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## An improved species distribution model for Scots pine and downy oak under future climate change in the NW Italian Alps --Manuscript Draft--

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<b>Abstract:</b>	<p>Context: Scots pine is currently declining in most inner alpine sectors of southern Europe. The relative contribution of climate, land use change and disturbances on the decline is poorly understood. What will be the future distribution of the species? Is vegetation shifting towards oak-dominated forests? What is the role of extreme drought years?</p> <p>Aims: determine drivers of current distribution of Scots pine and downy oak in Aosta valley (SW Alps); extrapolate species distribution models to year 2080 (SRES A1B); assess the ability of pine vitality response to the extreme droughts in 2003 and 2006 to predict modeled vegetation changes.</p> <p>Methods: ensemble distribution models using climate, topography, soil, competition, natural disturbances, and land use. Species presence was derived from a regional forest inventory. Pine response to drought of 2003-06 was assessed by NDVI differencing and correlated to modeled cover change between 2080 and present.</p> <p>Results: Scots pine and downy oak were more likely to occur under higher climatic aridity. Scots pine was also associated to higher wildfire frequency, land use intensity, and lack of competition. In a warming scenario, pine experienced an elevational displacement. This was partially counteracted if no land abandonment was hypothesized. Downy oak cover increased in all scenarios. Short- and long-term drought responses of pine were unrelated.</p> <p>Conclusion: Warming will induce an upward displacement of pine, but this can be partially mitigated by maintaining a more intense land use. The drought-induced decline in pine vitality after extreme years did not overlap to the modeled species response under climate warming; responses to short-term drought must be more thoroughly understood in order to predict community shifts.</p>

Dear Editors,

please receive the second revised version of the manuscript "An improved species distribution model for Scots pine and Downy oak under future climate change in the NW Italian Alps", by me and prof. Renzo Motta.

This work was presented as a talk in the ClimTree 2013 conference in Zurich. I am aware that the submission is well after the deadline for the special issue of your journal. If it's not possible to include the paper in the special issue, please consider this a normal submission of a research paper.

The paper has not been previously submitted to any other journal. The main topic is the effect of climate change and drought on the regional distribution of Scots pine and Downy oak in northern Italy. Although only locally fit, the species distribution model has some unique features which we believe could be of interest to other researchers around the world, such as the inclusion of soil, natural disturbance, and biotic competition.

We also compared SDM predictions to the effect of two severe dry years on forest canopies assessed by remote sensing.

The paper has been revised again following indications by the Editor, which improved it in both clarity and succinctness.

We believe our methods and conclusions are of relevance to the readers of your journal, especially in the context of climate-related forest research.

We look forward to publish our work in your journal.  
Sincerely,

the corresponding author  
Giorgio Vacchiano

Line 82: Add 'it' before ,was favored'  
ADDED

Line 87–88: better: ,Scots pine often forms stable communities due to limited competitiveness of other conifer tree species.'  
EDITED

Lines 132, 136, 138, 180, 199, 218, 220, 224, 235, 238, 439, 664, 677, 679, 681, 683, 686 Table 1:  
Replace '-' (hyphen) and '≠' by '–' (en-dash)  
REPLACE

Line 162: replace ,april' by ,April' and 'september' by ,September'  
REPLACED

Line 197: delete '-'  
DELETED

Line 239: 'meter' instead of 'm'?  
EDITED

Line 268: Give a reference after;; Wiens et al. 2010? Just to be correct about the definition.  
REFERENCE ADDED

Lines 294-295: it would be interesting to know with which simple climate variable (or elevation?) AI was best correlated (including a quantification, R<sup>2</sup>). Perhaps this information can be added in a short comment here;; I consider it a result, too. AI may be a rather sophisticated parameter, though better to understand by a closest relative.

ADDED: "Pearson's correlation between AI and Worldclim variables was always higher than 0.95 (e.g., R =-0.995 vs. mean annual temperature, R =0.993 vs. annual precipitation, R =-0.962 vs. GDD)."

Line 315: add 'to' between 'and 1473'  
ADDED

Line 355: Improve the sentence by e.g. add 'In contrast, ...' before 'It can also'  
EDITED

Lines 365–367: Please clarify here. Perhaps there is only a little thing missing here.  
EDITED: "Wildfire polygons were not labeled as surface or crown fires; however, surface fires are more common in the study area, especially at low elevations on south-facing slopes".

Line 385: I prefer here a slash instead an en-dash  
EDITED

Line 390: replace 'than' by 'as'  
EDITED

Line 395: replace 'than' by 'from'  
EDITED

Line 415: replace 'suc' by 'such'  
EDITED

Lines 421–423: The sentence sounds to me unclear. ,To cascade on' is presumably not correct. Please re- phrase this sentence.  
EDITED: "This is reflected by the higher importance of some explanatory variables, such as Roads, Buildings, TPI, or Erosion, under models capable of detecting non-linear species responses".

Line 430: delete ', ' before 'that'  
DELETED

Lines 428-435: There is too much information in this long sentence. Please split into two sentences in order to clarify the different impacts.

EDITED: "The effect of extreme years on the realized niche of Scots pine will likely depend on the frequency and severity of droughts, rather than on decadal climate means such as the ones we used in our projections. Other parameters might be important in their extreme yearly or seasonal values, such as high precipitation events promoting a new generation after a mortality episode...".

Line 441: What is meant by 'their'? If management is meant, then write 'effects of management actions' to clarify this important sentence.

EDITED

Literature- Check for consistent abbreviations of all journal titles.

ALL CHECKED AND EDITED WHERE NEEDED

Line 666: add 'given' after 'are'

ADDED

Table 1: Check for citations Corine land Cover (1990) and ISTAT (2012). They are only referenced in the text. I propose nevertheless to reference them in the Literature section.

TWO REFERENCES ADDED

**An improved species distribution model for Scots pine and downy oak under future climate change in the NW Italian Alps**

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**Short title:** Drought and distribution of Scots pine and downy oak

**Keywords:** Drought, Pine decline, *Pinus sylvestris* L., Potential niche, *Quercus pubescens* Willd., Succession

Total number of characters: 54308

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Number of figures in supplementary material: 2

**Contribution of the coauthors:** GV designed the study, conducted the analysis and wrote the paper. RM supervised the work and revised the manuscript.

# 1 An improved species distribution model for Scots pine and downy oak under future 2 climate change in the NW Italian Alps

## 3 4 **Abstract**

5 Context: Scots pine is currently declining in most inner alpine sectors of southern Europe.  
6 The relative contribution of climate, land use change and disturbances on the decline is  
7 poorly understood. What will be the future distribution of the species? Is vegetation  
8 shifting towards oak-dominated forests? What is the role of extreme drought years?

9 Aims: determine drivers of current distribution of Scots pine and downy oak in Aosta  
10 valley (SW Alps); extrapolate species distribution models to year 2080 (SRES A1B);  
11 assess the ability of pine vitality response to the extreme droughts in 2003 and 2006 to  
12 predict modeled vegetation changes.

13 Methods: ensemble distribution models using climate, topography, soil, competition,  
14 natural disturbances, and land use. Species presence was derived from a regional forest  
15 inventory. Pine response to drought of 2003-06 was assessed by NDVI differencing and  
16 correlated to modeled cover change between 2080 and present.

17 Results: Scots pine and downy oak were more likely to occur under higher climatic aridity.  
18 Scots pine was also associated to higher wildfire frequency, land use intensity, and lack of  
19 competition. In a warming scenario, pine experienced an elevational displacement. This  
20 was partially counteracted if no land abandonment was hypothesized. Downy oak cover  
21 increased in all scenarios. Short- and long-term drought responses of pine were unrelated.

22 Conclusion: Warming will induce an upward displacement of pine, but this can be  
23 partially mitigated by maintaining a more intense land use. The drought-induced decline in  
24 pine vitality after extreme years did not overlap to the modeled species response under  
25 climate warming; responses to short-term drought must be more thoroughly understood in  
26 order to predict community shifts.

## 27 28 **1. Introduction**

29 Scots pine (*Pinus sylvestris* L.) forests at the southern edge of their distribution are currently  
30 facing decline and succession, resulting from a combination of climate warming, land use  
31 changes, and increased abiotic and biotic disturbances (Gimmi et al. 2010; Vacchiano et al.  
32 2012).

33 From a physiological standpoint, drought has been identified as the primary driver of pine  
34 decline, as it affects foliage production, carbon allocation (Galiano et al. 2011), cambial  
35 activity (Eilmann et al. 2011; Oberhuber et al. 2011), hydraulic capacity (Sterck et al. 2008),  
36 and the likelihood of xylem cavitation (Martinez-Vilalta and Pinol 2002). Additionally,  
37 drought can predispose weakened trees to inciting mortality agents, such as mistletoe, bark  
38 beetles, or root-rot fungi (Dobbertin et al. 2007; Gonthier et al. 2010; Rigling et al. 2010;  
39 Sangüesa Barreda et al. 2012).

40 On top of this, at the landscape level Scots pine forests in southern Europe have recently  
41 experienced a decrease in management intensity, shifting from open-canopy, even-aged  
42 stands maintained by broadleaves coppicing, wood pasture, litter raking, and pitch collection  
43 (Gimmi et al. 2007), to denser forests following depopulation of mountain areas and  
44 abandonment of traditional land-use practices. Under such scenario, succession by mid-  
45 tolerant species such as downy oak (*Quercus pubescens* Willd.) is favored over Scots pine  
46 regeneration (Urbietta et al. 2011; Rigling et al. 2013). Both mechanisms, land use changes  
47 and climate extremes, are at work at the same time (Gimmi et al. 2010), determining  
48 feedbacks and interactions difficult to disentangle and providing a challenge for forecasting  
49 future vegetation patterns.

