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Projections of current and future European potential vegetation types

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ABSTRACT

The extent and condition of natural ecosystems is a key factor enabling species populations to thrive. However, the distribution of ecosystems is changing owing to both climatic and anthropogenic factors. Recently negotiated European policy directives, such as the Nature Restoration Regulation, argue for the restoration of natural ecosystems. Yet to determine what is to be restored the range of possible outcomes should be explored, also with regards to future climatic conditions. Here the concept of potential natural vegetation (PNV) is applied and mapped in a data-driven manner at European extent, exploring where PNV transitions are most likely to happen under contemporary and future conditions. Specifically, I predict current and future potential coverage of six natural vegetation types at 1 km^2 grain using Bayesian machine learning approaches, relying on a range of contemporary vegetation type records and climate and soil data for prediction. Most current land cover and land use could develop towards no single, but multiple PNV states. Results also indicate that suitable areas for some vegetation types, such as wetlands, might become rarer under future climatic conditions. Furthermore, the challenge of transitioning to PNV was found to be particularly high for current intensively cultivated landscapes. Overall data-driven PNV mapping holds considerable promise for assessing land potentials and supporting restoration assessments. Future work should expand the thematic grain of vegetation maps and also consider feedback with biotic factors.

1. Introduction

Natural ecosystems are key for the preservation of species and provisioning of nature contributions to people (Betts et al., 2017). The occurrence of natural ecosystems is driven by its dominant vegetation, itself determined by complex interactions of biotic factors, climate, topography, soil and lithology (Jiménez-Alfaro et al., 2014; Jung et al., 2020; Keith et al., 2022; Sayre et al., 2020). Many natural ecosystems are under threat from current and future anthropogenic and climatic factors (Berdugo et al., 2020; Huntley et al., 2021), and restoring them seems to be the most promising way to bring nature on a path towards recovery (Keith et al., 2013; Leclère et al., 2020; Nicholson et al., 2021). The Kunming-Montreal Global Biodiversity Framework explicitly calls for the effective restoration of ecosystems (CBD, 2023), while the European Biodiversity Strategy for 2030 lists the establishment of trees and widespread restoration of ecosystems among its ambitions (European Commission, 2020). However, a key question that influences the success of ecosystem restoration is the probability by which natural vegetation can be established. Within Europe the range of plausible options available, given current and future environmental constraints, remains often unclear and dependent on the restoration objective.

The Potential Natural Vegetation (PNV) concept describes a hypothetical scenario of dominant natural vegetation in an area, under the assumption that human influence would largely cease (Loidi et al., 2010). The concept of PNV is not new and its usefulness has been intensely debated since its conception (Tüxen, 1956). Common critiques are that successional pathways are highly uncertain given historical human legacies (Chiarucci et al., 2010; Loidi and Fernández-González, 2012). Furthermore, the creation – or in some cases re-establishment - of habitats does take time with success far from being guaranteed (Crouzeilles et al., 2016; Prach et al., 2016). Active human interventions, such as habitat recreation, management practices, or supportive ecological processes such as rewilding (Jepson et al., 2018; Perino et al., 2019; Svenning et al., 2024) are likely necessary to establish a given natural system. In some cases pathways towards potential future vegetation can also be undesirable from a management perspective, for example afforestation in regions that will be increasingly fire prone (Jäger et al., 2024). Despite these limitations, the PNV concept continues to be useful for broad-scale assessments that define lower and upper land potentials of what might be possible or plausible (Fig. 1).

PNV has previously been mapped across spatial and temporal scales

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using different methdologies (Hengl et al., 2018). At local scales, ecological fieldwork and experimental studies use PNV concepts to highlight the plausibility of local vegetation successions, taking historical legacies and local contexts into account (Johnson and Miyanishi, 2008; Walker et al., 2010). Other work used soil cores and archaeobotanical approaches to infer historic PNV states (Courtney Mustaphi et al., 2021; Finsinger et al., 2021). Bohn and Gollup used botanical knowledge and phyto-socioecological techniques to make an expert-based assessment of European PNV (Bohn and Gollub, 2006). Although these European maps remain unrivalled in terms of thematic detail, their spatial resolution can be coarse, and they do not account for anticipated changes in future climatic conditions.

