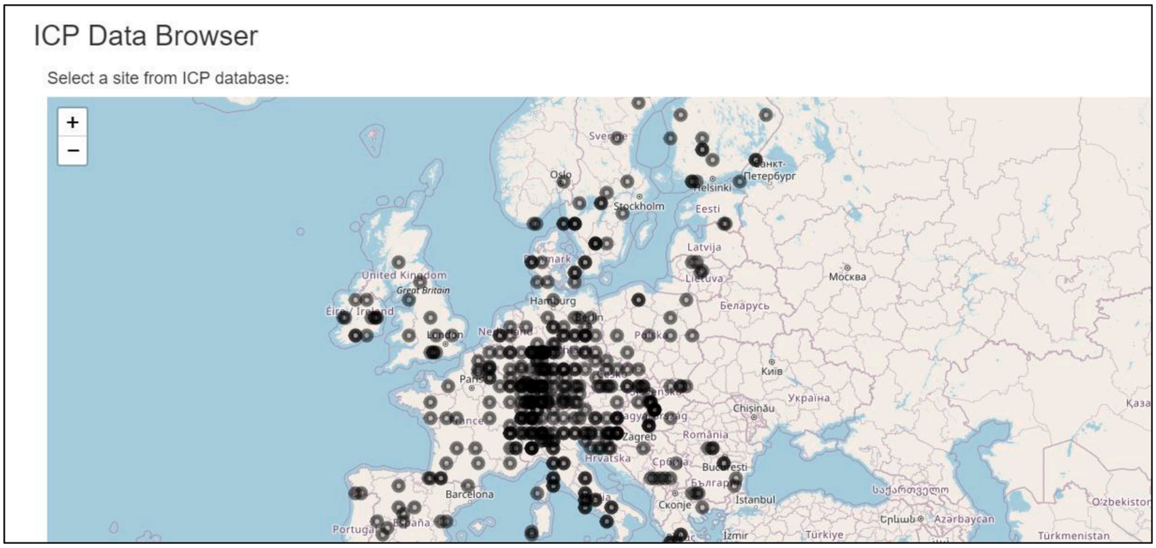

Fig. 2. ICP NFI data points in ForestScope.

2- Power Law Equations:
   ◦ $Biomass = a\ .D^b$ where a and b are again country-species-component specific coefficients, with D indicating the diameter.
   ◦ Combined Diameter and Height Equations:
     When both diameter and height are considered, the equation takes the form:
     ◦ $Biomass\ = a\ .D^b.\ H^c$

This equation includes an additional height component (H) and its relative coefficient (c).

In scenarios where specific local data from the Zianis et al. (2005) dataset is not available, our package defaults to the generalized approach detailed by Forrester et al. (2017). This method uses logarithmic transformations and beta coefficients to estimate the biomass of different tree components such as stems, roots, foliage, and dead branches for each plot, as follows:

$$Biomass_C = \exp\left(\beta_{0C} + \beta_{1C}(\log(d) + 0.087\ \times \log(H)\right)$$

where c represents the plant component (foliage, stem, or root), β_{0C} and β_{1C} are the modifiers depending on the species, d is the tree diameter and H is the tree height.

In addition to species data preparation, the stand data function also manages the thinning data, which is vital for understanding stand management practices. It determines the age of thinning interventions and calculates the rate of stem removal. This is achieved by analysing inventory data, which includes stand-level stem volume removed and remaining.

2.2.7. Experimental model application

As an addition to the data processing and analysis capabilities of ForestScope, an experimental vegetation model, a modified version of the 3PG (Physiological Principles Predicting Growth) model, has been integrated into its features. This integration enhances ForestScope's ability to demonstrate the practical modelling case using the processed data, as well as simulating and understanding forest growth and stand dynamics, thus providing a more robust framework for ecological analysis. Due to its easy accessibility, flexible design, and minimal parameter requirements, the model has been used to evaluate forest productivity and the effects of climate change across multiple biomes (Gupta and Sharma, 2019).