50 Recession of Scots pine forests in southern European landscapes would affect the provision  
51 of important ecosystem services, such as protection from hydrogeological hazards, plant and  
52 animal diversity, timber, and recreation. A shift from Scots pine to oak can also be  
53 problematic because of the loss of useful life traits, as the ability to rapidly colonize open or  
54 disturbed ground (Vacchiano et al. 2013). Predictions of future vegetation changes and  
55 knowledge of the suitability of pine vs. oak to expected environmental conditions will help  
56 managers in developing adaptation strategies to sustain the fulfillment of the desired forest  
57 functions (Chmura et al. 2011).

58 The aims of this work are: (1) to detect drivers of current pine and oak occurrence in a  
59 mountain region of the southwestern Alps, by fitting species distribution models (SDM) on  
60 climate, soil, anthropogenic, stand structure and disturbance-related predictors; (2) to apply  
61 the models using future (2080) scenarios, in order to assess if and where vegetation shifts are  
62 likely to occur under climate and management changes; and (3) to compare the effects of the  
63 Europe-wide drought events of 2003 and 2006 (Thabeet et al. 2010) on Scots pine vitality  
64 against SDM predictions in 2080, in order to assess the potential role of extreme drought  
65 response as an early warning of future vegetation changes.

## 67 2. Methods

1 68

### 3 69 *Study species*

5 70 Scots pine is the most widespread coniferous species in Europe, and the most widespread  
6  
7 71 pine in the world (Mirov 1967). Scots pine is a species of continental climates, able to grow  
8  
9 72 in areas with annual precipitation ranging from 200 to 1800 mm (Burns and Honkala 1990).

10 73 The upper/northern and lower/southern limits of the species correspond with isotherms -1 °C  
11  
12 74 (mean temperature of the coldest month) and +33 °C (mean temperature of the warmest  
13  
14 75 month) respectively (Dahl 1998), even if pine can tolerate more extreme temperatures  
15  
16 76 without tissue damage, especially at the cold end (-90 °C: Sakai and Okada 1971).

17  
18 77 Scots pine is a light demanding, early seral species that can establish both in acid and  
19  
20 78 limestone soils (Richardson 1998; Debain et al. 2003). Its ecology is largely characterized by  
21  
22 79 stress tolerance. On the one hand this allows it to occupy a range of habitats that are  
23  
24 80 unfavorable to other tree species, through tolerating various combinations of climatic and  
25  
26 81 edaphic stress (Richardson 1998). On the other hand, this implies that Scots pine is excluded  
27  
28 82 from more favorable sites through competition. In recent decades, it was favored by past fires  
29  
30 83 (Gobet et al. 2003), heavy forest cuts, and by the recent increase of fallow lands (Farrell et al.  
31  
32 84 2000; Kräuchi et al. 2000; Caplat et al. 2006, Picon-Cochard et al. 2006). In the absence of  
33  
34 85 disturbances it will eventually be overgrown or replaced by broadleaves or mixed  
35  
36 86 broadleaved-coniferous forest. However in the drier, central alpine sectors (<700 mm year-1  
37  
38 87 rainfall) Scots pine often forms stable communities due to limited competitiveness of other  
39  
40 88 conifer tree species (Ozenda 1985).

41  
42 89 Scots pine populations are negatively affected by drought in all demographic processes, i.e.,  
43  
44 90 regeneration (Carnicer et al. 2013, Galiano et al. 2013), growth (Vilà-Cabrera et al. 2011),  
45  
46 91 and mortality (Dobbertin et al. 2005, Bigler et al. 2006). On the other hand, downy oak  
47  
48 92 exhibits better ecophysiological adaptations (Nardini and Pitt 1999; Eilmann et al. 2006,  
49  
50 93 2009; Zweifel et al. 2009) and higher growth (Weber et al. 2007) under comparable climate  
51  
52 94 conditions. Oaks also have an advantage over Scots pine in the regeneration phase following  
53  
54 95 stand-replacing fire, owing to their resprouting ability – as opposed to limitations in Scots  
55  
56 96 pine regeneration due to short dispersal distance and obligate seeder traits (Moser et al. 2010;  
57  
58 97 Vacchiano et al. 2013). Such differences, and the fact that oaks are characterized by lower  
59  
60 98 shade intolerance, make them a suitable species for secondary succession of declining or  
61  
62 99 outcompeted pine stands.

60 100



101 *Study area*

102 The study area covers the Aosta valley region in Northwestern Italy (3262 km<sup>2</sup>) (Figure 1).  
103 Topography is shaped by a main east–west oriented valley with several north–south  
104 protrusions. Mean annual temperature in Aosta (45°26' N, 7°11' E, 583 m a.s.l.) is 10.9 °C  
105 (years 1961-1990; Tetrarca et al. 1999). Climate is warm-summer continental (Dfb)  
106 according to the Köppen classification (Peel et al. 2007); July and January monthly means  
107 may differ by as much as 22°C. Mean annual rainfall in Aosta amounts to very low values in  
108 comparison with localities in other central Alpine valleys (494 mm, years 1961–1990;  
109 Biancotti et al. 1998), with a period of water deficit (Bagnouls and Gausson 1957) extending  
110 from June to September. Winter precipitation usually comes as snow. The study area exhibits  
111 both crystalline (granites) and metamorphic bedrocks, but most landscape is covered by  
112 quaternary deposits of glacial, gravitative, or colluvial origin. Soils belong to the series of  
113 western and central Alpine soil on igneous and metamorphic rocks (Costantini et al. 2004)  
114 and are mostly represented by shallow soils (Lithic, Umbric and Dystric Leptosols), eroded  
115 soils (Eutric and Calcaric Regosols), acid soils with organic matter, iron oxides and  
116 aluminum accumulation (Dystric Cambisols, Haplic Podzols, Humic Umbrisols), or alluvial  
117 soils (Eutric Fluvisols).  
118 Scots pine stands in the study area cover 5372 ha (Gasparini and Tabacchi 2011), i.e., 6% of  
119 the total forest area, and thrive on both acidic and basic substrates of well-exposed, bottom to  
120 mid-elevation slopes. Stands dominated by Scots pine are mostly young, averaging 920 trees  
121 per hectare (TPHA) and a basal area (BA) of 26 m<sup>2</sup> ha<sup>-1</sup> (Gasparini and Tabacchi 2011).  
122 Quadratic mean diameter (QMD) is 21 cm; but trees larger than 35 cm are extremely rare  
123 (about 2%) (Camerano et al. 2007). Stand top height can vary from 10 to 25 m according to  
124 site fertility (Vacchiano et al. 2008). Depending on successional stage and climatic factors,  
125 species composition may range from 100% pine (especially on recently disturbed sites or dry,  
126 southern slopes) to mixtures with Swiss mountain pine (*Pinus montana* Mill.), European  
127 larch (*Larix decidua* Mill.), Norway spruce (*Picea excelsa* Karst.), silver fir (*Abies alba*  
128 Mill.), beech (*Fagus sylvatica* L.), sessile oak (*Quercus petraea* (Mattus.) Liebl), European  
129 chestnut (*Castanea sativa* Mill.), and mostly with downy oak, which has similar thermal and  
130 moisture needs.  
131 Downy oak stands covers 3468 ha in the study area (Gasparini and Tabacchi 2011), at  
132 elevations of 300–1200 m (but up to 1500 m on rocky outcrops, and 1800 m for isolated  
133 individuals), predominantly on shallow soils and carbonatic substrates. Xerophilous stands on  
134 south-facing slopes are sparse and slow-growing (1000 TPHA, BA 20 m<sup>2</sup> ha<sup>-1</sup>), with young

135 individuals often developed from former coppices, grazed woodland, or after invasion on  
136 abandoned fallow lands (QMD 10–25 cm, mean height 5–10 m) (Gasparini and Tabacchi  
137 2011). Just as in Scots pine, meso-xerophilous stands on north-facing slopes exhibited higher  
138 growth (mean height: 10–15 m) and a mixture degree. Scots pine and downy oak can replace  
139 each other in the course of forest dynamics, e.g., by regeneration of pine in sparse and  
140 degraded oak woodlands, or the succession of closed-canopy, or declining, pine forests to  
141 more tolerant oak (Zavala and Zea 2004).

#### 142 143 *Drivers of pine and oak distribution*

144 In order to model the occurrence of Scots pine and downy oak in the study area, we used a  
145 diverse set of explanatory variables including vectorial as well as raster information at  
146 different spatial resolutions. All variables were resampled at a common spatial resolution of 1  
147 km, i.e., the coarsest resolution among all explanatory variables, and clipped to a land use  
148 mask of current forest distribution. In fact, we decided to exclusively presence/absence of  
149 pine and oak in areas with forest cover, since the model could be calibrated against current  
150 vegetation conditions only. Rasterization of vector layers and raster resampling were carried  
151 out by aggregating to cell means if raster grain was finer than 1 km, and by bilinear (for  
152 continuous layers) or nearest neighbor interpolation (for categorical layers) if grain exceeded  
153 1 km (Figure S1). Explanatory variables included the following:

154  
155 (1) elevation, slope, aspect, southness (i.e., a linearization of aspect: Chang et al. 2004), and  
156 topographic position index (TPI: Guisan et al. 1999) computed from a 10 m digital terrain  
157 model. A higher TPI is indicative of ridges or hilltops;

158  
159 (2) climate means (years 1961-1990) at a 1 km resolution, extracted from the Worldclim  
160 database (Hijmans et al. 2005). These included mean, minimum, and maximum yearly  
161 temperatures (TMIN, TMEAN, TMAX), yearly precipitation (P), precipitation cumulated in  
162 the growing season (April-September, GSP), and yearly solar radiation (RAD). Additionally,  
163 using mean, minimum, and maximum monthly temperature grids, we computed growing  
164 degree days (GDD; base temperature = 5°C) (Fronzek and Carter 2007), and an aridity index  
165 (AI) as the difference between monthly precipitation and potential evapotranspiration (PET).  
166 PET for month *i* was computed as