As an alternative to expert-based assessments, data-driven tools such as machine learning or simulation models can estimate PNV under current and future climatic conditions. Previous work have mapped the potential distribution of biomes (Bonannella et al., 2023; Hengl et al., 2018), species habitats (Jung, 2020), plant functional traits (Boonman et al., 2020; Joshi et al., 2022), actual and potential photosynthetic activity (Hackländer et al., 2024) or the potential distribution of land cover and vegetation types (Bastin et al., 2019; Hengl et al., 2020; Jiménez-Alfaro et al., 2014). Among different machine learning approaches in particular Bayesian models have recently gained traction, among others because of their ability to summarize posterior prediction uncertainty (Carlson, 2020). The impact of anticipated future climate change on vegetation can also be estimated (Bonannella et al., 2023; Hickler et al., 2012; Huntley et al., 2021; Zabel et al., 2014). For example, this can be particularly helpful to assess how high-altitude treelines of forests might change in the future. For Europe however, no PNV estimates exist for different vegetation types at a resolution useful for regional planning.

Maps of current PNV are commonly used for spatial planning studies (Kowarik, 2016). They offer an alternative point of departures that, instead of looking backwards to restore a (pre-)historic state of vegetation (Keane et al., 2009), can be forward looking by also taking into account broad-scale future climatic conditions. Most importantly PNV estimates can be useful to delineate the upper restoration potential for biodiversity and climate mitigation (Chapman et al., 2025; Hackländer et al., 2024; Roebroek et al., 2023; Strassburg et al., 2020). Previous studies have used potential current vegetation estimates to quantify benefits of restoring land to biodiversity while maximizing carbon sequestration benefits (Chapman et al., 2025; Strassburg et al., 2020). For example, Roebroek et al., 2023 estimated that existing forests could increase their carbon contributions by up to 16 % if released from anthropogenic management. Although such planning scenarios are often highly uncertain, they can help to narrow done some first boundaries on the potential benefits of proposed restoration actions.

In this work a quantitative broad-scale assessment of the current and future potential natural vegetation (PNV) is made for the European continent, specifically the EU27 countries plus Switzerland, the United Kingdom and the western Balkan countries. I integrate natural vegetation and species habitat observations from different vegetation and land-cover datasets and utilize Bayesian machine learning approaches to predict current and future PNV under different climate scenarios. Furthermore, using contemporary land-use data, opportunities, but also potential challenges for different restoration pathways are investigated through a comparison with existing European vegetation. Posterior predictions are made openly available to support future efforts in identifying potential pathways towards restoring natural vegetation in Europe.

2. Methods

The aim of this work is to create a series of vegetation-type specific PNV predictions for the European continent, quantify its contemporary and future extent and evaluate options for different landscapes. The modelling extent was chosen because of its relevance to the Nature Restoration Regulation (NRR) and to consider adjacent countries. Thematically I rely on the natural vegetation types described by the MAES ecosystem classification scheme, the most commonly applied legend for ecosystem accounting by European member states (Maes et al., 2014). For natural vegetation at level 1 it distinguishes between Grassland, Forest and woodland, Heathland and shrub, sparsely vegetated land, Inland wetlands and marine inlets and transitional waters (Rivers and lakes are ignored for this exercise). It should be stressed that this is a simplified thematic legend, which ignores the complexity and nuances of vegetation dynamics and phytosociological endpoints and can thus at best serve as a broad description of vegetation types. Further, given the unpredictability of future PNV trends each vegetation type was modelled separately opposed to estimating the exclusive (e.g. either or) probability of PNV (but see section on predictive modelling).