The 3PGmix model, built on the foundations of the original 3PG model, is a process-based tool designed for simulating forest growth (Forrester and Tang, 2015). It predicts stand productivity by focusing on key factors like the absorbed photosynthetically active radiation and the canopy quantum efficiency, which is influenced by various environmental conditions including vapor pressure deficit, soil water availability, stand age, air temperature, and soil fertility.

The modified version 3PGmix, extends these capabilities by including well-established soil models such as YASSO (Liski et al., 2005; Viskari et al., 2022), ICBM (Kätterer and Andrén, 2001), and RothC (Coleman and Jenkinson, 2014) into the framework which enables simulations of C, N, and phosphorus (P) pools and fluxes in both aboveground and belowground components of forest ecosystems (A.L.D. Augustynczik et al., 2025). This expanded focus allows for a comprehensive understanding of nutrient dynamics and their impacts on forest growth. The model also includes routines for C allocation, prioritizing root allocation in less favourable sites and balancing growth among roots, foliage, and stems (For further details see A.L.D. Augustynczik et al., 2025).

ForestScope provides essential inputs for the model, including climate variables like precipitation, temperature, radiation, vapor pressure deficit, and frost days. It also provides data on stand structure, such as age, tree density per hectare, and biomass of foliage, roots, and stems. Additionally, ForestScope delivers details on site-specific C and N content, along with forest management practices such as the timing and intensity of thinning and the density of remaining trees after intervention.

3. Results and discussion

3.1. Soil data comparison

The comparative analysis of RMSE values against ICP soil data indicates that the HWSDv2.0 database typically outperforms the HWSDv1.2 and ISRIC database in estimating various soil properties, such as AWC (in mm), SOC (in g/kg) at different depths, and the composition of soil particles like sand, silt, and clay (in % by weight) (Fig. 3, Table S1). In the case of SOC, HWSDv2.0 has a marginally better performance in both the top and bottom layers than ISRIC (Table S1). HWSDv2.0 yields a lower RMSE for AWC compared to ISRIC (30.16 mm and 37.27 mm respectively), suggesting more accurate soil moisture content representation by HWSDv2.0. Regarding soil texture, HWSDv2.0 typically has better overall accuracy for clay, silt, and sand content, except for clay and silt in top layer where ISRIC records a slightly lower RMSE. These findings align with HWSDv2.0′s closer correlation with the ICP soil data in evaluated properties, highlighting its