1  
2  
3 168  
4  
5 169  $0.0023 \text{ RAD}_i (\text{TMEAN}_i + 17.8) \frac{(\text{TMAX}_i - \text{TMIN}_i)}{2} \text{ days}_i$   
6  
7 170

8 171 after Zimmermann et al. (2007);  
9

10 172 (3) soil variables at a 1 km resolution, extracted from the European Soil database (European  
11 Soil Bureau 1999). We selected variables potentially important for tree establishment and  
12 173 growth, namely: available water capacity of the topsoil (AWC), accumulated soil temperature  
13 class (ATC), total organic carbon of the topsoil (OC), base saturation (BS), erodibility (ERO),  
14 174 depth to rock (DR), dominant surface textural class (TEXT), and volume of stones (VS). All  
15 175 variables were coded as dummy values;  
16  
17 176  
18  
19 177

20  
21 178 (4) natural disturbances, such as landslides or severe soil erosion (source: Corine Land Cover  
22 179 1990 raster coverage, resolution: 500 m), avalanche tracks, and wildfires > 10 ha for the  
23 180 years 1961–1991(sources: Regione Autonoma Valle d’Aosta, Ufficio Neve e Valanghe; and  
24 Regione Autonoma Valle d’Aosta, Corpo Forestale Regionale, Nucleo Antincendo Boschivi);  
25 181  
26 182

27  
28 183 (5) competition by the pre-existing canopy, assessed by extracting the Normalized Difference  
29 184 Vegetation index (NDVI) from a Landsat 5 Thematic Mapper image (path 195, row 28) taken  
30 185 on June 30th, 1987 (resolution: 30 m). The acquisition period was chosen as to be at the peak  
31 186 at the growing season; the image had 10% cloud cover, but clouds were clustered over high  
32 187 elevation, unforested terrain. The image was first converted to top of the atmosphere radiance  
33 188 using standard equations and calibration parameters obtained from the metadata of each  
34 189 scene (Chander et al. 2009). Then, we computed NDVI using band TM4 (near infrared) and  
35 190 band TM3 (visible red) and used it as a proxy of standing forest biomass (Tucker et al. 1979;  
36 191 Pettorelli et al. 2005). As an additional index of competition by forest vegetation, we used  
37 192 percent tree cover from the recently released Landsat Vegetation Continuous Fields (VCF)  
38 193 dataset (Sexton et al. 2013), at a resolution of 30m, based on a Landsat 5 TM image acquired  
39 194 on July 27th, 2001;  
40  
41 195

42  
43 196 (6) land use intensity was assessed by using proxy variables, i.e., total road length and total  
44 197 building surface per 500 m pixel, as extracted from a vector regional map. Moreover, the  
45 198 degree of land abandonment was estimated at the municipality level by the percent variation  
46 199 in resident population in the period 1951–1991 (source: ISTAT).  
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200

1  
2 201 In order to limit collinearity of independent variables, predictors exhibiting a Pearson's  
3 202 correlation coefficient  $> |0.9|$  were excluded from further analysis.

4  
5 203

6  
7 204 *Model runs under future scenarios*

8  
9 205 Simulation experiments for the future projections of species distribution relied on the same  
10 206 set of explanatory variables. However, values for variables used in future scenarios were  
11 207 chosen as follows:

12  
13 208

14  
15 209 (1) Climate means for the 2080 decade were extracted from 30-arcsec gridded simulations by  
16 210 the ECHAM5/MPI-OM model from the Max-Planck Institute for Meteorology, Germany  
17  
18 211 (Raible et al. 2006), under the high emission scenario SRES A1B. Under the assumption of a  
19  
20 212 constant solar radiation, we computed GDD, GSP, PET, and AI from the ECHAM-5 grids.  
21  
22 213 For the 2080 scenario, we did not extrapolate the model to pixels exhibiting AI values  
23  
24 214 exceeding the range of current ones (Elith and Leathwick 2009);

25  
26 215

27  
28 216 (2) Fire frequency and size are supposedly responsive to climate change (Moriondo et al.  
29 217 2006). In order to simulate the influence of fire preceding the 2080 decade, we used wildfire  
30  
31 218 polygons for the years 1981–2000, i.e., a period that included several extreme fire seasons  
32  
33 219 resulting in a +39% and +26% increase in the frequency and total area burned, respectively,  
34  
35 220 by large fires ( $>10$  ha) relative to 1961–1980;

36  
37 221

38  
39 222 (3) We simulated two alternative land-use scenarios: 1) urbanization and land abandonment,  
40 223 i.e., every municipality was assigned a “business as usual” scenario of population change  
41  
42 224 using figures for the period 1951–1991, and 2) maintenance of high land use, i.e., all  
43  
44 225 municipalities were assigned 0% variation in population respective to 1951, thereby  
45  
46 226 assuming a continued presence of man and its activities at all rural settings.

47  
48 227

49  
50 228 Soil characteristics are also responsive to climate change (Singh et al. 2011); however, we  
51 229 kept these variables at current conditions for the 2080 simulation, since no quantitative  
52  
53 230 scenarios are available to estimate future changes. Altogether, three scenarios were  
54  
55 231 simulated: current conditions, 2080 climate with unchanged land use, and 2080 climate with  
56  
57 232 intense land use.

58  
59 233

234 *Model building*

1  
2 235 Presence/absence of pine and oak in the years 1992–1994 served as a response variable,  
3  
4 236 which we extracted from a regional forest inventory based on a 500 m regular grid. At every  
5  
6 237 grid node, the species and diameter at breast height (DBH) of each living tree (DBH > 7.5  
7  
8 238 cm) were measured within a variable-radius circular plot (radius: 8–15 m depending on tree  
9  
10 239 density). Plot coordinates were recorded to the nearest meter. Scots pine and downy oak were  
11  
12 240 labeled as present where at least one tree of each species was recorded, and absent otherwise.  
13  
14 241 We assumed that both pine and oak distribution are in equilibrium with the environment  
15  
16 242 (Rohde 2005). For this reason, and because our aim was to model potential niche, no  
17  
18 243 migration constraints were included in the model.  
19  
20 244 We used an ensemble modeling approach (Araujo and New 2007), by fitting and averaging  
21  
22 245 predictions obtained by a generalized linear model (GLM), artificial neural network (ANN)  
23  
24 246 and multiple adaptive regression spline (MARS) using the same set of responses, predictors,  
25  
26 247 and scenarios. Model specifications were as follows: (a) for GLM, a backward stepwise  
27  
28 248 algorithm was used, based on Akaike Information Criterion (AIC); (b) for ANN, the initial  
29  
30 249 number of cross-validations to find best size and decay parameters was set to five; (c) for  
31  
32 250 MARS, the cost per degree of freedom charge was set to 2, and the model was pruned in a  
33  
34 251 backward stepwise fashion. All models were fit on a binomial distribution with logit link,  
35  
36 252 without interactions between predictors, and using a maximum of 100 iterations.  
37  
38 253 For each of the three models, we computed variable importance ratings and response curves.  
39  
40 254 To do so, all variables but one are set constant to their median value, and only the remaining  
41  
42 255 one is allowed to vary across its whole range. In the case of categorical variables (e.g., soil),  
43  
44 256 the most represented class was used. The variations observed and the curve thus obtained  
45  
46 257 show the sensibility of the model to that specific variable.  
47  
48 258 We carried out k-fold cross-validation of the model by subdividing the data into a 3:1  
49  
50 259 proportion (k = 4). Model specificity and sensitivity were computed for the selected  
51  
52 260 thresholds; the threshold to convert continuous predictions into binary ones was iteratively  
53  
54 261 chosen to maximize the area under the curve (AUC).  
55  
56 262 The ensemble prediction was computed from all model realizations with AUC >0.75. The  
57  
58 263 probability of occurrence for the ensemble prediction was the mean of the selected models'  
59  
60 264 predictions, weighted by the model AUC. Model residuals were scrutinized to detect the  
61  
62 265 absence of trends against predicted values and independent variables; a variogram was fitted  
63  
64 266 to assess the degree of residual spatial autocorrelation. Ensemble models were run for the  
65  
66 267 whole study region to obtain a map of potential species distribution under current and future

268 climate, assuming niche conservatism (Wiens et al. 2010). We classified simulated  
269 presence/absence of both species using an occurrence probability threshold of 0.6, and  
270 assessed projected area changes and elevational shifts in the distribution of pine and oak  
271 under the climate change and climate change + intense land use scenarios. All analyses were  
272 carried out using the Biomod2 package (Thuiller et al. 2013) for R (R Core Development  
273 Team 2013).

### 275 *Effect of extreme drought events*

276 The response of extant Scots pine forests to drought events in years 2003 and 2006 was  
277 assessed by the temporal difference in NDVI ( $\Delta$ NDVI: year of drought – year before  
278 drought). NDVI was computed from two 16-day Maximum Value Composites (MVC)  
279 MODIS images (resolution: 30-arcsec) taken at the end of the summer (Julian Days 226-241).  
280 Cloud cover of the MVC was between 1 and 4% for the four images. Pixels with a quality  
281 analysis score of 2 and 3 (i.e., targets covered by snow/ice or cloudy pixel) as well as NDVI  
282 lower than 0.2 or null (open water) were filtered out (Vacchiano et al. 2012).