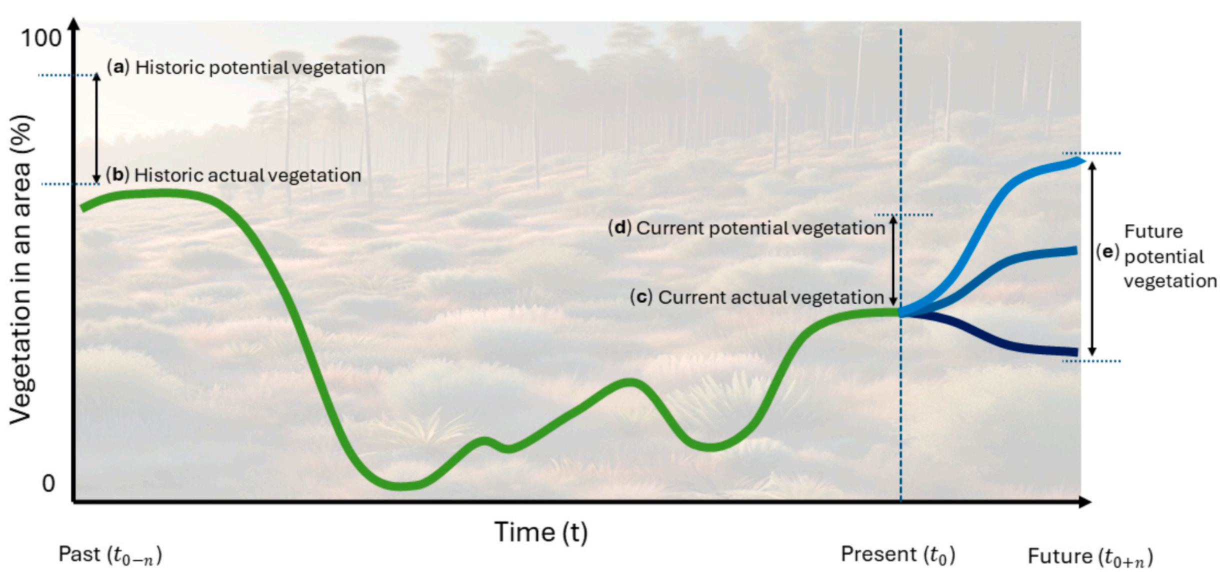

Fig. 1. Idealized trajectory of actual and potential natural vegetation from past to future states. Highlighted are historic potential (a) and actual (b) vegetation levels and their corresponding states (c, d) in the present. Depending on the future trajectory different future potential vegetation levels (e) might be possible. A hypothetical natural vegetation site is shown in the background as hallucinated by DALL-E 3.

2.1. Input training data and covariates

The aim of the predictive modelling is to characterize current as well as potential future PNV. To parametrize the models a range of different data sources on the distribution of MAES vegetation types was acquired, focussing primarily on contemporary vegetation cover that can be related to climatic, soil and topographic covariates. The vegetation data originated not from a single, but multiple openly available data sources. Specifically, data originated from the repeated Land Use/Cover Area survey (J. R. C. European Commission, J.R.C, 2020), European Article 17 reporting data (EEA, 2020), EUNIS habitat distribution plots (Hennekens, 2019), Natura 2000 reporting data (EEA, 2023) as well as vegetation occurrence information from the Global Biodiversity Information Facility (GBIF.Org User, 2024). For GBIF all vegetation occurrences were filtered with regards to their spatial accuracy and spatially aggregated to a centre of a 1km^2 grid cell. They were then individually linked (e.g. per species) to published European expert-based crosswalks to identify indicative vegetation types (Chytrý et al., 2020). As an example, if a grid cell contains observations of at least 5 different diagnostic species known to occur exclusively in wetlands, then it is assumed that this grid cell is potentially suitable for harbouring wetlands ecosystems. It is acknowledged that this threshold is ambiguous but is deemed sufficient for broad-scale analyses. Furthermore, these indicative occurrences were also combined with other data sources (see above), which helped to mediate spatial biases (Appendix Fig. S1). Only GBIF observations with low coordinate uncertainty between 2000 and 2024 were considered. All vegetation cover data was thematically harmonized to the MAES legend, geographically aggregated to a 1km^2 grid and reprojected to a Lamberts-equal area grid (Appendix S1).

