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1 **Title:** Mapping current and future European potential vegetation to support restoration planning

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5 **Abstract:**

6 The extent and intactness of natural ecosystems is a key factor enabling species populations to  
7 thrive. However, the distribution of ecosystems is changing owing to both climatic and  
8 anthropogenic factors. Recently negotiated European policy directives, such as the Nature  
9 Restoration Law, argue for the restoration of natural ecosystems. Yet to determine what is to be  
10 restored the range of possible outcomes should be first explored, also with regards to future climatic  
11 conditions. Here the concept of potential natural vegetation (PNV) is applied and mapped in a data-  
12 driven manner at European extent, exploring where PNV transitions are most likely to happen under  
13 contemporary and future conditions. Specifically, I predict the distribution of current and future  
14 potential coverage of six natural vegetation types at 1 km<sup>2</sup> grain using Bayesian machine learning  
15 approaches. I find that most current land cover and land use could develop to no single, but multiple  
16 PNV states, although options for some types, such as areas suitable for wetlands might become  
17 rarer under future climatic conditions. Furthermore, the challenge of transitioning to PNV was found  
18 to be particularly high for current intensively cultivated landscapes. Overall data-driven PNV  
19 mapping holds considerable promise for assessing land potentials and supporting restoration  
20 assessments. Future work should expand the thematic grain of vegetation maps and consider  
21 feedback with biotic factors.

22 Keywords: Potential natural vegetation, Climate change, Restoration, Habitat mapping

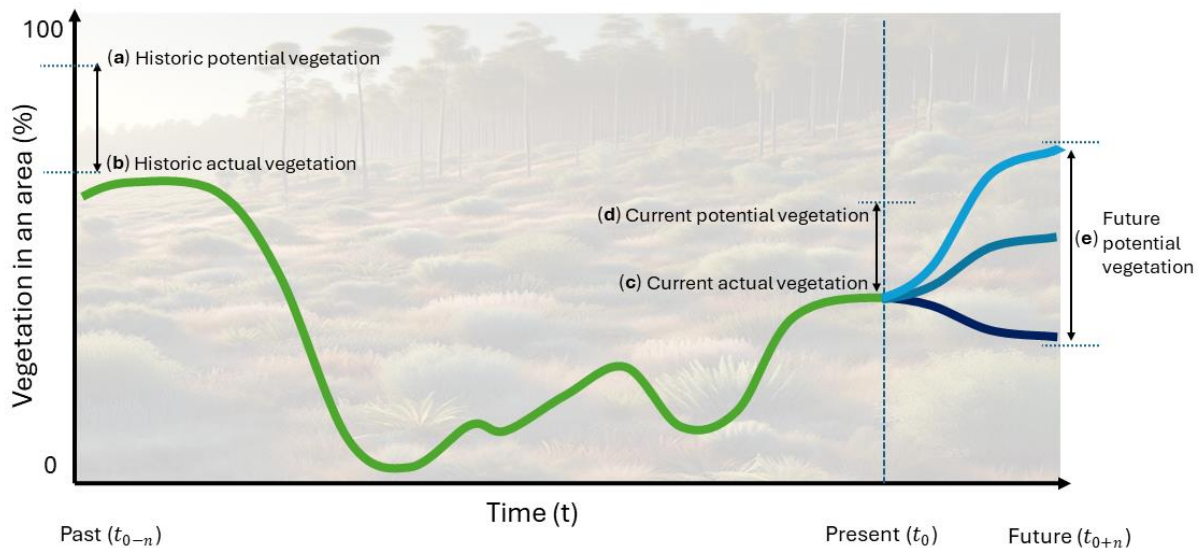
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24 **Introduction:**

25 Intact ecosystems are key for the preservation of species and provisioning of nature contributions to  
26 people (Betts et al., 2017). The occurrence of natural ecosystems is driven by its dominant  
27 vegetation, itself determined by complex interactions of biotic factors, climate, topography, soil and  
28 lithology (Jiménez-Alfaro et al., 2014; Jung et al., 2020; Keith et al., 2022; Sayre et al., 2020). Many  
29 natural ecosystems are under threat from current and future anthropogenic and climatic factors  
30 (Berdugo et al., 2020; Huntley et al., 2021), and restoring them seems to be the most promising way  
31 to bring nature on a path towards recovery (Keith et al., 2013; Leclère et al., 2020; Nicholson et al.,  
32 2021). The Kunming-Montreal Global Biodiversity Framework explicitly calls for the effective  
33 restoration of ecosystems (CBD, 2023), while the European Biodiversity Strategy for 2030 lists the

34 establishment of trees and widespread restoration of ecosystems among its ambitions (European  
35 Commission, 2020). However, a key question that influences the success of ecosystem restoration  
36 is the probability by which natural vegetation can be established; especially as the range of options  
37 available, given current and future environmental constraints, remains often unclear.

38 The Potential Natural Vegetation (PNV) concept describes a hypothetical scenario of dominant  
39 natural vegetation in an area under the assumption that human influence would largely cease (Loidi  
40 et al., 2010). The concept of PNV is not a new one and its usefulness has been intensely debated  
41 since its conception (Tüxen, 1956). Common critiques are that successional pathways are highly  
42 uncertain given historical human legacies (Chiarucci et al., 2010; Loidi and Fernández-González,  
43 2012). Furthermore, the creation - or in some cases re-establishment - of habitats does take time  
44 and success is far from guaranteed (Crouzeilles et al., 2016; Prach et al., 2016). Active human  
45 interventions, such as through habitat recreation, management practices, or supportive processes  
46 such as rewilding (Jepson et al., 2018; Perino et al., 2019; Svenning et al., 2024) are in many cases  
47 likely necessary to establish a given ecosystem. Despite these limitations, the PNV concept  
48 continues to be useful across scales by qualitatively or quantitatively putting land potentials into  
49 context and defining lower and upper boundaries (Figure 1).