283 In order to distinguish reflectance anomalies from random or systematic error (Morisette and  
284 Khorram 2000), we classified as “decline” all pixels with  $\Delta$ NDVI < (mean - 3 standard  
285 deviations), as computed from the full scene (Fung and LeDrew 1988; Vacchiano et al. 2012).  
286 Finally, we compared the modeled change in pine occurrence probability (2080 – current) of  
287 “decline” vs. non-decline pixels by means of Wilcoxon signed-rank test (Sokal and Rohlf  
288 1995).

### 290 **3. Results**

291 Scots pines were detected in 460 (27%) out of 1730 inventory plots, and downy oak in 181  
292 (10%). After screening for collinearity, 18 predictors were retained for subsequent analyses  
293 (Table 1). Since most climate-related variables were correlated to each other and to elevation,  
294 we retained only aridity index (AI) as the main climate predictor; Pearson’s correlation  
295 between AI and Worldclim variables was always higher than 0.95 (e.g., R =-0.995 vs. mean  
296 annual temperature, R =0.993 vs. annual precipitation, R =-0.962 vs. GDD).

297 AI was the most important predictor for the current distribution of both pine and oak (Table  
298 2), with higher occurrence probability at low water balance levels (Figure S2). However,  
299 MARS captured a reduced probability of occurrence for Scots pine at very low values of the  
300 aridity index (i.e., very dry sites). Beyond aridity, variables associated to high probability of  
301 Scots pine occurrence were southness, TPI, population change, building density, and past

302 fires – the last two only in the ANN model. Soil erosion, NDVI, and road density (in the  
ANN model) decreased the probability of pine presence (Figure S2a). Explanatory variables  
of oak distribution exhibited a similar behavior: southness and TPI, but also slope, soil depth,  
and soil temperature class were associated to high presence probability, while road and  
building densities produced a low presence probability (Figure S2b).

The ensemble models were successfully cross-validated (AUC = 0.865 for pine, and 0.944  
for oak), and correctly predicted most observations (sensitivity = 83.4% and 96.9%,  
specificity = 72.7% and 80.9%, respectively) (Figure 2). Residuals were immune from spatial  
autocorrelation and trends against any of the predictors.

In 2080 (SRES A1B emission scenario, continuing population trend), the mean probability of  
occurrence of Scots pine declined slightly (0.33 versus a current 0.36 across the whole study  
area) (Figure 3). However, it increased under the intense land use scenario (0.45) (Figure 4).

The area with a probability of occurrence of Scots pine >0.6 decreased from 8700 to 8000 ha  
under the climate warming scenario, and increased to 8800 ha under climate warming +  
intense land use. The probability of occurrence of Scots pine always declined at lower  
elevations, and increased at higher ones (Figure 5); mean elevation of simulated presence  
points shifted from 1328 m to 1528 m a.s.l. under climate warming, and to 1473 under  
climate warming + intense land use, i.e., an upward shift of the potential niche of 200 and  
145 m, respectively.

Oak increased its probability of occurrence under all scenarios (6100 ha under current  
conditions, 10100 ha under climate change only, and 14700 ha under climate change +  
intense land use ). Mean elevation of simulated presence points (probability of occurrence  
>0.6) shifted from 705 to 922 and 933 m a.s.l., respectively, i.e., an upward shift of 215 and  
222 m.

The area of Scots pine pixels classified as “decline” was 147 in year 2003, and 102 in year  
2006. However, in neither year we observed a significant difference between decline and  
non-decline pixels in the modeled probability of occurrence of Scots pine (Figure 6).

#### 4. Discussion

Many processes are at work in determining pine decline. Drought is either a direct or a  
predisposing factor of mortality (Rebetez and Dobbertin 2004; Choat et al. 2013); also, land  
use change may eventually result in competitive exclusion of light demanding Scots pine, and  
at low elevations Scots pine reaches more rapidly decay stages, since trees weakened by  
drought are easily killed by “inciting” or “contributing” biotic agents (Dobbertin et al. 2005;

336 Bigler et al. 2006; Vacchiano et al. 2012).

1  
2 337 Climate warming and drought are related (i.e., the frequency of drought spells is expected to  
3  
4 338 increase under climate change: Allen et al. 2010); however, extreme drought events may be  
5  
6 339 more important than average climate trends in determining plant population viability and  
7  
8 340 distribution (Katz and Brown 1992; Bréda and Badeau 2008), and they can induce shifts in  
9  
10 341 species composition and distribution (Jentsch et al. 2007). Published models of Scots pine  
11  
12 342 distribution under scenarios of climate change have produced contrasting results (e.g.,  
13  
14 343 Casalegno et al. 2011; Meier et al. 2011), probably as a result of different datasets and  
15  
16 344 processes being included or not in the models (e.g., dispersal constraints, biotic competition,  
17  
18 345 choice of climate and drought-related variables).

19  
20 346 In order to take into account the different factors governing drought sensitivity, we included  
21  
22 347 in our models its meteorological, topographic, and soil-related component. At the resolution  
23  
24 348 and extent analyzed, the probability of occurrence of Scots pine increased under climatic and  
25  
26 349 topographic aridity. This is consistent with the biogeography of the species, that forms pure  
27  
28 350 stands in most inner-alpine valleys such as the study area, preferentially on south-facing  
29  
30 351 slopes and ridge positions (Ozenda, 1985). Accordingly, low aridity reduced the probability  
31  
32 352 of presence of Scots pine. In Aosta valley, temperature and precipitation are strongly  
33  
34 353 correlated to elevation (which for this reason was excluded from the analysis), therefore the  
35  
36 354 AI variable contained also information regarding the upper elevational limits of the habitat  
37  
38 355 suitable for Scots pine.

39  
40 356 Another important driver of Scots pine occurrence was biotic competition, as expressed by  
41  
42 357 NDVI of the forest canopy. As expected, the early-seral pine cannot establish successfully  
43  
44 358 under thick canopy cover (Vickers 2000). In contrast, it can also establish successfully on  
45  
46 359 non-forested land, such as abandoned pastures and meadows (Poyatos et al. 2003), but this  
47  
48 360 process could not be taken into consideration in future simulations, since our correlative  
49  
50 361 models were calibrated on current vegetation conditions only.

51  
52 362 In addition to topo-climatic and competition variables, that are routinely assessed in SDM,  
53  
54 363 we also evaluated the effect of soil properties (albeit using a coarse resolution and dummy  
55  
56 364 coding), and natural and anthropogenic disturbances (Matias and Jump 2012). Scots pine did  
57  
58 365 not exhibit any soil preference, consistently with its edaphic plasticity (Médail 2001).

59  
60 366 However, its occurrence was moderately associated to the absence of steep slopes and severe  
61  
62 367 land erosion, which should be adverse to permanent vegetation cover, and to recurring  
63  
64 368 wildfires. Wildfire polygons were not labeled as surface or crown fires; however, surface  
65



369 fires are more common in the study area, especially at low elevations on south-facing slopes  
1 370 (Vacchiano et al. 2013).

3 371 We also evaluated the effect of human land use on species distribution by using proxy  
4 372 variables (Garbarino et al. 2009). Increased population and road density resulted in increased  
5 373 occurrence of Scots pine. Management practices such as timber harvesting, litter collection,  
6 374 and forest grazing may in fact prevent succession to more competitive late-seral species  
7 375 (Weber et al. 2008; Gimmi et al. 2010). The association between pine and population / road  
8 376 density may also be due to recent establishment of Scots pine after agricultural abandonment  
9 377 (Poyatos et al. 2003). Building density was negatively correlated to the probability of  
10 378 occurrence of both Scots pine and downy oak, likely due to the spatial segregation of forests  
11 379 vs. developed or urbanized areas in the main valley.

12 380 These factors help explain the response of Scots pine distribution in 2080 under the A1B  
13 381 warming scenario, i.e., a modest reduction of habitat suitability, but a significant increase of  
14 382 its optimum elevation. At low elevations, in fact, aridity could reach the lower limits for the  
15 383 species to persist, as suggested by the MARS response curve (Garzon et al. 2008). This  
16 384 change is partially counteracted in a scenario where land abandonment is prevented from  
17 385 occurring: in this case, the probability of occurrence of Scots pine would still decrease at low  
18 386 elevations but, on average, the human factor could be sufficient to prevent the decline of  
19 387 Scots pine throughout its current distribution. This analysis is correlative, and does not  
20 388 explore the physiological and successional processes behind such land use/climate change  
21 389 tradeoff. However, it is indicative of the fact that land use changes can be as strong as climate  
22 390 change in determining future species composition and dominance of mountain forests  
23 391 (Dirnbock et al. 2003), and that they deserve a deeper attention in modeling species' response  
24 392 to future climate conditions.

25 393 The distribution of downy oak shared the same topo-climatic features as Scots pine (high  
26 394 aridity / low elevation, southern aspects, low erosion, high soil temperature), but was also  
27 395 associated to lower land use intensity (road density) and higher soil depth. Canopy density  
28 396 (NDVI) and natural disturbances were not influential, since downy oak is more shade-tolerant  
29 397 than pine (Monnier et al. 2013). The response of downy oak to climate warming was different  
30 398 from Scots pine, and produced an increased probability of occurrence throughout the study  
31 399 region. Previous research has demonstrated that downy oak is better adapted than Scots pine  
32 400 to both short- and long-term drought, due to its different physiological responses, i.e.,  
33 401 stomata closure, resistance to embolism, seedling vitality (Eilmann et al. 2006; Poyatos et al.  
34 402 2008; Moran-Lopez et al. 2012).