The selection of covariates is a critical choice for machine-learning based PNV modelling. Generally speaking any covariates directly linked to land cover, land use or actual photosynthetic activity are to be avoided (Hackländer et al., 2024; Hengl et al., 2018). Predictions were informed by previous PNV estimates as covariates (Bohn and Gollub, 2006; Hengl et al., 2020) as well as a set of other static and dynamic layers. Static variables include altitude and derivates such as slope, aspect, roughness, northness and eastness, and the topographic position index (TPI) as a characterization of the relief, all of which were calculated in R and based on the Copernicus EU DEM (European Space Agency and Airbus, 2022). Estimates of European Lithology were taken from a new Pan-European lithology map and harmonized to the same grid as other variables (Isik et al., 2024). Tor predict potential natural wetlands I included data on topographic wetness as those likely to be regularly flooded (Tootchi et al., 2019). For predicting potential marine inlets and transitional waters the distance of each grid cell to the coast was calculated (in meters). With regards to dynamic variables current and future downscaled climatologies were obtained from CHELSA (Karger et al., 2017). Contemporary climate conditions range between 1980 and 2010 and were used for model parametrization. For the future, data on three Shared Socioeconomic Pathways (SSPs) relying on SSP1–2.6, SSP3–7.0 and SSP5–8.5 respectively. All projections were calculated for the period 2020 to 2100 in 30 year steps and for a set of five different General Circulation Models (GCMs). All covariates were aggregated (arithmetic mean for continuous, mode for categorical) to a common 1 km^2 grain size, reprojected to a Lamberts Equal-Area projection and rescaled for the predictive modelling (subtraction of mean and division by standard deviation) to improve model convergence and extrapolation. Multi-collinearity of the covariates was not considered an issue given that the used modelling approaches (see below) apply strong regularizations penalties during inference and collinear variables were attributed with little additional information gain.

2.2. Predictive modelling

For the modelling I used the *ibis.iSDM* R-package (Jung, 2023), which consists of an integrated modelling suite allowing to integrate different datasets as well as create spatial and temporal projections. Two different Bayesian modelling approaches were used to identify the relative probability of any given ecosystem in space and time, both of which allow to estimate a full posterior distribution for current and future suitability, and thus the summary of different statistical moments including a true quantification of lower and upper relative probabilities. First, i utilized linear Bayesian regularized regression models with Spike-and-Slab priors, which are particular useful in the regularization of high-dimensional regression problems with multiple covariates (Friedman et al., 2010; Scott, 2023). Linear models can be useful for projections beyond observed unit scales as they make fewer assumptions about extrapolation (Norberg et al., 2019). Second, a Bayesian additive regression tree (BART) model was parametrized, which has the advantage that it can represent complex non-linear relationships, and through leaf pruning and regularization is assumed to be more robust to overfitting (Carlson, 2020; Dorie, 2022; Jung, 2023). Both models were parametrized using contemporary vegetation occurrence and covariate data, with different models being trained for each vegetation type (see above) and then projected to future conditions. From each fitted and projected model, the arithmetic mean, median and lower (25 %) and upper percentile (75 %) was extracted as well as the coefficient of variation and standard deviation of the whole posterior. For final predictions all statistical moments were averaged depending on their cross-validated predictive performance (see below).

To assess the predictive performance of the model a spatial block cross-validation scheme was applied using the ‘spatialsample’ R-Package (Mahoney et al., 2023). For each vegetation type, all available vegetation data was split into three randomly selected spatial blocks and two repeats, thus allowing for a independent training and testing subset. A threshold and validation were calculated on the arithmetic mean by maximizing the F1 score as a measure of predictive performance (SI Table 1). The F1 score was chosen to reduce the effect of class imbalances, although comparisons are made only for each vegetation type and spatial blocks were split to equal ratios, thus ensuring comparable sample sizes. For all further analysis a weighted ensemble of both models calculated from the average F1 score across spatial folds was used.

2.3. Posthoc correction and overlays

The point of potential vegetation is not to estimate the distribution of managed or actual vegetation types (Hengl et al., 2018). However an argument can be made that certain transitions from current actual to current or future PNV are highly unlikely and should not be further considered in further assessments (i.e., ecosystem accounting). A typical example includes transitions from highly urbanized anthropic areas to PNV (e.g. forest or wetlands), which is unlikely to happen beyond marginal extents. Similarly, any open-water bodies (larger rivers, lakes) are unlikely to transition to natural vegetation with exception of very marginal changes to wetlands or marine inland vegetation. A mask was created from the latest 2018 Corine layer (European Environment Agency, 2019) containing continuous and discontinuous urban land cover as well open water grid cells at 100 m grain size. The resulting mask was fractionally aggregated (% covered) to a 1 km grain and all grid cells containing more than 50 % of urban or open water were excluded from all PNV maps.