50

51 *Figure 1: Idealized trajectory of actual and potential natural vegetation from past to future states. Highlighted are historic*  
52 *potential (a) and actual (b) vegetation levels and their corresponding states (c, d) in the present. Depending on the future*  
53 *trajectory different future potential vegetation levels (e) might be possible. Transparent background image generated by*  
54 *DALL-E 3.*

55 PNV has been estimated in different ways across scales and temporal baselines (Hengl et al.,  
56 2018). At local scales, ecological fieldwork and experimental studies use PNV concepts to highlight  
57 the plausibility of local vegetation successions, taking historical legacies and local contexts into

58 account (Johnson and Miyanishi, 2008; Walker et al., 2010). Other work have used soil cores and  
59 archaeological approaches to infer a historic PNV state based on what has been lost (Courtney  
60 Mustaphi et al., 2021; Finsinger et al., 2021). Bohn and Gollup used botanical knowledge and phyto-  
61 socioecological techniques to make an expert-based assessment of European PNV (Bohn and  
62 Gollub, 2006). Although these European maps remain unrivalled in terms of thematic detail, their  
63 spatial resolution can be coarse, and they do not account for anticipated changes in future climatic  
64 conditions.

65 As an alternative to expert-based assessments, data-driven tools such as machine learning or  
66 simulation models can provide an alternative way to estimate PNV under current and future  
67 conditions, often considering both climate and anthropogenic effects. Previous work have mapped  
68 the potential distribution of biomes (Bonannella et al., 2023; Hengl et al., 2018), species habitats  
69 (Jung, 2020), plant functional traits (Boonman et al., 2020; Joshi et al., 2022), actual and potential  
70 photosynthetic activity (Hackländer et al., 2024) or the potential distribution of land cover and  
71 vegetation types (Bastin et al., 2019; Hengl et al., 2020; Jiménez-Alfaro et al., 2014). The impact of  
72 anticipated future climate change on PNV can also be simulated or projected, which can be  
73 particular useful for assessing land potentials (Bonannella et al., 2023; Hickler et al., 2012; Huntley  
74 et al., 2021; Zabel et al., 2014). For Europe however, no PNV estimates exist for different functional  
75 vegetation types at a resolution useful for regional planning.

76 Maps of current PNV have been used for spatial planning studies (Kowarik, 2016), offering  
77 alternative points of departures that, instead of looking backwards to restore a (pre-)historic state of  
78 vegetation (Keane et al., 2009), can be forward looking also taking into account broad-scale changes  
79 such as climate change. Most importantly PNV estimates can be useful to delineate the upper  
80 restoration potential for biodiversity and climate mitigation (Chapman et al., 2023; Hackländer et al.,  
81 2024; Roebroek et al., 2023; Strassburg et al., 2020). For example, previous studies have used  
82 potential current vegetation estimates to quantify benefits of restoring land to biodiversity while  
83 maximizing carbon sequestration benefits (Chapman et al., 2023; Strassburg et al., 2020), while  
84 Roebroek et al., 2023 estimated that existing forests could increase their carbon contributions by up  
85 to 16% if released from anthropogenic management. Although such scenarios are likely implausible,  
86 they can help to draw some first boundaries for narrowing the potential benefits of such actions.

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

## 96 **Methods:**

97 The aim of this work is to create a series of vegetation-type specific PNV predictions for the European  
98 continent, quantify its contemporary and future extent and evaluate options for different landscapes.  
99 Thematically I rely on the natural vegetation types described by the MAES ecosystem classification  
100 scheme, the most commonly applied legend for ecosystem accounting by European member states  
101 (Maes et al., 2014). For natural vegetation at level 1 it distinguishes between Grassland, Forest and  
102 woodland, Heathland and shrub, sparsely vegetated land, Inland wetlands and marine inlets and  
103 transitional waters (Rivers and lakes are ignored for this exercise). Given the unpredictability of  
104 future PNV trends each vegetation type was modelled separately opposed to estimating the  
105 exclusive (e.g. either or) probability of PNV (but see predictive modelling).

### 106 *Input training data and covariates*

107 The aim of the predictive modelling is to characterize current as well as potential future PNV for a set  
108 of natural vegetation types according to MAES. To parametrize the models a range of different data  
109 sources on the distribution of MAES vegetation types was acquired, focussing primarily on  
110 contemporary vegetation cover that can be related to climatic, soil and topographic covariates. The  
111 vegetation data originated not from a single, but multiple openly available data sources. Specifically,  
112 data originated from the repeated Land Use/Cover Area survey (J. R. C. European Commission, 2020),  
113 European Article 17 reporting data (EEA, 2020), EUNIS habitat distribution plots (Hennekens, 2019),  
114 Natura 2000 reporting data (EEA, 2023) as well as vegetation occurrence information from the Global  
115 Biodiversity Information Facility (GBIF.Org User, 2024). For GBIF all vegetation occurrences were  
116 spatially aggregated to a centre of a 1km<sup>2</sup> grid cell. The grid cells in which – based on a European  
117 expert-based crosswalk (Chytrý et al., 2020), more than 5 typically descriptive species for a MAES  
118 habitat type have been observed, were then further used as indicative vegetation type by extracting  
119 the centroid of the grid cell. All vegetation cover data was thematically harmonized to the MAES  
120 legend, geographically aggregated to a 1km<sup>2</sup> grid and reprojected to a Lamberts-equal area grid  
121 (Appendix S1).

122 The selection of covariates is a critical choice for any PNV modelling, and generally speaking any  
123 covariates directly linked to land cover, land use or actual photosynthetic activity are to be avoided  
124 (Hackländer et al., 2024; Hengl et al., 2018). Predictions were informed by previous PNV estimates  
125 (Bohn and Gollub, 2006; Hengl et al., 2020) and a set of both static and dynamic covariates. Static  
126 variables include altitude and derivatives such as slope, aspect, roughness, northness and eastness,  
127 and the topographic position index (TPI) as a characterization of the relief, all of which were  
128 calculated in R and based on the Copernicus EU DEM (European Space Agency and Airbus, 2022).  
129 Estimates of European Lithology were taken from predicted Pan-European lithology estimates and  
130 harmonized to the same grid as other variables (Isik et al., 2024). For predicting wetland PNV data on  
131 topographic wetness was included to consider areas that are likely regularly flooded or could  
132 potentially be wetlands (Tootchi et al., 2019). For predicting potential marine inlets and transitional

133 waters the distance of each grid cell to the coast was calculated (in meters). With regards to dynamic  
134 variables current and future downscaled climatologies were obtained from CHELSA (Karger et al.,  
135 2017). For the future, data on three Shared Socioeconomic Pathways (SSPs) relying on SSP1-2.6,  
136 SSP3-7.0 and SSP5-8.5 respectively. All projections were calculated for the period 2020 to 2100 and  
137 the GFDL-ESM4 General Circulation Model. All covariates were aggregated (arithmetic mean for  
138 continuous, mode for categorical) to a common 1km<sup>2</sup> grain size, reprojected to a Lamberts Equal-  
139 Area projection and for the predictive modelling rescaled (subtraction of mean and division by  
140 standard deviation) to facilitate model convergence and extrapolation.