403 Population change was not among the most important predictors of current downy oak  
1 404 distribution. However, we detected a moderate association between population increase and  
2  
3 405 higher probability of occurrence of oak. This can be due either to the practice of coppicing  
4  
5 406 oaks for firewood, or to the fact that depopulated areas are located in the remotest part of  
6  
7 407 lateral valleys, where elevation and sites are far below optimum for downy oak.  
8  
9 408 The use of ensemble modeling is justified by the need to reduce model uncertainty due to  
10  
11 409 different modeling approaches (Marmion et al. 2009). Ensemble models in Biomod2 are  
12  
13 410 obtained by averaging model prediction and excluding models with low predictive power  
14  
15 411 (AUC <0.75); model predictions are weighted by the AUC of their respective modeling  
16  
17 412 approach. In this study, all three model approaches produced an AUC >0.75. However,  
18  
19 413 differences in importance of explanatory variables and shape of response curves were  
20  
21 414 apparent. MARS are more flexible than GLM as they are fit using piecewise linear splines,  
22  
23 415 and are particularly useful when assuming that the shape of species' responses is not linear  
24  
25 416 (Leathwick et al. 2005). ANN, on the other hand, are not based on specific distribution  
26  
27 417 functions of the response. They are robust to noisy and non-linear responses, and allow for  
28  
29 418 categorical predictors (such as soil characteristics in this study). Therefore, they are  
30  
31 419 particularly appropriate in an exploratory context. On the other hand, they are sensitive to  
32  
33 420 multicollinearity and prone to overfitting, and interpretation of causal relationships for  
34  
35 421 individual predictors is not straightforward (Manel et al. 1999). The differences are apparent  
36  
37 422 in species response curves (Figure S2), with MARS and ANN capable of detecting non-linear  
38  
39 423 responses to some explanatory variables that were not picked up by GLM, despite a similar  
40  
41 424 predictive performance. This is reflected by the higher importance of some explanatory  
42  
43 425 variables, such as Roads, Buildings, TPI, or Erosion, under models capable of detecting non-  
44  
45 426 linear species responses (Table 2).

427 Finally, contrary to our expectations, we did not detect any overlap between drought-induced  
46  
47 428 Scots pine decline in years 2003 and 2006, and change in occurrence probability under a  
48  
49 429 warming scenario. Widespread tree mortality can occur under extreme dry spells, but it is  
50  
51 430 uncertain whether one or two extreme years are sufficient to trigger major shifts in forest  
52  
53 431 composition (e.g., Vicente-Serrano et al. 2013). The effect of extreme years on the realized  
54  
55 432 niche of Scots pine will likely depend on the frequency and severity of droughts, rather than  
56  
57 433 on decadal climate means such as the ones we used in our projections. Other parameters  
58  
59 434 might be important in their extreme yearly or seasonal values, such as high precipitation  
60  
61 435 events promoting a new generation after a mortality episode (Matias and Jump 2013), late  
62  
63 436 frost preventing uphill expansion of sensitive species such as downy oak (Burnand 1976),

437 and natural disturbances such as large, stand-replacing fires (Moser et al. 2010).

1  
2 438 What is certain, however, is that downy oak is equipped with better adaptations to drought,  
3  
4 439 and is likely to replace Scots pine at lower elevations under a warming scenarios, whereby an  
5  
6 440 increased frequency of droughts is to be expected (Dai 2012). Management actions have the  
7  
8 441 potential to mitigate this shift (Vilà-Cabrera et al. 2013), e.g., thinning to 40–60% initial  
9  
10 442 basal area to mitigate drought effects on Scots pine on xeric sites (Giuggiola et al. 2013).  
11  
12 443 However, effects of management actions must be more thoroughly explored to evaluate  
13  
14 444 tradeoffs with each species' resistance and resilience in the face of climate forcing.

15 445

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665 **Tables**

1  
2 666 Table 1 – Explanatory variables used in this study (minimum, maximum, mean, standard  
3 667 error), computed for currently forested areas only

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671 Table 2 – Variable importance (0–1) for SDM of current Scots pine and downy oak  
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 2 672 distribution fitted by generalized linear model (GLM), artificial neural network (ANN) and  
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 4 673 multiple adaptive regression spline (MARS). Codes for explanatory variables are given in  
 5 674 Table 1.  
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Variable	Scots pine			Downy oak		
	GLM	MARS	ANN	GLM	MARS	ANN
AI	0.650	0.645	0.733	0.848	0.830	1.000
Slope	0.000	0.086	0.006	0.038	0.087	0.023
TPI	0.145	0.162	0.000	0.099	0.103	0.000
Southness	0.180	0.393	0.283	0.210	0.269	0.220
ATC	0.000	0.017	0.000	0.078	0.042	0.000
AWC	0.000	0.000	0.000	0.000	0.000	0.000
DR	0.000	0.000	0.000	0.251	0.138	0.000
ERO	0.000	0.000	0.000	0.000	0.000	0.000
OC	0.000	0.000	0.000	0.044	0.000	0.000
VS	0.000	0.000	0.000	0.160	0.000	0.000
Avalanches	0.000	0.000	0.000	0.000	0.000	0.000
Wildfires	0.010	0.000	0.000	0.000	0.000	0.000
Erosion	0.000	0.061	0.319	0.011	0.028	0.109
Depop	0.069	0.029	0.000	0.027	0.041	0.000
Roads	0.000	0.000	0.459	0.016	0.029	0.159
Buildings	0.000	0.017	0.367	0.027	0.155	0.201
VCF	0.000	0.028	0.018	0.000	0.024	0.023
NDVI	0.134	0.093	0.000	0.006	0.074	0.000

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681 **Captions of figures**

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3 683 Fig. 1 – Location of the study region and area covered by forests (in green).

6 684 Fig. 2 – Occurrence probability (0–1) of (a) Scots pine, and (b) downy oak under current  
7 climate. Ensemble model (mean of GLM, MARS, and ANN). Presence points from the  
8 685 regional forest inventory in black.  
9 686

12 687 Fig. 3 – Occurrence probability (0–1) of (a) Scots pine, and (b) downy oak under 2080  
13 climate and current land use scenario. Ensemble model (mean of GLM, MARS, and ANN).  
14 688

17 689 Fig. 4 – Occurrence probability (0–1) of (a) Scots pine, and (b) downy oak under 2080  
18 climate and intensive land use scenario. Ensemble model (mean of GLM, MARS, and ANN).  
19 690

22 691 Fig. 5 – Change in probability of occurrence (2080–current) of (a) Scots pine and (b) downy  
23 692 oak for different elevation classes under 2080 climate (above) and 2080 climate + intensive  
24 land use scenario (below).  
25 693

28 694 Fig. 6 – Change in probability of occurrence (2080–current) of Scots pine for decline and  
29 non-decline pixels in dry years 2003 (left) and 2006 (right), under 2080 climate (above) and  
30 695 2080 climate + intensive land use scenario (below).  
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36 698 **Supplementary material**

38 699

40 700 Fig. S1 – Explanatory variables used in this study. Codes for explanatory variables are in  
41 701 Table 1

43 702

45 703 Fig. S2 – Response curves for SDM of (a) Scots pine, and (b) downy oak in current  
46 conditions. Models: GLM (solid line), MARS (dashed), ANN (dotted). Codes for explanatory  
47 704 variables are in Table 1.  
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<b>code</b>	<b>description</b>	<b>range</b>	<b>mean</b>
bio01	Mean annual temperature <sup>a</sup>	-0.6 – 11.1	4.9
bio05	Max temperature of warmest month <sup>a</sup>	10.8 – 26.7	18.5
bio06	Min temperature of coldest month <sup>a</sup>	-10.8 – -2.9	-6.9
bio07	Temperature annual range <sup>a</sup>	21.3 – 29.6	25.4
bio10	Mean temperature of warmest quarter <sup>a</sup>	6.4 – 20	12.8
bio11	Mean temperature of coldest quarter <sup>a</sup>	-7.2 – 2	-2.8
bio12	Annual precipitation <sup>a</sup>	796 – 1828	1263.3
bio18	Precipitation of warmest quarter <sup>a</sup>	225 – 465	335.6
GDD	Growing degree days above 5 °C	257 – 2656	1181.2
GSP	Precipitation april-september	437 – 913	663.5
<b>AI</b>	Aridity index (bio12 -PET)	-638 – 1252	311.0
DTM	Elevation <sup>b</sup>	308 – 2493	1514.3
<b>slope</b>	Slope from DTM	0 – 44	17.0
<b>TPI</b>	Topographic Position Index	-3.0 – 3.1	-0.4
<b>southness</b>	Linearization of aspect	0 – 180	97.2
<b>ATC</b>	Soil accumulated temperature class <sup>c</sup>	1 – 3	-
<b>AWC</b>	Available water capacity in the topsoil <sup>c</sup>	1 – 3	-
BS	Soil base saturation <sup>c</sup>	1 – 2	-
<b>DR</b>	Soil depth to rock <sup>c</sup>	1 – 4	-
<b>ERO</b>	Soil erodibility <sup>c</sup>	3 – 5	-
<b>OC</b>	Organic carbon in the topsoil <sup>c</sup>	1 – 3	-
TEXT	Soil texture (from coarse to fine) <sup>c</sup>	0 – 2	-
<b>VS</b>	Volume of stones in the soil <sup>c</sup>	0 – 2	-
<b>Avalanches</b>	Number of avalanche polygons <sup>b</sup>	0 – 3	0.1
<b>Wildfires</b>	Number of fire polygons, 1961-1990 <sup>b</sup>	0 – 3	0.0
<b>Erosion</b>	Total area subject to landslide or erosion <sup>d</sup>	0 – 14523	656.9
<b>Depop</b>	Change in population 1951-1991 <sup>e</sup>	-59 – 135	2.1
<b>Roads</b>	Total road length <sup>b</sup>	0 – 8485	1812.0
<b>Buildings</b>	Total buildings area <sup>b</sup>	0 – 40190	1591.8
<b>VCF</b>	Tree cover from Landsat (2001) <sup>f</sup>	0 – 99	29.9
<b>NDVI</b>	NDVI from Landsat (1987)	0.20 – 0.66	0.30