An initial assessment of the possible restoration challenge and most likely transition from actual to current PNV was performed. Here it was assumed that a) areas with greater current land-use intensity as mapped by existing land systems maps provide a greater transition challenge (Dou et al., 2021), b) distance to nearby natural land cover facilitates the transition and c) transitions from structurally similar types are less of a challenge (e.g. pasture to natural grassland transition). A simplified crosswalk was created that assigns a score (low to high) for each possible transition from current to potential vegetation (SI Table 2). For each class and grid cell in the current land systems map (Dou et al., 2021) a challenge score C is then estimated as the minimum (e.g. most likely) transition from current to any modelled PNV type as follows: $C_{iv} = \min\left(\frac{s_v}{p(v)_i}\right)$, where i is a grid cell, v is one of probable PNV types, s is the cost of transition (SI Table 2) and $p(v)$ is the estimated probability of encountering PNV of a given class v. Thus, the lower the probability of encountering a PNV type and the higher the score s, the more challenging the transition from current to PNV (under these assumptions) a particular vegetation transition. The resulting challenge score (higher is more challenging) was then visualized using quantile distributions as well as the class v for which C is the smallest (Fig. 3). Notably, this assessment can only serve as illustrative first perspective as active management interventions, restoration objectives and local contexts are not explicitly considered (but see discussion).

3. Results

Most land area in Europe can potentially develop into multiple trajectories under contemporary climate conditions (Fig. 2). With exception of Marine inlets and transitional waters, which were largely constrained to coastal areas and thus small in potential area extent (median $q_{50} = 0.44$ million km^2), all vegetation types could potentially occur in less than half of all European land area ($q_{50} = 1.82$ million km^2 for Heathland and shrubs up to $q_{50} = 2.1$ million km^2 for Woodland and Forests), although with broad geographic differences (Fig. 2). While contemporary potential sparsely vegetated areas and Heathlands and shrubs were mainly concentrated in the mediterranean geographic regions, particular wetland vegetation types could potentially occur mostly in northern Europe including Scandinavia (SI Fig. 2). The predictive performance of the various models varied (SI Table 1), with Marine Inlets being most consistently predicted (Average F1 = 0.89), while all other vegetation types had a lower predictive performance ranging between a F1 score of 0.7 and 0.67 (SI Table 1). This indicates that for most vegetation types there is considerable uncertainty in the posterior predictions (see also SI Fig. 3).

Despite the possibility of multiple plausible transitions to PNV (Fig. 2), some transitions can be assumed to more likely to occur if actively or passively restored based on contemporary land system distributions. Across Europe, Woodland and Forests are the most likely class to transition from current land systems (40.5 % of all land area, Fig. 3a), followed by Grassland (27.8 %) and sparsely vegetated areas (12.2 %). The relative challenge of transition to contemporary PNV is is particularly large in regions with high land-use intensity such as the Po-Valley, Italy (Fig. 3b). Some of the lowest challenges of transitioning to PNV can be observed in the Scottish Highlands, UK, and the Pyrenees, Spain. It should be stressed that this assessment is only valid in the context of the mapped land-use intensity classes, the transition scores (SI Table 2) and mapped probabilities (SI Fig. 1). Different vegetation endpoints are fully possible, as also represented by the spatial distribution of probabilities (Fig. 2).