#### 141 *Predictive modelling*

142 For the modelling I used the *ibis.iSDM* R-package (Jung, 2023), which consists of an integrated  
143 modelling environment customized to different datasets as well as spatial and temporal projections.  
144 Two different Bayesian modelling approaches were used to identify the relative probability of any  
145 given ecosystem in space and time, both of which have the capability of estimating a full posterior  
146 distribution for current and future suitability, and thus estimates of several statistical moments  
147 including a true quantification of lower and upper relative probabilities. First, a linear Bayesian  
148 regularized regression model was applied using Spike-and-Slab priors which are particular useful in  
149 the regularization of high-dimensional regression problems (Friedman et al., 2010; Scott, 2023).  
150 Linear models can be useful for projections beyond observed unit scales as they make fewer  
151 assumptions about extrapolation (Norberg et al., 2019). Second, a Bayesian additive regression tree  
152 (BART) model was parametrized, which has the advantage that it can represent complex non-linear  
153 relationships, and through leaf pruning and regularization is assumed to be more robust to overfitting  
154 than other non-linear approaches (Carlson, 2020; Dorie, 2022; Jung, 2023). Both models were  
155 parametrized using contemporary vegetation cover and covariates, with different models being  
156 trained for each vegetation type (see above) and then projected to future conditions. From each  
157 fitted and projected model, the arithmetic mean, median and lower (25%) and upper percentile  
158 (75%) was extracted as well as the coefficient of variation and standard deviation of the whole  
159 posterior. For final predictions all statistical moments were averaged depending on their cross-  
160 validated predictive performance (see below).

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

170 *Posthoc correction and overlays*

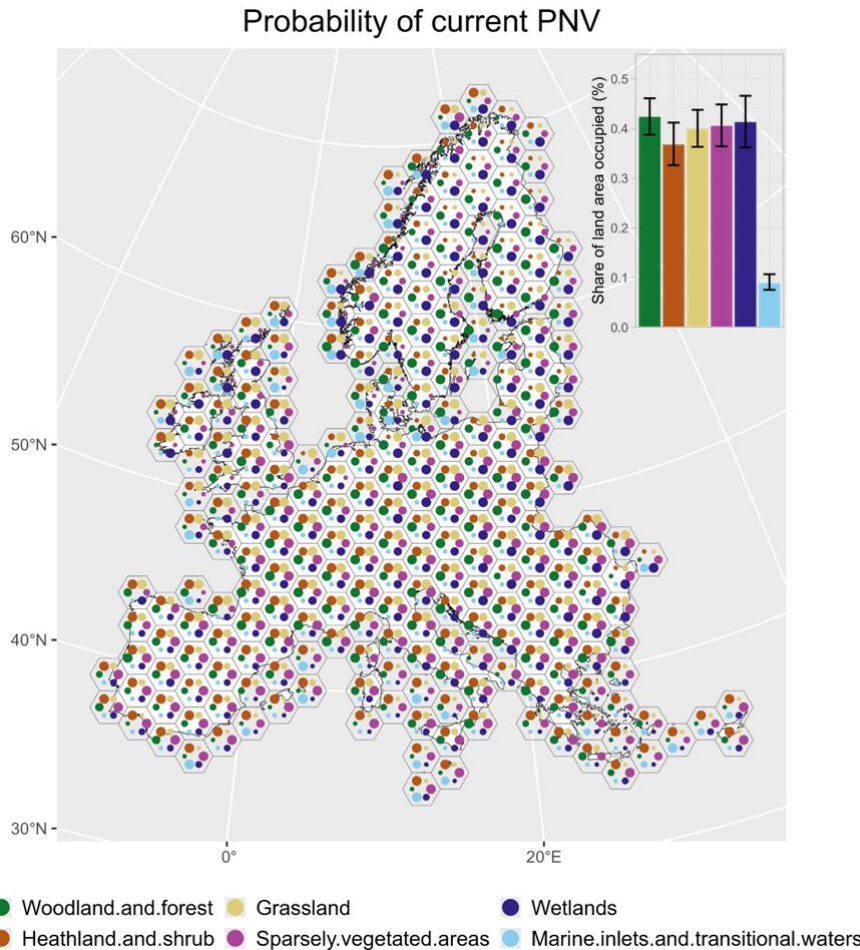
171 Although the point of PNV is not to estimate the distribution of potential managed or actual  
172 vegetation types (Hengl et al., 2018), an argument can be made that certain transitions from current  
173 actual to current or future PNV are highly unlikely and should not be further considered in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

182 To estimate a possible restoration challenge and most likely transition from actual to current PNV,  
183 several overlays were performed. Here it is assumed that a) areas with greater current land-use  
184 intensity as mapped by existing land systems maps provide a greater challenge (Dou et al., 2021), b)  
185 distance to nearby natural land cover facilitates the transition and c) transitions from structurally  
186 similar types are less of a challenge (e.g. pasture to natural grassland transition, see SI Table 2 for a  
187 simplified crosswalk). Notably, this assessment can only serve as illustrative first perspective as  
188 active management interventions are not explicitly considered. For each class and grid cell in the  
189 land systems map a Challenge score  $C$  of the transition challenge is then estimated as the minimum  
190 across all PNV types as follows:  $C_{iv} = \min \left( \frac{s_v}{p(v)_i} \right)$ , where  $i$  is a grid cell,  $v$  is one of the PNV types,  $s$  is  
191 the cost of transition (SI Table 2) and  $p(v)$  is the estimated probability of encountering PNV of a given  
192 class  $v$ . Thus, the lower the probability of encountering PNV and the higher the score  $s$ , the more  
193 challenging the transition from current to potential natural vegetation. The resulting challenge score  
194 (higher is more challenging) was then visualized as quantiles together the with class  $v$  for which  $C$  is  
195 the smallest (Figure 3).