Bold: Explanatory variables in species distribution models

Data sources: <sup>a</sup> Hijmans et al. (2005); <sup>b</sup> Regione Autonoma Valle d'Aosta; <sup>c</sup> European Soil E

<b>units</b>	<b>resolution</b>
°C	30 arcsec
°C	30 arcsec
°C	30 arcsec
°C	30 arcsec
°C	30 arcsec
°C	30 arcsec
mm	30 arcsec
mm	30 arcsec
°C	30 arcsec
mm	30 arcsec
mm	30 arcsec
m asl	10 m
°	10 m
-	10 m
°	10 m
dummy	1 km
dummy	1 km
dummy	1 km
dummy	1 km
dummy	1 km
dummy	1 km
dummy	1 km
dummy	1 km
dummy	1 km
count	10 m
count	10 m
m <sup>2</sup>	500 m
% change	municipality
m	500 m
m <sup>2</sup>	500 m
%	30 m
0-1	30 m

bureau (1999); <sup>d</sup> European Environment Agency (2013); <sup>e</sup> ISTAT (2012); <sup>f</sup> Sexton et al. (2013)

Variable	Scots pine			Downy oak		
	GLM	MARS	ANN	GLM	MARS	ANN
AI	0.650	0.645	0.733	0.848	0.830	1.000
Slope	0.000	0.086	0.006	0.038	0.087	0.023
TPI	0.145	0.162	0.000	0.099	0.103	0.000
Southness	0.180	0.393	0.283	0.210	0.269	0.220
ATC	0.000	0.017	0.000	0.078	0.042	0.000
AWC	0.000	0.000	0.000	0.000	0.000	0.000
DR	0.000	0.000	0.000	0.251	0.138	0.000
ERO	0.000	0.000	0.000	0.000	0.000	0.000
OC	0.000	0.000	0.000	0.044	0.000	0.000
VS	0.000	0.000	0.000	0.160	0.000	0.000
Avalanches	0.000	0.000	0.000	0.000	0.000	0.000
Wildfires	0.010	0.000	0.000	0.000	0.000	0.000
Erosion	0.000	0.061	0.319	0.011	0.028	0.109
Depop	0.069	0.029	0.000	0.027	0.041	0.000
Roads	0.000	0.000	0.459	0.016	0.029	0.159
Buildings	0.000	0.017	0.367	0.027	0.155	0.201
VCF	0.000	0.028	0.018	0.000	0.024	0.023
NDVI	0.134	0.093	0.000	0.006	0.074	0.000

figure S2a  
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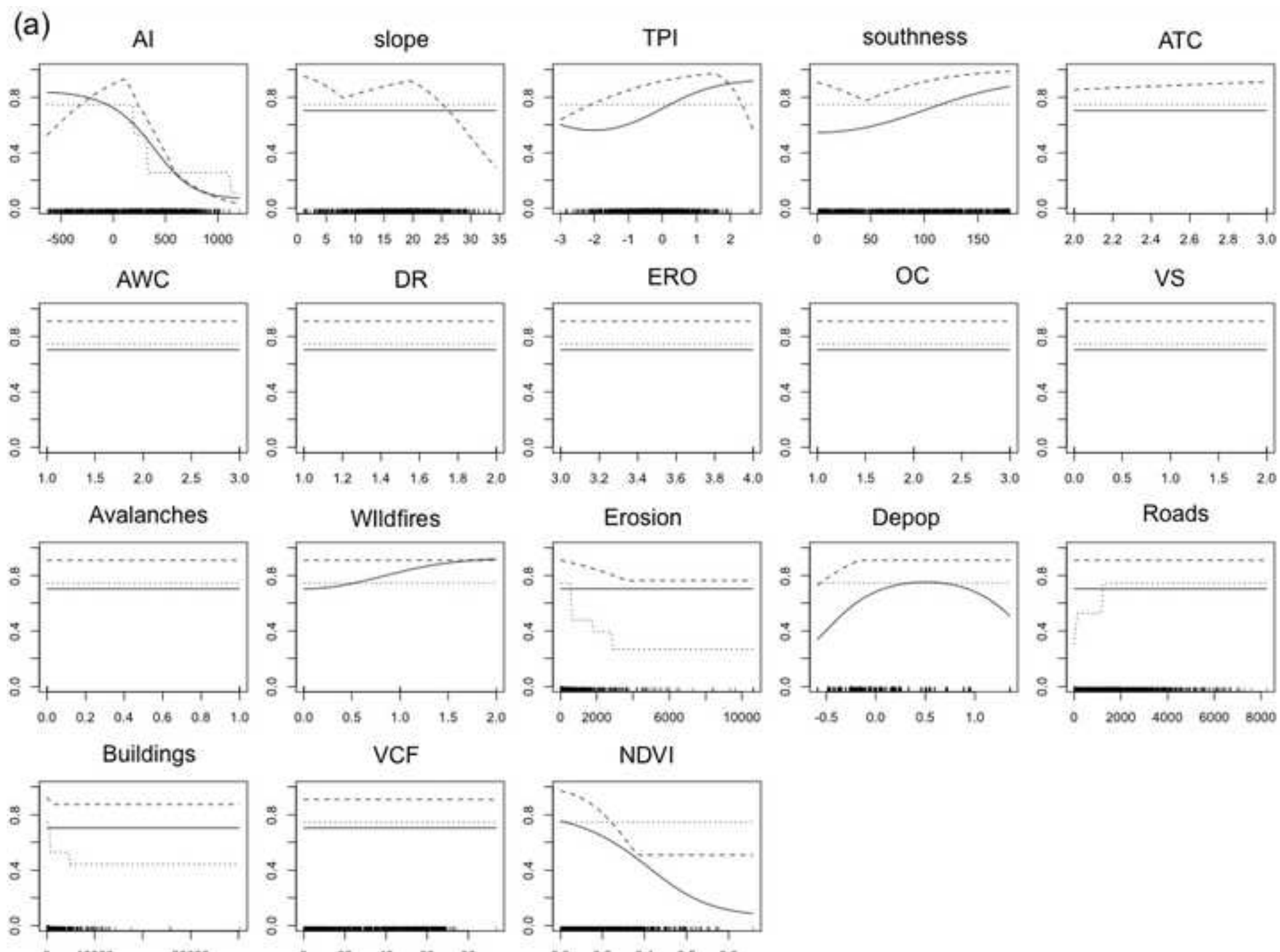