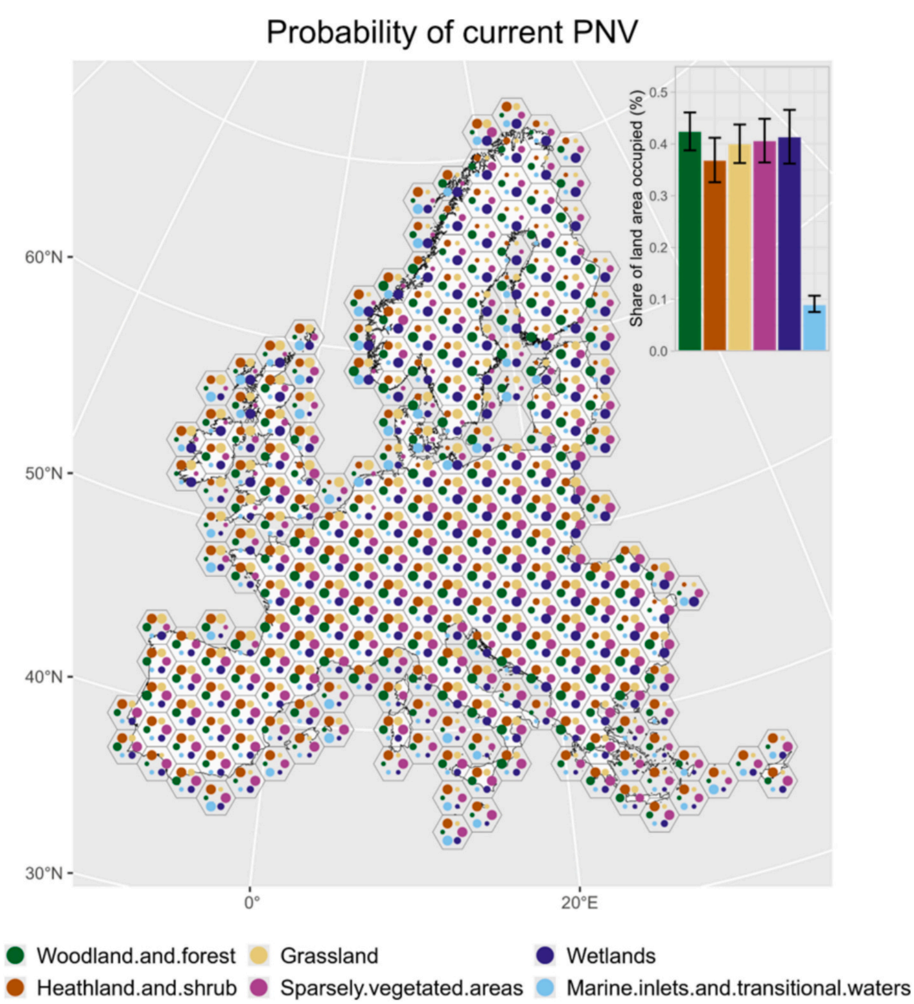

Fig. 2. Probability of current PNV for six different vegetation types. Coloured points within hexagons show the average posterior probability of a vegetation class. The size of points within hexagons are rescaled relative to their probability. Inset bargraph show the total share of land relative to the total land area (grey) that could potentially be occupied by each PNV. Individual predictions can be found in SI Fig. 2.