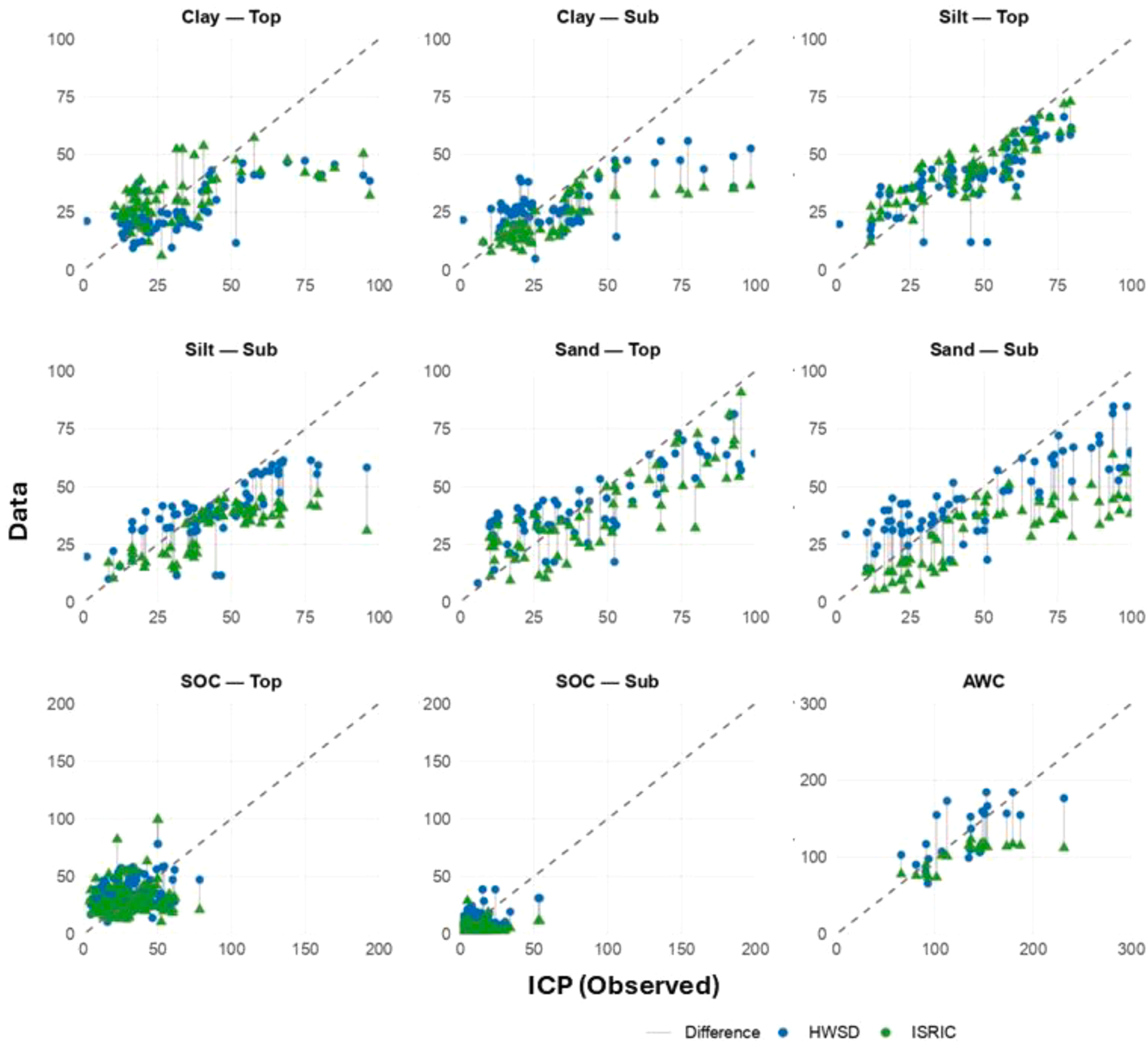

Fig. 3. ISRIC and HWSD soil data at top and bottom soil layers evaluation against the ICP data.

potential for more precise soil property assessments. The differences in performance between the two databases may be attributed to the methods and data sources used in their development.

However, these findings align with earlier studies comparing the ISRIC and HWSD databases, where HWSD consistently demonstrated better performance over ISRIC in predicting soil properties like pH, cation exchange capacity, and soil organic C (Batjes, 2016; Hengl et al., 2014). Consequently, our results indicate that HWSD v2.0 is the more reliable source for plot-scale soil information, and ForestScope therefore defaults to HWSD inputs when field measurements are unavailable (Figure S1). To keep potential scale mismatches transparent, every value exported by ForestScope carries a provenance flag ("FIELD" or "DATABASE") together with the attribute-specific RMSE reported in Table S1; these metrics quantify the residual bias and uncertainty that arise when gridded products are down-scaled to individual ICP plots. Users can thus propagate, filter or down-weight gap-filled observations in subsequent analyses.

It is crucial to recognize that the effectiveness of the ISRIC and HWSD databases can vary based on specific soil properties and geographical areas. National soil surveys have been shown to surpass these databases in accuracy for certain properties in specific regions (Arrouays et al., 2020). Thus, when choosing a soil database for particular applications, it is vital to weigh the strengths and limitations of each database and assess their performance in the targeted geographic area. ForestScope's provenance flags and uncertainty annotations are therefore intended to alert analysts to locations where database-derived values should be treated with caution, or replaced altogether, when higher-resolution national data become available.