figure S2b  
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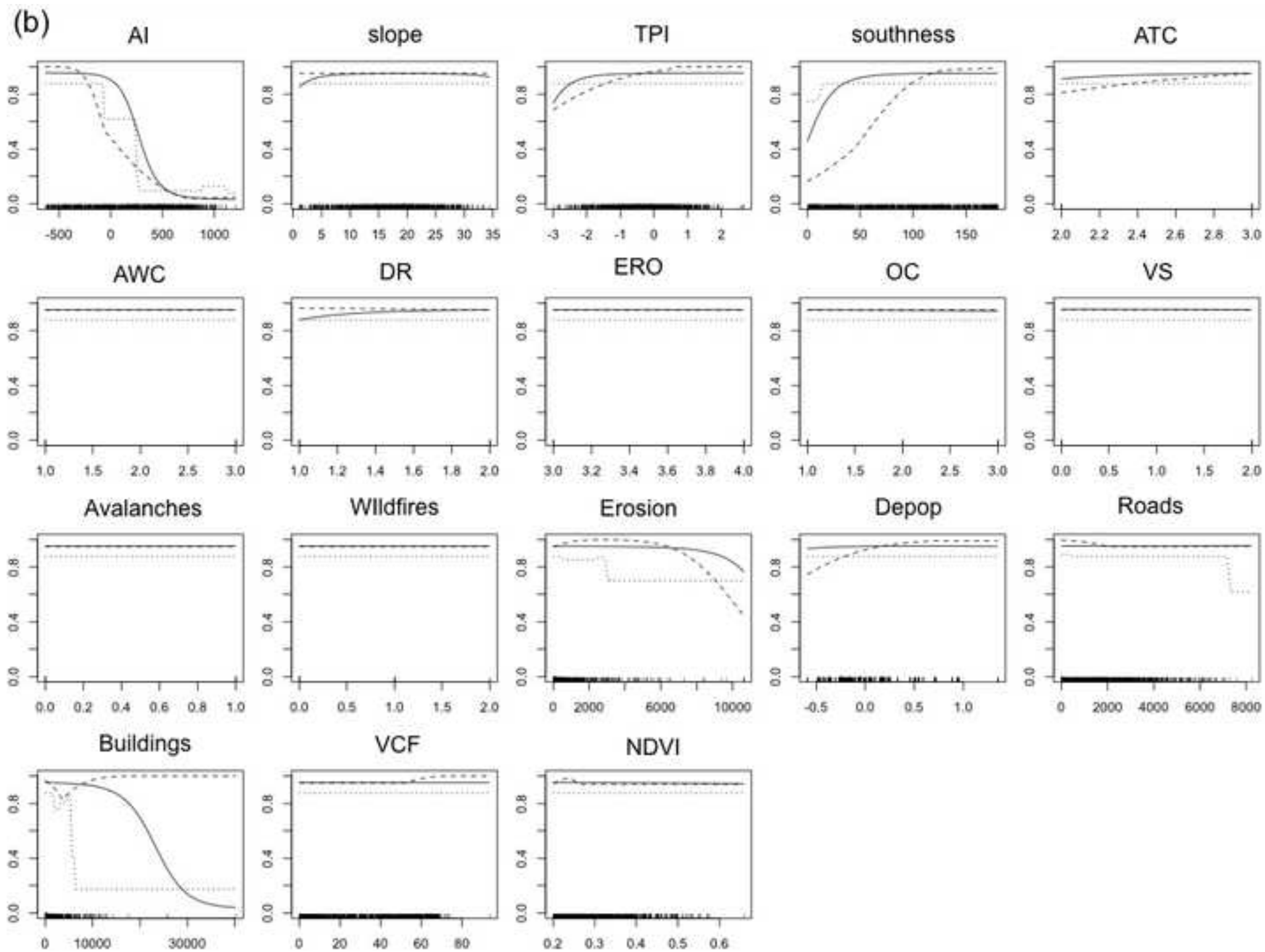
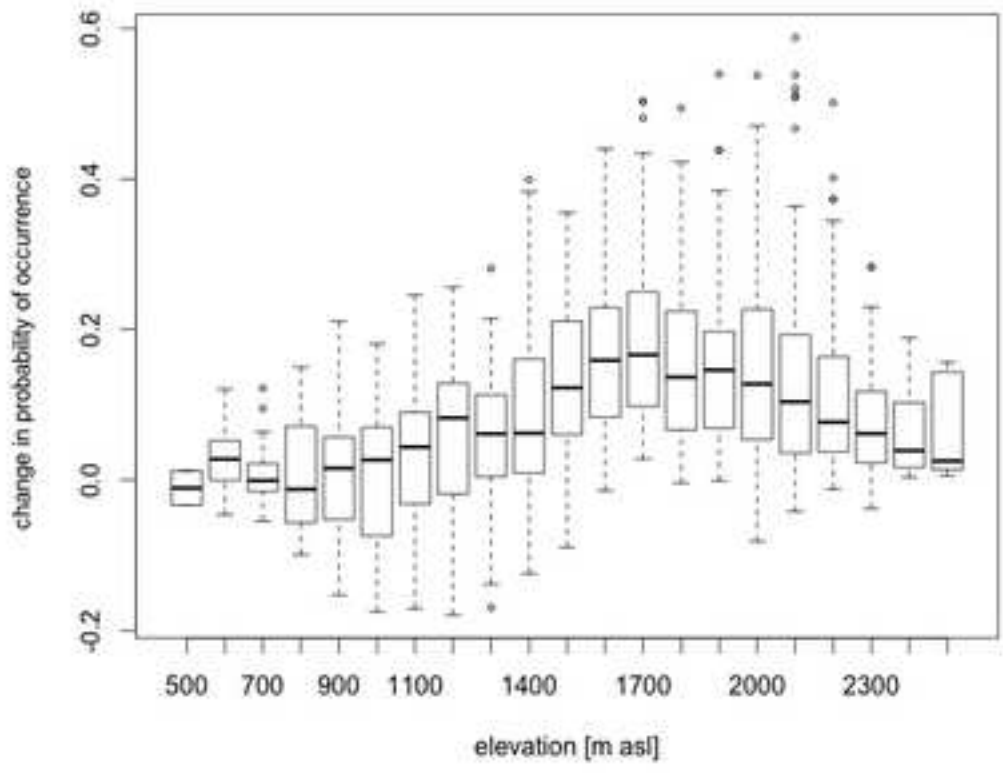
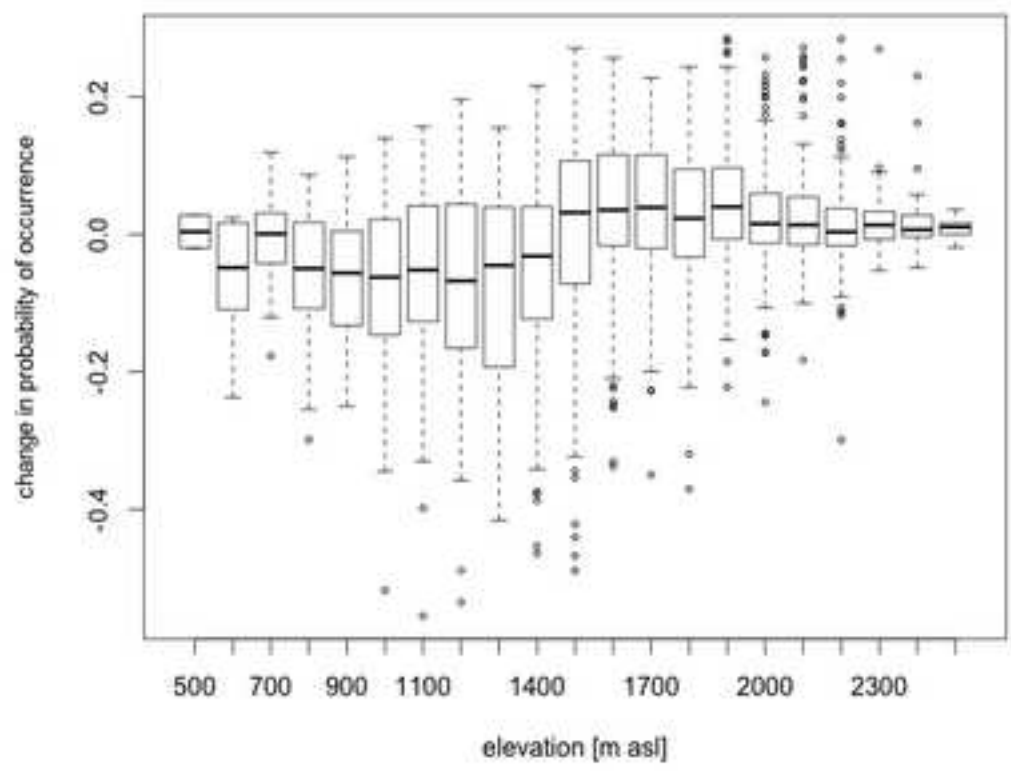


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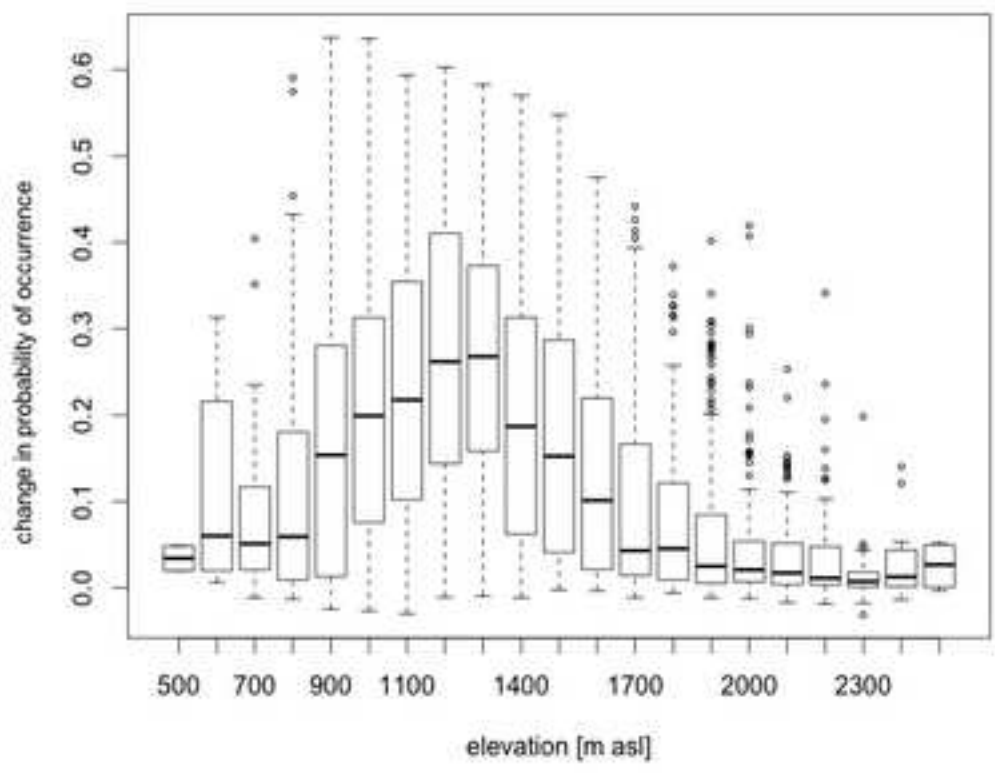
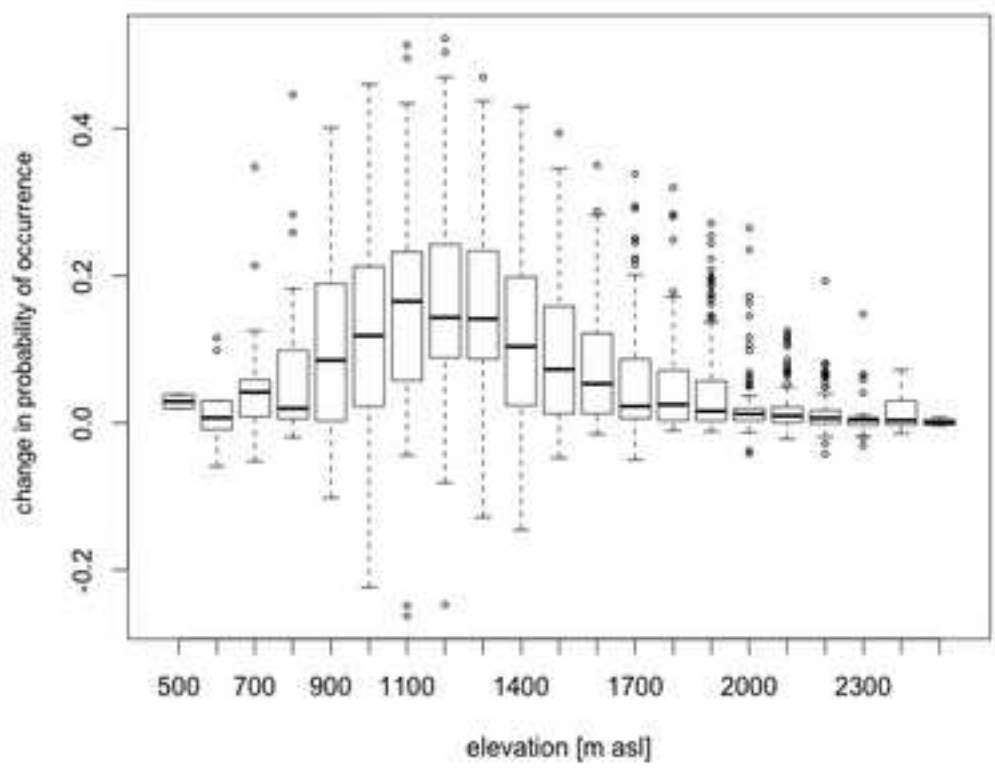