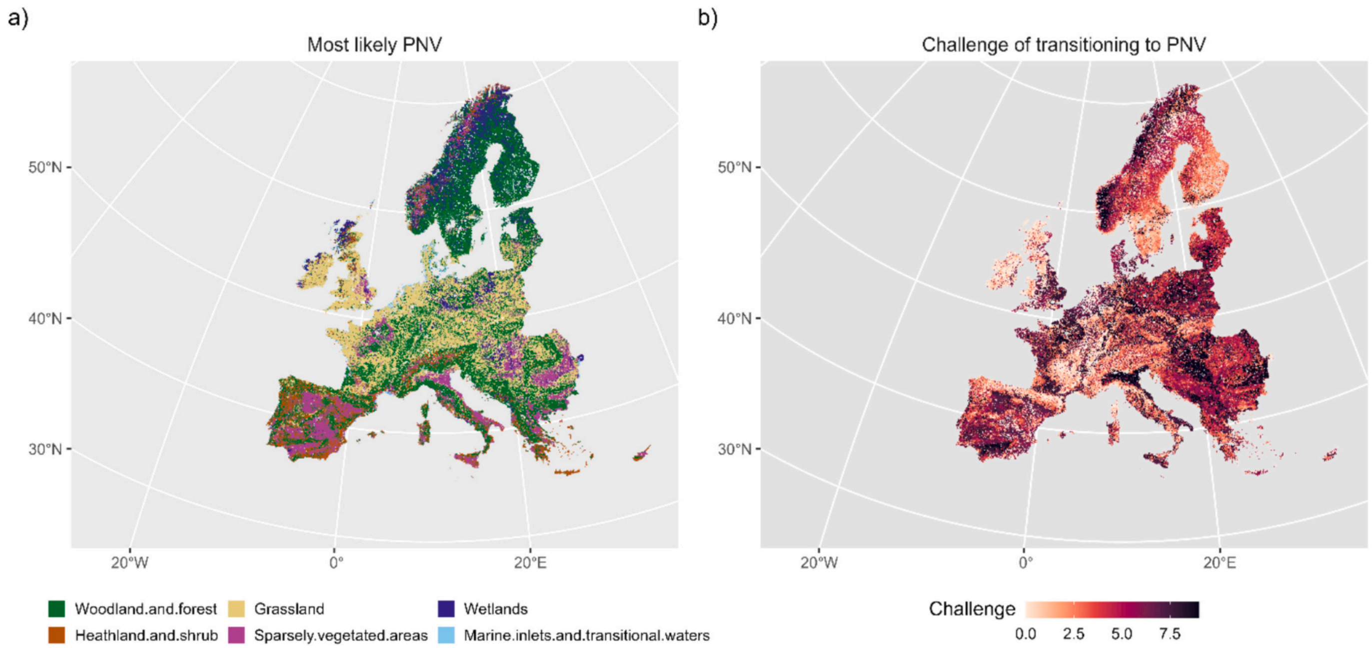

Fig. 3. Most likely natural potential vegetation type when transitioning from current land-systems and the challenge (0–10 score) of transitioning to PNV. Based on the coverage of contemporary land systems (Dou et al., 2021) and broad scores of transitioning from transition from land systems to PNV (SI Table 2). Note that the visibility of individual grid cells can be overemphasized owing to spatial aggregation for the figure.

The extent of PNV can vary depending on the biophysical conditions and this is true especially in future climates. Compared to contemporary climatic conditions (dated up to the year 2010), under future climates shifts in PNV might occur (Fig. 4). Most notably, the total amount of area suitable for forests, grasslands and to a lesser degree marine inlets is projected to increase, while the amount of potentially sparse vegetated areas and wetlands is projected to decrease (Fig. 4). Although there are few differences among future socio-economic pathways (Fig. 4), geographically, several relevant trends can be observed under future climate conditions (SI Fig. 4). For example, the results indicate that forest cover in mountainous high-altitude regions such as the alps and southern Spain is more likely to occur. The relatively stable suitable area (± 9 million ha) in heath and shrublands (Fig. 4) can be differentiated geographically by increases in western Europe as well as decreases in southern Europe (SI Fig. 4). Overall, those results emphasize that PNV is indeed dynamic, and reference periods should be identified for targeted applications.

4. Discussion

How land develops in the future is not predetermined. In this work a data-driven attempt is made to estimate potential natural vegetation (PNV) across Europe for contemporary and future conditions. The results show that most land areas in Europe can naturally develop into multiple trajectories (Fig. 2), although the most likely transitions are challenged by existing land-use practices (Fig. 3). Furthermore, future

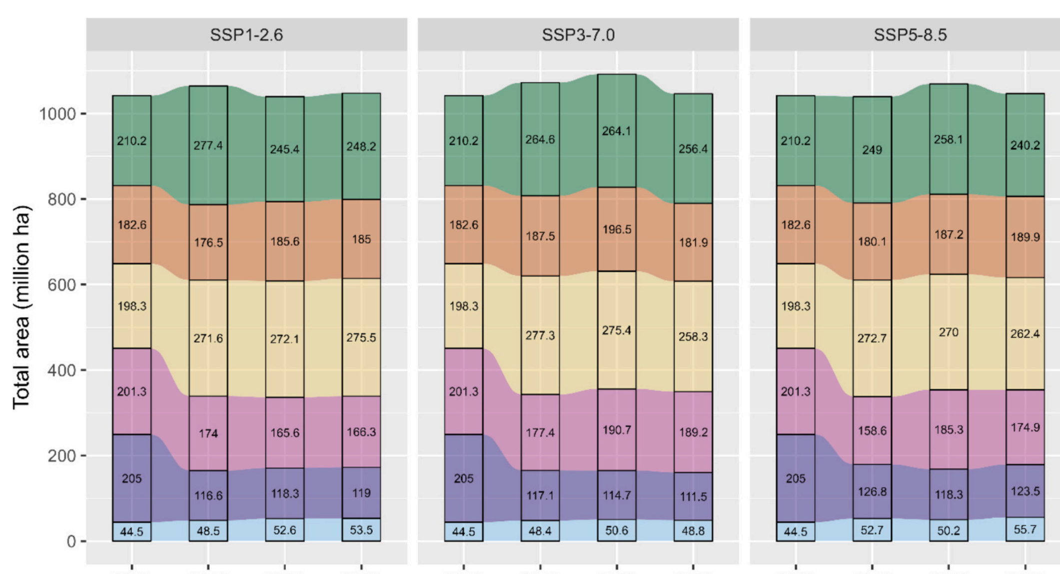

Fig. 4. Total amount of predicted suitable area per PNV type, time period and future scenario. The year 2010 shows the total summed area (in million ha) for the current PNV, while facets indicate climate scenarios for 3 different socio-economic development pathways. Colours as in Figs. 2 and 3.