The **soil_data** function implemented in ForestScope demonstrates its capability to manage diverse and complex soil data effectively. It successfully streamlines data processing workflows, enabling efficient handling and analysis of critical soil parameters. These parameters directly support both empirical analyses and modelling studies focused on soil properties (Nakhavali et al., 2018)

3.2. *Climate data comparison*

The analysis of climate data across various climate models reveals differences in their performance. In terms of precipitation (in mm), the datasets displayed a range in RMSE values, with CHELSA showing a more accurate prediction of mean precipitation, while UKESM was at the higher end of the RMSE spectrum (Fig. 4, Table S2). This pattern was also evident in the temperature data (in K), with CHELSA maintaining lower RMSE values, suggesting its stronger predictive capability for mean temperatures compared to the other datasets (Figure S2, Table S3). Delving into the extremes of temperature, the datasets again showed variability in their RMSE values. CHELSA stood out for having the most precise estimates for both the lowest and highest temperatures, indicating its potential superiority in capturing temperature variations (Figure S3 and S4, Table S4). In contrast, the GFDL dataset appeared to have the greatest room for improvement, especially in predicting maximum temperatures.

Regarding radiation predictions (in W m^{-2}), the datasets were in closer agreement, with similar RMSE values across the board (Figure S5, Table S5). This similarity primarily stems from the limited number of observational points (2052 in total) available from the ECA dataset for comparison. This is a significantly smaller dataset when compared to those used for other climate parameters, leading to a more uniform agreement in our findings. However, it is important to note that a larger pool of observational data would likely provide a more comprehensive and clear comparison of solar radiation across different climate models.

Moreover, the methodology adopted by the CHELSA dataset deserves special attention. This dataset employs a downscaling technique that integrates various climate data sources and utilizes advanced statistical methods (Karger et al., 2017). Such an approach enables the generation of high-resolution climate data, which are more reflective of local conditions. This, in turn, potentially enhances the accuracy of climate variable predictions, giving the CHELSA dataset an edge over the ISIMIP models.

Consequently, within the ForestScope framework, the CHELSA climate data are opted to be used as the primary input (Figure S6). This decision also extends to our analysis and methodologies for filling in missing climate data points in the ICP NFI dataset.

3.3. Application

ForestScope is configured to integrate inputs from the HWSD soil database and CHELSA climate data, as previously described. Additionally, it requires NFI data, sourced from the ICP data repository (Figure S7), to extract and organise stand and management information. Once these data sources are provided, ForestScope processes and structures the data into organized data frames suitable for use in modelling or analytical frameworks. These frames include: Site Information (site number, country, latitude, longitude), Climate Data (minimum, maximum, and average temperature, precipitation, solar radiation, frost days, atmospheric CO2), Soil Data (soil class, AWC, SOC, N, P), Species Data (species name, planting period, fertility, stem count, vegetation biomass, C content), and Management Data (age, vegetation biomass removal, basal area, and volume).

To demonstrate this process, a site in Northern Germany (site number: 101; latitude: 54, longitude: 10) as a case study was selected (see Fig. 5). The system efficiently extracted and organized the data into various data frames, which are also downloadable for extended research or modelling applications.

In the experimental phase of ForestScope, the processed data enables the execution of modelling experiments using three distinct soil C models. Among these, the RothC model only includes N and P limitation factors. The models generate outputs covering a range of aspects: climate, stand composition, canopy dynamics, stock levels, water cycles, and forest production fluxes. Specifically, a comparative analysis conducted at the case study site with the RothC model reveals intriguing findings. Under conditions without nutrient limitation (Fig. 6-a), the model behaves differently compared to scenarios where both N and P are co-limiting (Fig. 6-b). The latter scenario shows a slight reduction in productivity, attributable to the restricted availability of N and P. This outcome aligns with recent nutrient limitation studies (Du et al., 2021; Nakhavali et al., 2022), underscoring the necessity of incorporating