196 **Results:**

197 Most land area in Europe can potentially develop into multiple trajectories under contemporary  
198 climate conditions (Figure 2). With exception of Marine inlets and transitional waters, which were  
199 largely constrained to coastal areas and thus small in potential area extent (median  $q_{50} = 0.44$   
200 million km<sup>2</sup>), all vegetation types could potentially occur in less than half of all European land area  
201 ( $q_{50} = 1.82$  million km<sup>2</sup> for Heathland and shrubs up to  $q_{50} = 2.1$  million km<sup>2</sup> for Woodland and  
202 Forests), although with broad geographic differences (Figure 2). While contemporary potential  
203 sparsely vegetated areas and Heathlands and shrubs were mainly concentrated in the  
204 mediterranean geographic regions, particular wetland vegetation types could potentially occur  
205 mostly in northern Europe including Scandinavia (SI Figure 2). The predictive performance of the  
206 various models varied (SI Table 1), with Marine Inlets being most consistently predicted (Average F1

207 = 0.89), while all other vegetation types had a lower predictive performance ranging between a F1  
 208 score of 0.7 and 0.67 (SI Table 1). This indicates that for most vegetation types there is considerable  
 209 uncertainty in the posterior predictions (see also SI Figure 3).

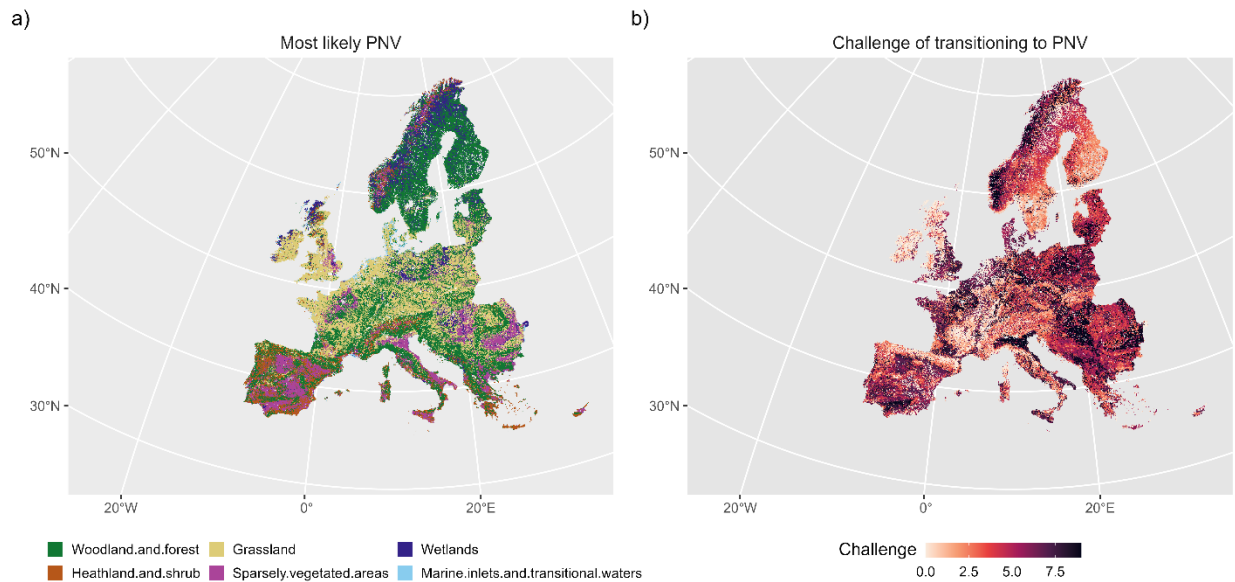


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 211 *Figure 2: Probability of current PNV for six different vegetation types. Coloured points within hexagons show the average*  
 212 *posterior probability of a vegetation class. The size of points within hexagons are rescaled relative to their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

215 Despite the possibility of multiple plausible transitions to PNV (Figure 2), a hypothesis can  
 216 be made about the most likely transition based on contemporary land use, assuming that it  
 217 is more challenging for land under more intensive contemporary use to transition to PNV.  
 218 Across Europe Woodland and Forests are most likely class to transition (40.5% of all land  
 219 area, Figure 3a), followed by Grassland (27.8%) and sparsely vegetated areas (12.2%). The  
 220 relative challenge of transition to contemporary PNV is – as perhaps expected – is  
 221 particularly large in regions with high land-use intensity such as the Po-Valley, Italy (Figure  
 222 3b). Some of the lowest challenges of transitioning to PNV can be observed in the Scottish  
 223 Highlands, UK, and the Pyrenees, Spain. It should be stressed that this assessment is only



224 valid in the context of the mapped land-use intensity classes, the transition scores (SI Table  
225 2) and mapped probabilities (SI Figure 1).



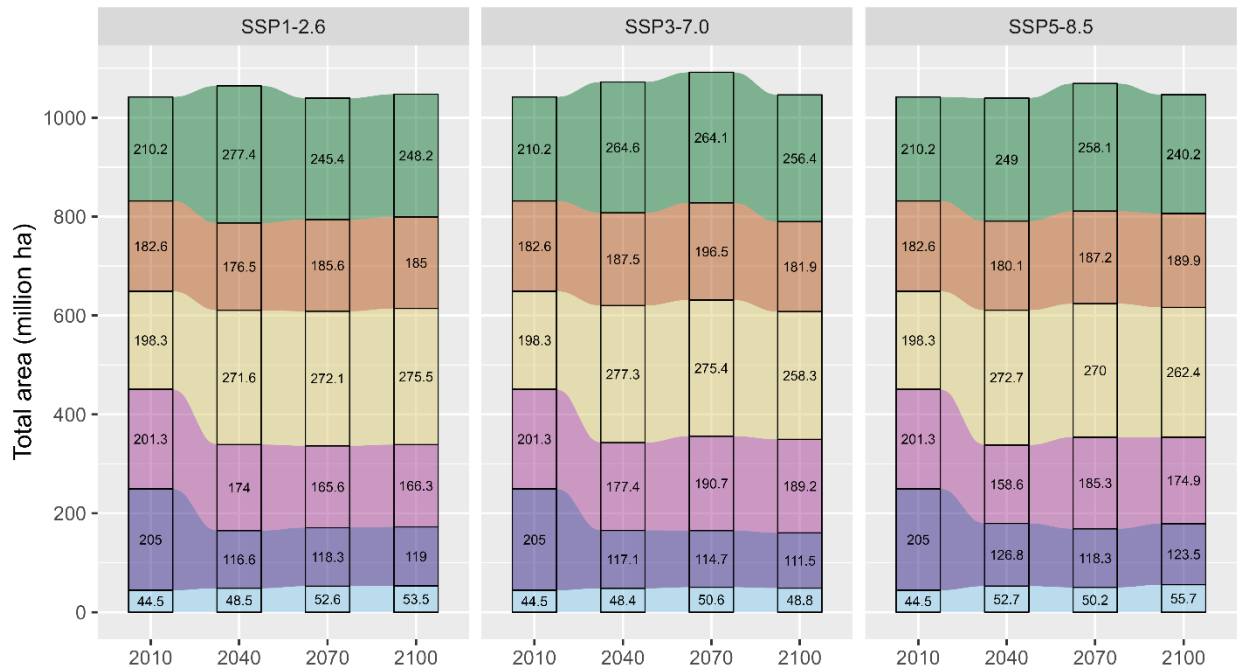
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227 *Figure 3: Most likely natural potential vegetation type when transitioning from current land-systems and the challenge (0-*  
228 *10 score) of transitioning to PNV. Based on the coverage of contemporary land systems (Dou et al., 2021) and broad*  
229 *scores of transitioning from transition from land systems to PNV (SI Table 2). Note that the visibility of individual grid cells*  
230 *can be overemphasized in the figure owing to spatial aggregation for the figure.*