climates affect PNV in many areas, with the establishment of forests and grasslands becoming regionally more likely, and sparse vegetation and wetlands less likely (Fig. 4). The purpose of this work is to provide a macroecological lens on the potential distribution of vegetation (Santini et al., 2021), so that possible landscape trajectories could be identified. Ultimately, the PNV layers created in this work could for example be used to constrain spatial prioritizations (Chapman et al., 2025), or inform integrated assessment and other land-use models in estimating nature-positive scenarios, such as through the Nature-Futures Framework (D'Alessio et al., 2025; Dou et al., 2023).

The purpose of this work was not to map the historical potential distribution of vegetation, but the potential vegetation under contemporary and future climate conditions (Hengl et al., 2018). Thus, predictions should not be compared against historic distribution of natural vegetation types, which might in many cases be irreversibly lost. Further, although PNV maps can be useful for spatial planning exercises, they should also not be taken as a normative outcome. How and where vegetation transitions might occur ultimately depends on local actions, restoration objectives and implementation (Loidi and Fernández-González, 2012). Here individual habitat class probabilities are reported (Fig. 2, SI Fig. 2) highlight that many different future trajectories might be possible. Yet, according to the most likely transition (Fig. 3), and perhaps contrary to expectations from ecoregional maps (Olson et al., 2001), much of European land found to have high potential of transitioning to grassland and other non-forested habitats, especially when departing from current land systems. There is evidence that historic (not contemporary or future) European PNV prior to human modification might have been composed of more non-forest vegetation types linked to the occurrence of large herbivores and other biotic factors (Pearce et al., 2023). It could thus be speculated that some of the historic PNV signal is still contained within contemporary climatic and lithological conditions. Yet overall, the PNV maps presented are only one of many possible outcomes and should thus be interpreted with care, intended to be used only for broad-scale land potential assessments. Further, applying expert-derived scores to transitions is a simplified approach, that is used here for illustrative purposes. Ideally the possibility of vegetation transitions should be informed by ecological evidence from the literature, which can also help to further improve the modelling framework. The mapping of PNV through data-driven predictive algorithms is a rather novel approach and there is certainly room for further developments and methodological improvements. Machine learning based approaches can provide reproducible and high-resolution assessments of PNV (Bonannella et al., 2023; Hengl et al., 2018), but can suffer from data biases. Furthermore it assumes that contemporary conditions can be extrapolated to novel climatic states. The relatively low predictive accuracy of the modelling results presented here might indicate that either covariates were missed or other complexity factors not appropriately considered (SI Table 1). Dynamic vegetation models on the other hand can provide a more mechanistic understanding of future vegetation change (Hickler et al., 2012), however they usually are more limited in the types of vegetation and spatial resolution they can represent. A promising future approach could be the development of "hybrid" predictive modelling approaches, such as physics informed machine learning (Shen et al., 2023), which can help bridge both machine learning and simulation-based approaches.

Other future work could consider also microclimatic conditions which have been shown to be locally important (Conradi et al., 2024), or include specific biotic interactions such as trophic rewilding through large megafauna to facilitate the creation of natural vegetation (Svenning et al., 2024). Previous studies of natural reforestation in temperate forests have found that natural recolonization tends to occur within the fringe of existing forests up to 200 m and a 20 year period (Bauld et al., 2023), although biotic processes, such as seed dispersal by flying animals, could further aid this process. The current thematic legend was chosen to mirror the broad classification used in European assessments of ecosystem extent (Maes et al., 2014). However a finer thematic disaggregation (e.g. (Jung et al., 2025)), also considering more detailed information on vegetation co-occurrence would be a very valuable addition and natural next step to further improve the presented work.

CRediT authorship contribution statement

Martin Jung: Writing – original draft, Visualization, Methodology, Formal analysis.

Code availability

The analytical code has been made publicly available at (https://github.com/Martin-Jung/EUPNVMapping/).

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoinf.2025.103418.

Data availability

All created data has been made openly available on a data repository in cloud-optimized geoTIFF format for the most-likely transition and current PNV (https://doi.org/10.5281/zenodo.13686776). All data is made available under a CC-BY 4.0 License.

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