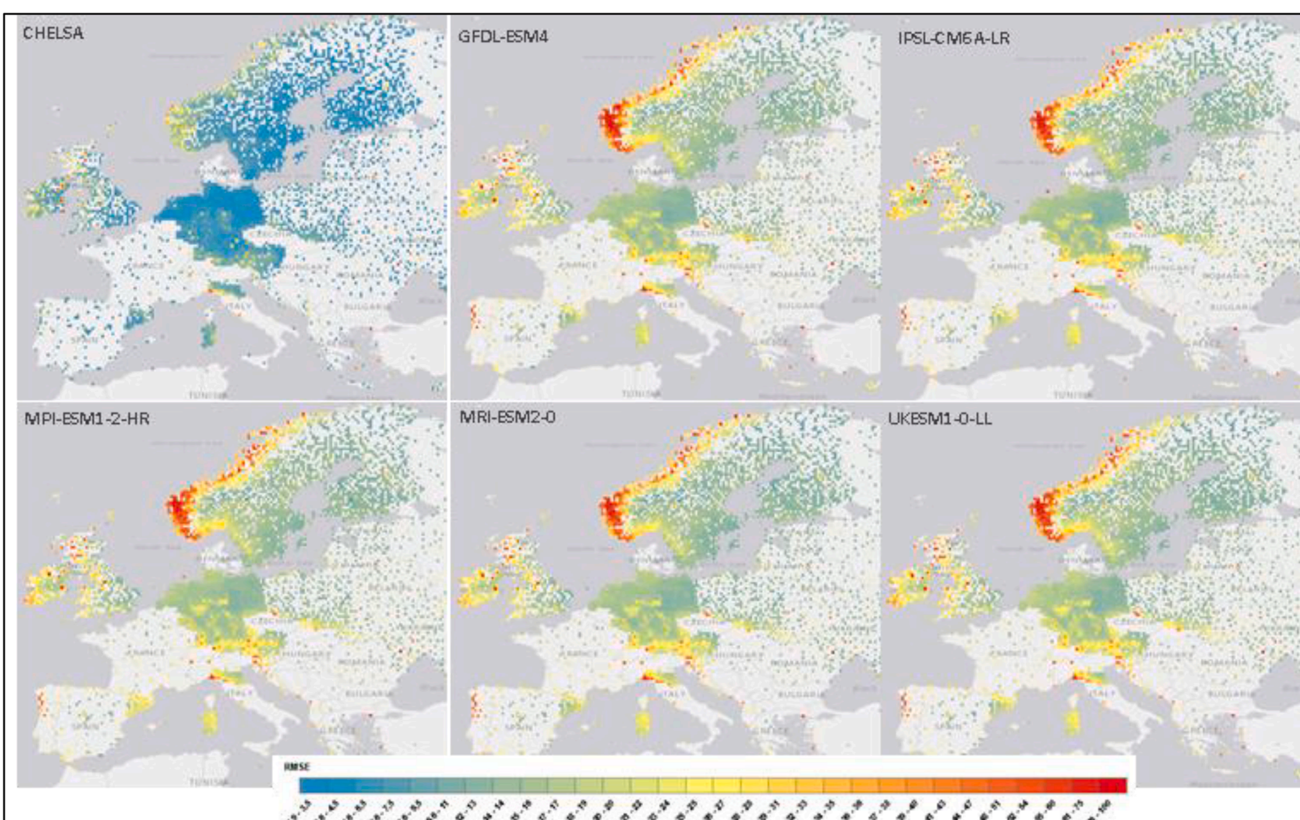

Fig. 4. Comparative Analysis of Precipitation Data from CHELSA and ISIMIP Models with ECA Observational Points.