231 The extent of PNV can vary depending on the biophysical conditions and this is true especially in  
232 future climates. Compared to contemporary climatic conditions (dated up to the year 2010), under  
233 future climate scenarios model projections indicate substantial shifts in PNV (Figure 4). Most  
234 notably, the total amount of area suitable for forests, grasslands and to a lesser degree marine inlets  
235 is projected to increase, while the amount of potentially sparsely vegetated areas and wetlands is  
236 projected to decrease (Figure 4). Although there are few differences among future socio-economic  
237 pathways (Figure 4), geographically, several relevant trends can be observed in a future climate (SI  
238 Figure 4). For example, under future climates it appears as if forest cover in mountainous high-  
239 altitude regions such as the alps and southern Spain is more likely to occur. The relatively stable  
240 suitable area ( $\pm 9$  million ha) in heath and shrublands (Figure 4) can be differentiated geographically  
241 by increases in western Europe as well as decreases in southern Europe (SI Figure 4). Overall, those  
242 results emphasize that PNV is indeed dynamic, and reference periods should be identified for any  
243 targeted applications.

244

245



246

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

250 **Discussion:**

251 How land develops in the future is not predetermined. In this work an attempt is made to provide a  
 252 data-driven potential natural vegetation (PNV) estimate across Europe for contemporary and future  
 253 conditions. The results show that most areas in Europe can naturally develop into multiple  
 254 trajectories (Figure 2), although the most likely transitions are met with considerable challenges by  
 255 existing land use (Figure 3). Furthermore, future climates affect the PNV in many areas with the  
 256 establishment of forests and grasslands becoming regionally more likely and sparse vegetation and  
 257 wetlands less likely (Figure 4). The purpose of this work is to provide a macroecological lens of the  
 258 distribution of vegetation (Santini et al., 2021), so that possible landscape trajectories could be  
 259 identified. Ultimately, the PNV layers created in this work could for example be used to constrain  
 260 spatial prioritizations (Chapman et al., 2023), or inform integrated assessment and other land-use  
 261 models in estimating nature-positive scenarios such as through the Nature-Futures Framework (Dou  
 262 et al., 2023).

263 The goal of this work was not to map the historical potential distribution of vegetation, but  
 264 the potential vegetation under contemporary and future climate conditions (Hengl et al., 2018).  
 265 Although PNV maps can be useful for spatial planning exercises, they should not be taken as a  
 266 normative outcome and how vegetation might develop ultimately depends on local actions and  
 267 implementation (Loidi and Fernández-González, 2012). For this reason, I also report habitat class  
 268 specific probabilities are reported (Figure 2, SI Figure 2), highlighting that many different future

269 trajectories might be possible even for the same area. Yet, according to the most likely transition  
270 (Figure 3), and perhaps contrary to expectations from ecoregional maps (Olson et al., 2001), much  
271 of European land found to have high potential of transitioning to grassland and other non-forested  
272 habitats, especially when departing from current land systems. Notably, there is evidence that  
273 historic (not contemporary or future) European PNV prior to human modification might have been  
274 composed of more non-forest vegetation types than previously assumed (Pearce et al., 2023). It  
275 could be that at least some of the historic PNV signal is still contained within contemporary climatic  
276 and lithological conditions. Yet overall, the PNV maps presented are but one of many perspectives  
277 and should thus be interpreted with care.

278 The mapping of PNV through data-driven predictive algorithms is a rather novel approach and  
279 there is certainly room for further developments and methodological improvements. Machine  
280 learning based approaches can provide reproducible and high-resolution assessments of PNV  
281 (Bonannella et al., 2023; Hengl et al., 2018), but can suffer from data biases and assume that  
282 contemporary conditions can be extrapolated to novel climatic states. Dynamic vegetation models  
283 on the other hand can provide a more mechanistic understanding of future vegetation change  
284 (Hickler et al., 2012), however they usually are more limited in the types of vegetation and spatial  
285 resolution they can represent. A promising future approach could be the development of “hybrid”  
286 predictive modelling approaches, such as physics informed machine learning (Shen et al., 2023).  
287 Other future work could consider also microclimatic conditions which have been shown to be locally  
288 important (Conradi et al., 2024), or include specific biotic interactions such as trophic rewilding  
289 through large megafauna to facilitate the creation of natural vegetation (Svenning et al., 2024).  
290 Previous studies of natural reforestation in temperate forests have found that natural recolonization  
291 tends to occur within the fringe of existing forests up to 200 m and a 20 year period (Bauld et al.,  
292 2023), although biotic processes such as seed dispersal by flying animals could further aid this  
293 process. Another useful extension could be the expansion of the thematic legend, using for example  
294 the indicative descriptions of the IUCN Ecosystem RedList (Keith et al., 2022).