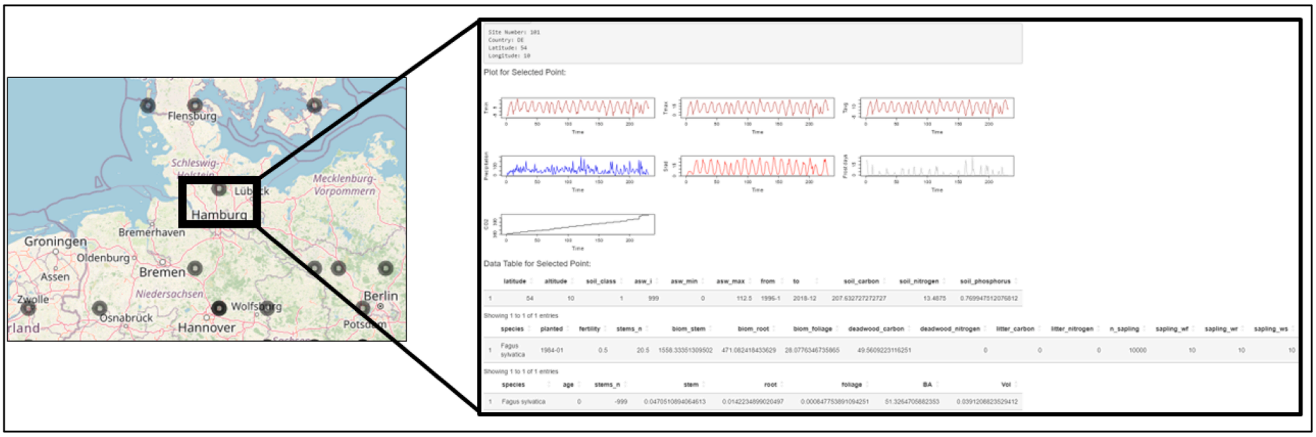

Fig. 5. Site Selection and Data Extraction Interface in ForestScope.

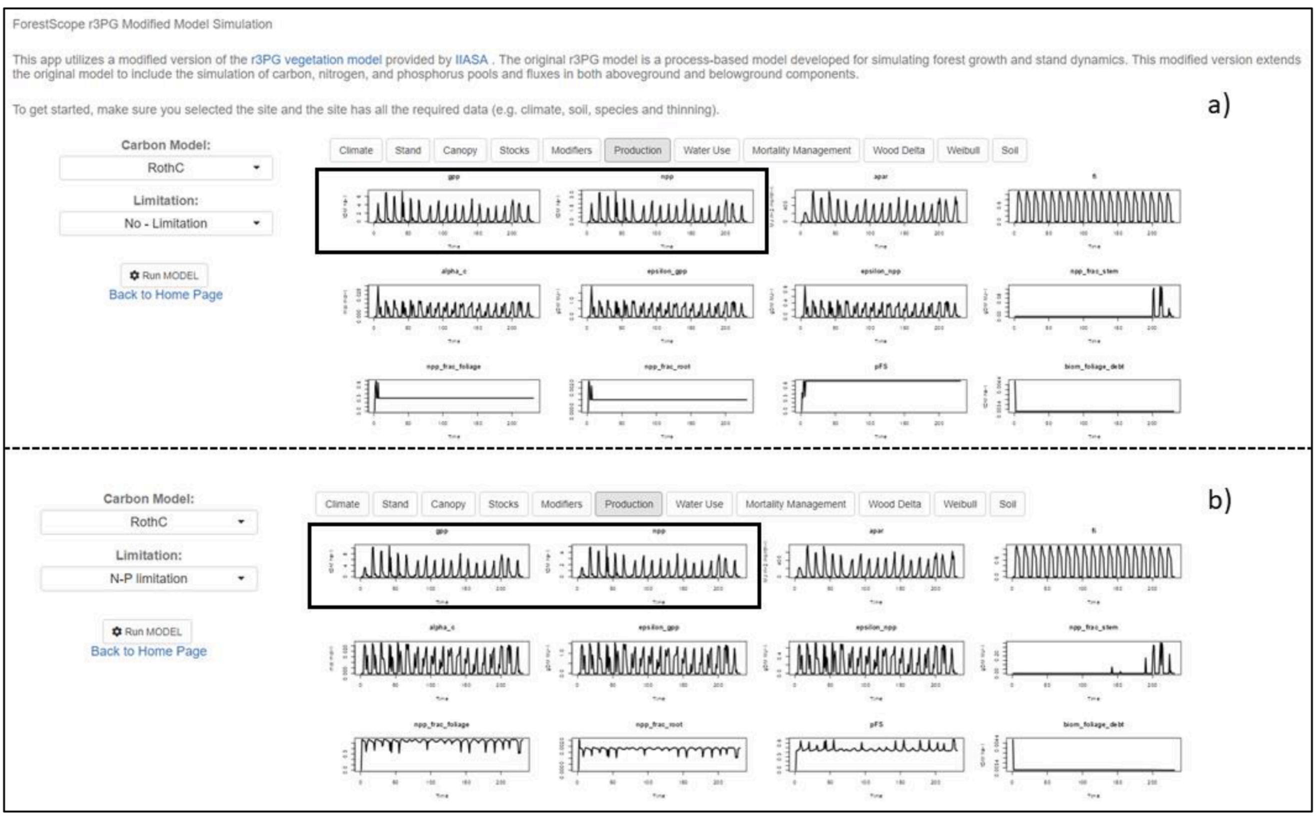

Fig. 6. ForestScope Application of Models and Experimental Setup with a) No Nutrient limitation b) with N and P co-limitation.

nutrient limitations into forest productivity models for more accurate estimations.

However, it is important to note that the models within ForestScope have not undergone complete calibration, with only the above-ground processes having been calibrated against observational data for regional and European scale studies so far (Augustynczik et al., 2025. Nakhavali et al., 2025). Therefore, while they offer valuable insights, users should apply these models with an understanding of this limitation in their current state.

4. Conclusion

ForestScope marks a constructive step in forest data analysis, providing a structured approach to processing and interpreting soil, climate, and stand data. Its ability to integrate data from various sources into a coherent framework is essential for advancing our understanding of forest ecosystems. By automating data harmonisation, it markedly reduces manual preprocessing effort, and its coupling with the process-based 3PGmix vegetation model offers a proof-of-concept that the platform can deliver model-ready inputs and site-level growth simulations within a single workflow. Although 3PGmix serves here as an illustrative application, the framework is readily extensible to other process-based or empirical models, allowing users to plug in alternative or more mechanistic models and thereby enable rapid testing of hypotheses and management scenarios at large spatial scales.

However, it is important to acknowledge the tool's current limitations, including its reliance on the accuracy and completeness of the input datasets and the need for further calibration of the integrated vegetation models. As such, while ForestScope offers valuable insights and a solid foundation for ecological analysis, ongoing development and validation are required to enhance its applicability and accuracy in diverse ecological scenarios. Nevertheless, ForestScope represents a significant yet evolving contribution to the field, highlighting both the complexities and potential of ecological data analysis in modelling work, as well as in sustainable forest management and conservation strategies.

Code and data availability

The web-based version of the ForestScope application can be accessed at: https://nakhavali.shinyapps.io/ForestScope_app/. Its source codes are made available at: https://github.com/iiasa/ForestScope_sc. For the ICP data, requests can be made through the ICP official website at http://icp-forests.net/page/data-requests. CHELSA climate data is accessible for download at https://chelsa-climate.org/downloads/, and the HWSD v2.0 soil data can be sourced from https://data.apps.fao.org/catalog/dataset/ff5c613c-75bb-46a9-a162-bc728059b465.

CRediT authorship contribution statement

Mahdi (André) Nakhavali: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Data curation, Conceptualization. **Andrey Lessa Derci Augustynczik:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Anna Repo:** Writing – review & editing. **Elia Vangi:** Writing – review & editing. **Petr Havlík:** Writing – review & editing, Supervision, Resources.

Declaration of competing interest

We declare that we have no conflict of interest.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ecolmodel.2025.111251.

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