#### 295 *Data availability:*

296 All created data has been made openly available on a data repository in cloud-optimized geoTIFF  
297 format for the most-likely transition and current PNV ([10.5281/zenodo.13686776](https://doi.org/10.5281/zenodo.13686776)) as well as on the  
298 EBV data portal in a standardized netCDF format (Quoß et al., 2022) as Essential biodiversity variable  
299 (<https://portal.geobon.org/>). All data is made available under a CC-BY 4.0 License.

#### 300 *Code availability:*

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

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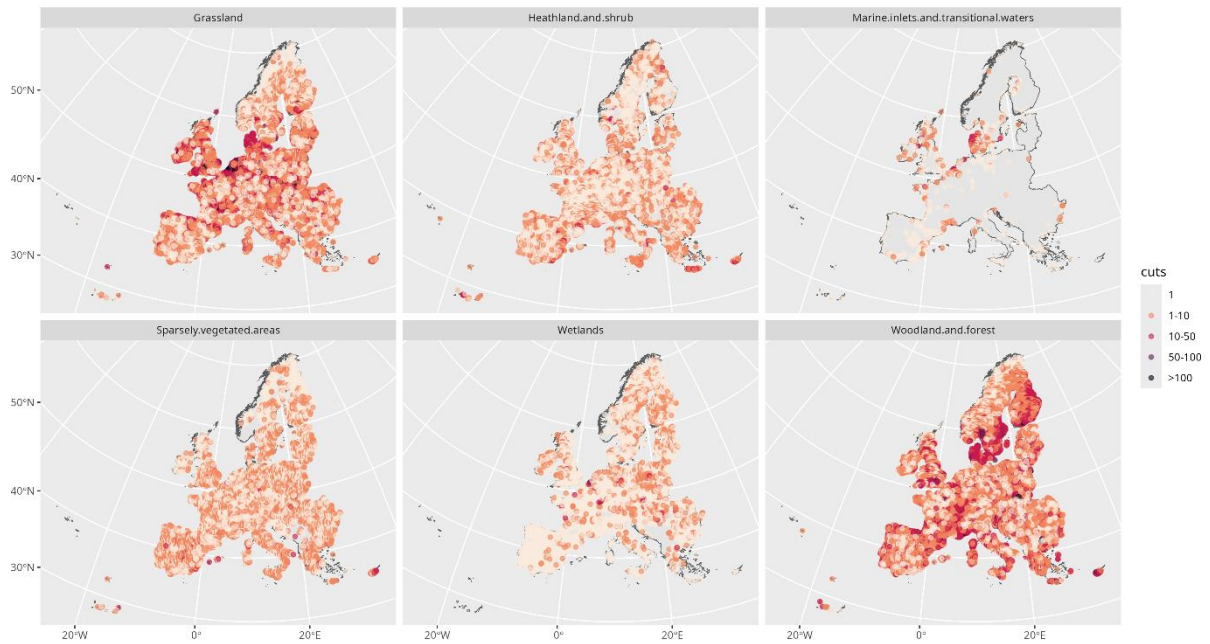
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594

## Supplementary Materials

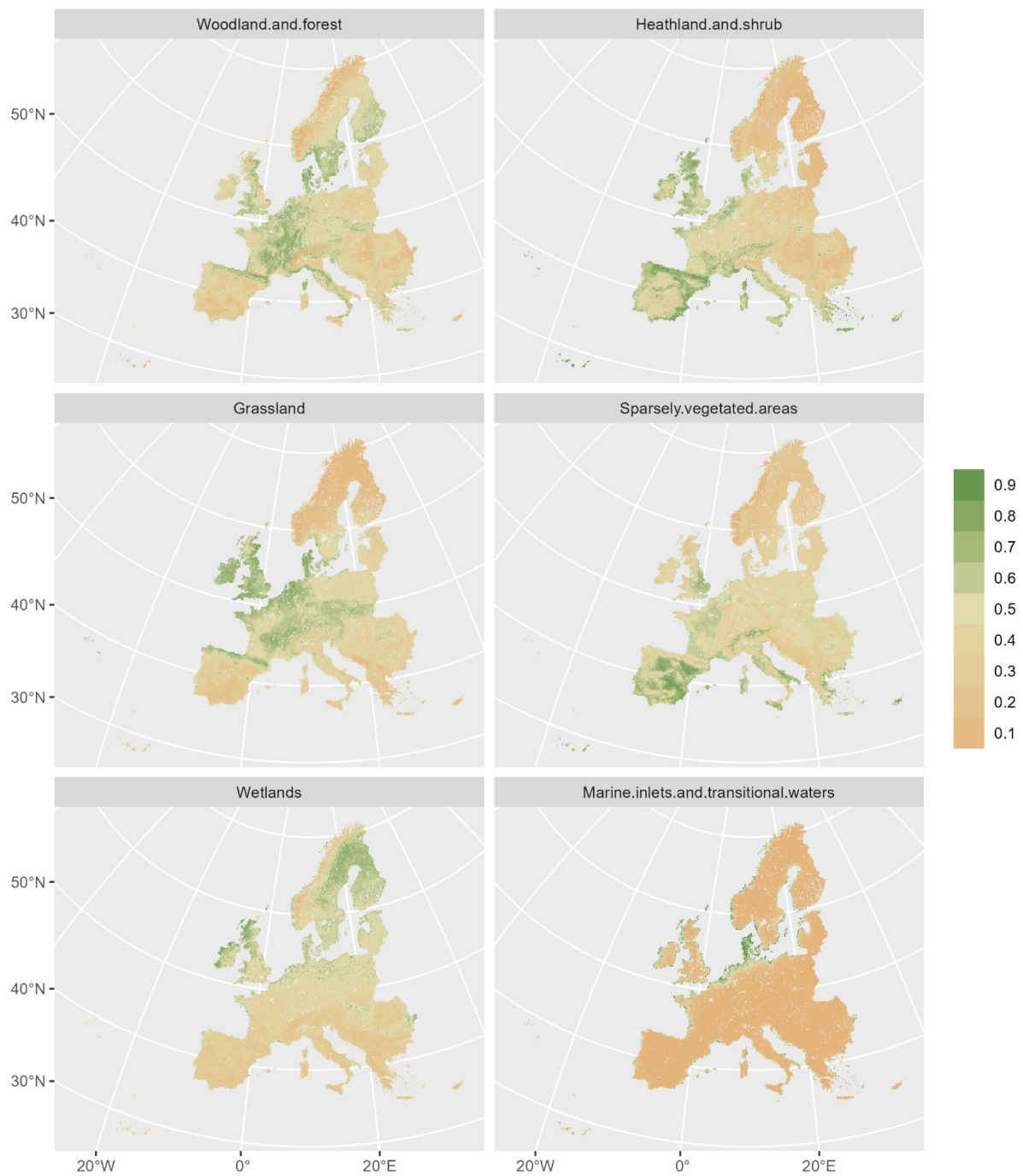
### Mapping current and future European potential vegetation in support of restoration planning



SI Figure 1: Vegetation cover training data used for delineation of European potential natural vegetation. Note that for visual display the background grid (grey landmass) has been aggregated to a 10 km<sup>2</sup> grain size. The colour of the points indicate the number of occurrences within each 10 km<sup>2</sup> grid cell. During inference not more than one training point for each covered 1 km<sup>2</sup> grid cell (the grain of prediction) was considered.

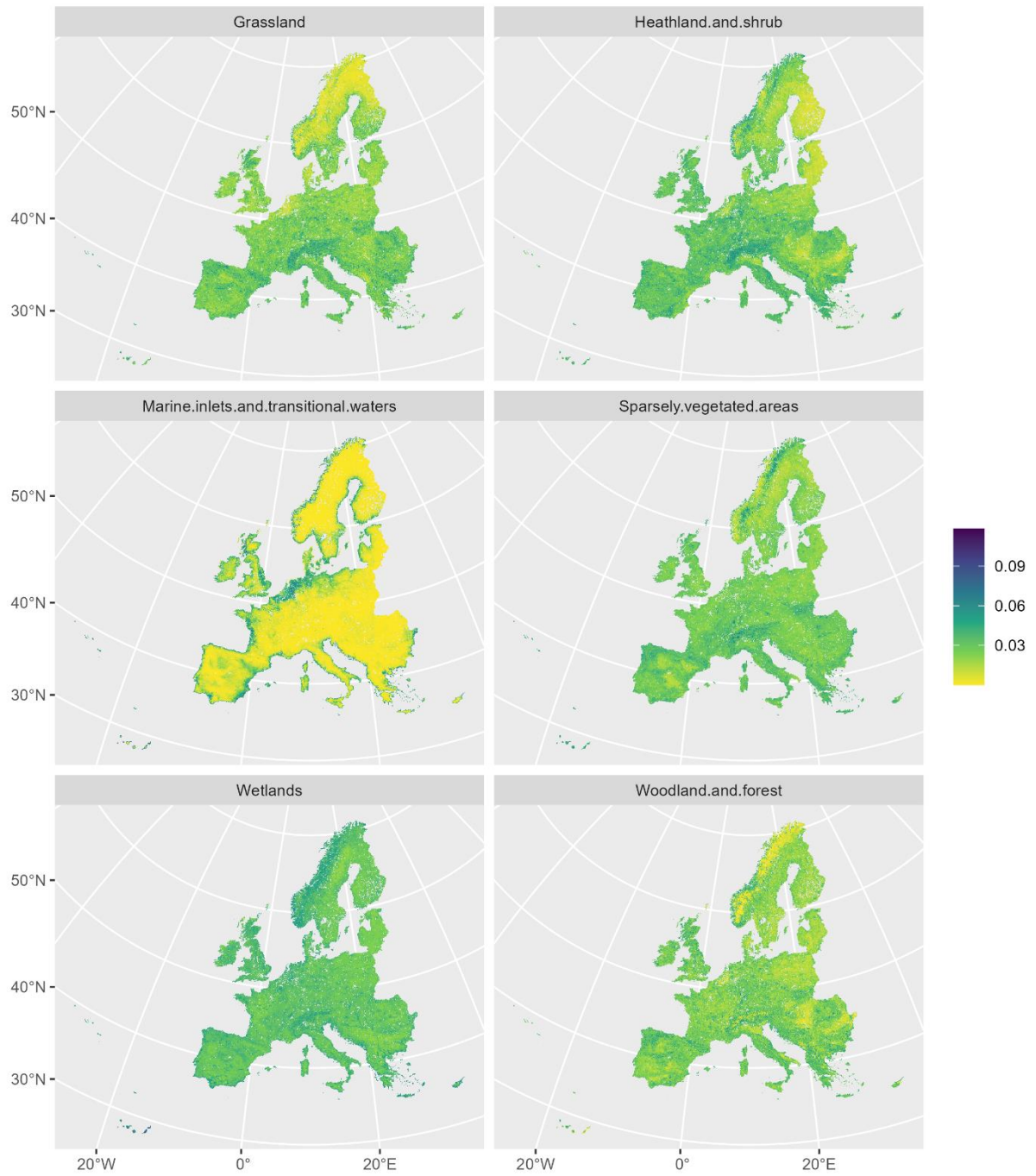
## Current potential natural vegetation (PNV)

Median predictions

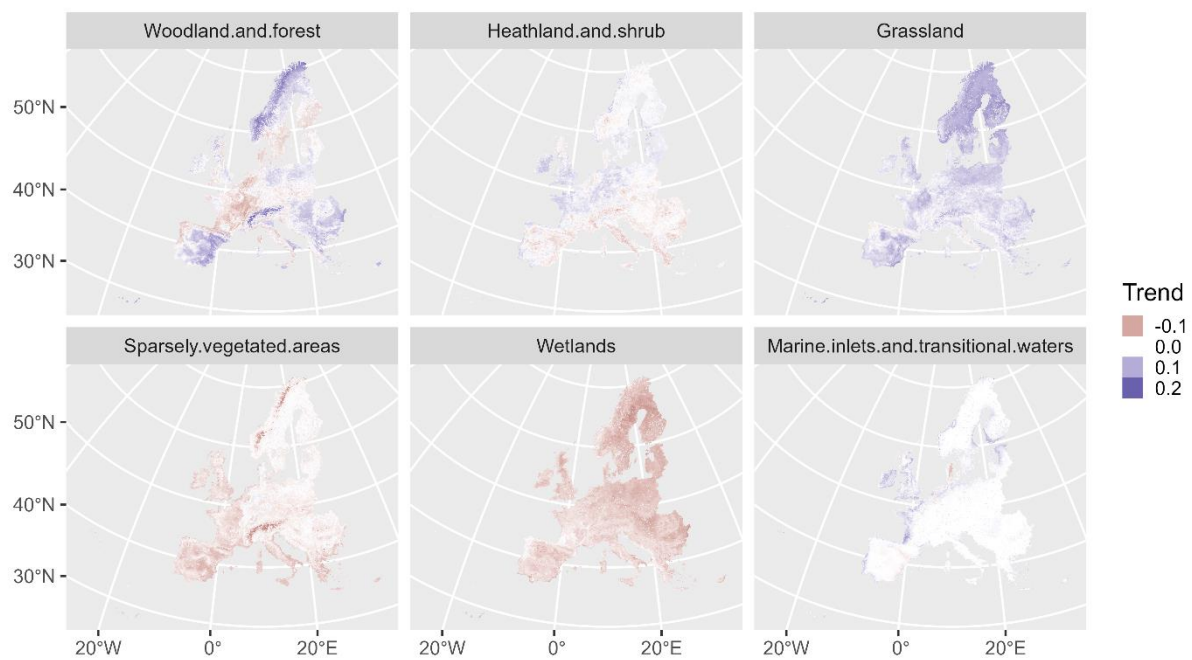


SI Figure 2: Posterior predictions (median) of current potential natural vegetation (PNV) for Europe from Bayesian Additive Regression Trees (BART). Predictions were made for each individual vegetation class.

Current potential natural vegetation (PNV)  
Standard deviation of posterior



SI Figure 3: Predictive uncertainty, quantified as standard deviation (SD) from the ensemble posterior. Darker colours indicate areas with greater predictive uncertainty.



SI Figure 4: Shows the relative trend in probability of occurrence from 2010 to 2100. Estimated from an ordinary linear regression at the grid cell level with the slope visualized as negative (red) or positive (blue) trends.

SI Table 1: Table with estimated prediction performance of the models. Performance was evaluated using a spatial block cross-validation design with three blocks and two repeat each. Shown are the average and standard deviation of F1 score and True Skill Statistic (TSS) for each predicted vegetation class.

Metric	Average	Standard deviation
<b>Woodland.and forest</b>		
f1	0.69	0.04
<b>Heathland.and shrub</b>		
f1	0.70	0.04
<b>Grassland</b>		
f1	0.68	0.03
<b>Sparsely.vegetated.areas</b>		
f1	0.68	0.04
<b>Wetlands</b>		
f1	0.67	0.04
<b>Marine.inlets.and.transitional.waters</b>		
f1	0.89	0.04

SI Table 2: Expert-based assessment with regards to the challenge of transitioning from current land use and use intensity to a potential natural vegetation state. Scores for each PNV class were specified on a scale from relatively less challenging (1) to very challenging (3). Scores were used to assemble the most likely transition (Figure 3).

code	dou_1	dou_2	dou_description	pnv_forest	pnv_heath	pnv_grass	pnv_sparse	pnv_wetland	pnv_marine
21	1. Settlement systems	1.1 Low-intensity settlement	Low-medium density, far away from urban cores	2	2	2	2	3	3
22		1.2 Medium-intensity settlement	Medium density or adjacent to urban core	3	3	3	3	3	3
23		1.3 High-intensity settlement	High imperviousness	3	3	3	3	3	3
41	2. Forest systems	2.1 Low-intensity forest	High probability as primary forest and low/medium wood production Low probability as primary forest and medium wood production	1	2	3	3	3	3
42		2.2 Medium-intensity forest	Low probability as primary forest and medium wood production Low probability as primary forest and high wood production	1	3	3	3	3	3
43		2.3 High-intensity forest	High wood production	1	3	3	3	3	3
61	3. Cropland systems	3.1 Low-intensity arable land	Low inorganic fertilizer input, small field size	2	1	1	1	3	3



62	3.2 Medium-intensity arable land	Medium inorganic fertilizer input, medium field size	3	3	2	3	3	3
63	3.3 High-intensity arable land	High inorganic fertilizer input, large field size	3	3	3	3	3	3
31	3.4 Low-intensity permanent crops	Vineyards, olive groves, fruit gardens, with understory vegetation, this class also has mixed annual and permanent crops	2	2	3	3	3	3
32	3.5 High-intensity permanent crops	Vineyards, olive groves, fruit gardens, without understory	3	3	3	3	3	3
51	4. Grassland systems	4.1 Low-intensity grassland	3	2	1	2	2	3

52	4.2 Medium-intensity grassland	Medium density of livestock, medium use of inorganic fertilizer, and medium mowing frequency	3	3	1	2	3	3
53	4.3 High-intensity grassland	High density of livestock, high inorganic fertilizer input, and/or high mowing frequency	3	3	1	2	3	3
80	5. Shrub	Areas dominated by shrub land cover or similar	1	1	3	2	3	3
90	6. Rocks and bare soil	Areas dominated by rocks, bare soil, or similar	3	3	2	1	3	3
71	7. Mosaic systems	7.1 Forest/shrub and cropland mosaics	1	1	1	2	2	2
72		7.2 Forest/shrub and grassland mosaic	1	1	1	2	2	2

74	7.3 Forest/shrubs and bare mosaics	Areas with small parcels of forest/shrubs and bare land	1	1	1	2	2	2	
75	7.4 Forest/shrubs and mixed agriculture mosaics	Areas with small parcels of forest/shrubs and mixed areas of cropland and grassland	1	1	1	2	2	2	
731	7.5.1 Low-intensity agricultural mosaic (cropland and grassland)	Low density of inorganic fertilizer input, small field size, and low livestock density	3	2	2	2	3	3	
732	7.5.2 Medium-intensity agricultural mosaic (cropland and grassland)	Medium use of inorganic fertilizer, medium field size, and medium livestock density	3	3	2	3	3	3	
733	7.5.3 High-intensity agricultural mosaic (cropland and grassland)	High inorganic fertilizer input, large field size, and/or large livestock density	3	3	2	3	3	3	
13	8. Snow, water,	8.1 Glaciers	Areas dominated by	3	3	3	1	3	3

11	wetland systems	8.2 Water body	glaciers, wetland, or water body	3	3	3	3	1	1
12		8.3 Wetland		3	3	1	2	1	1