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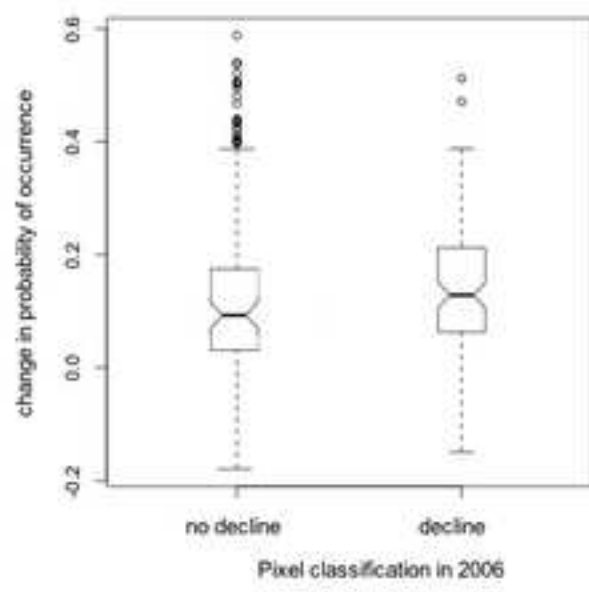
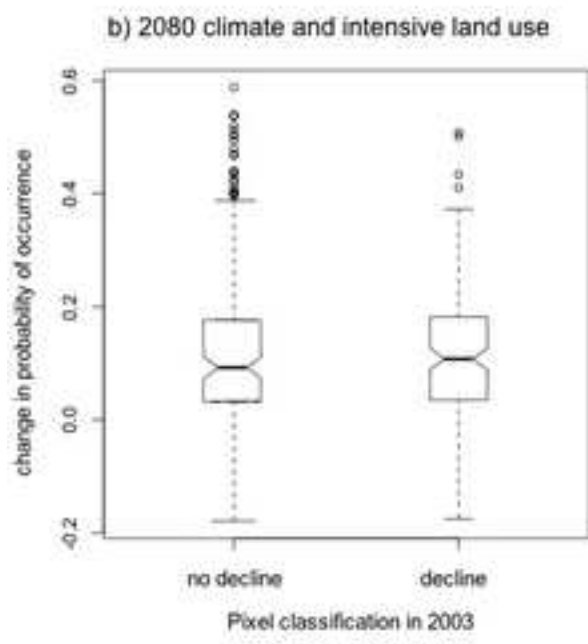
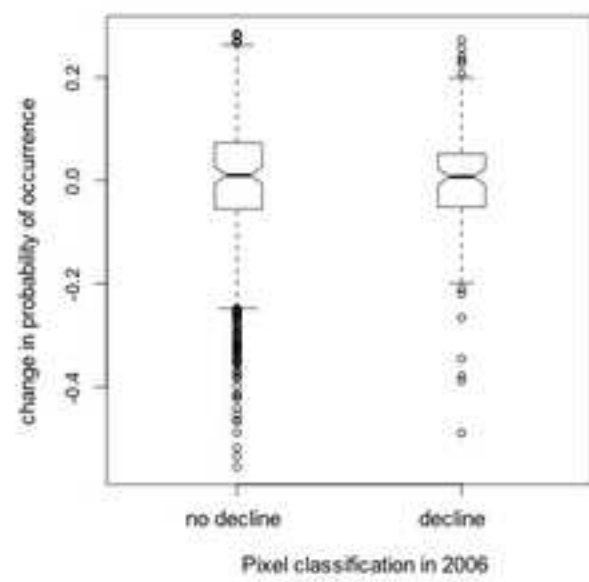
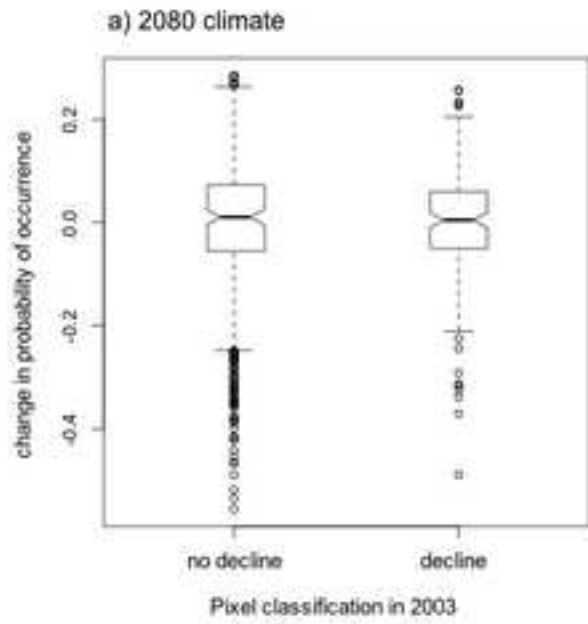


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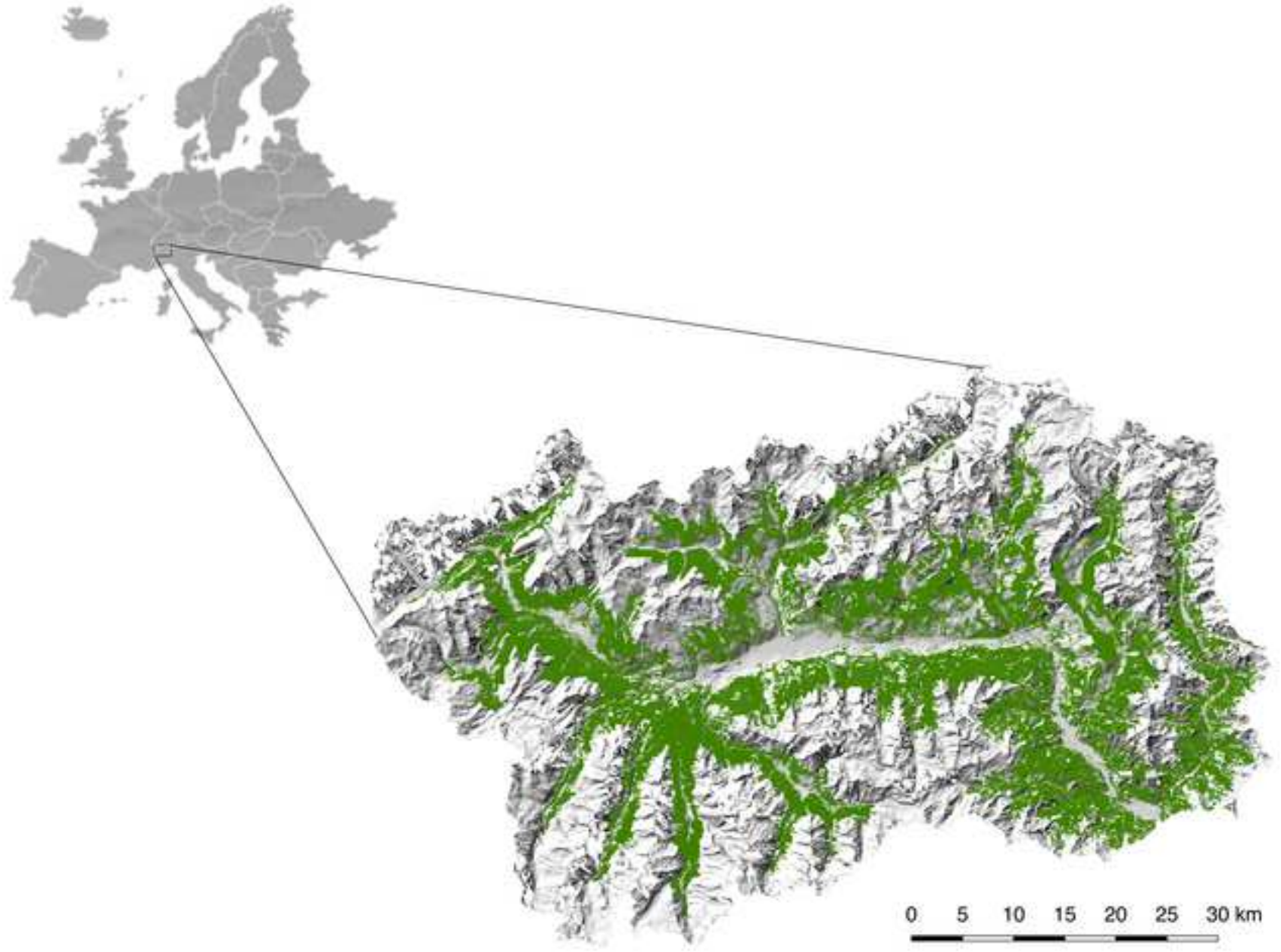
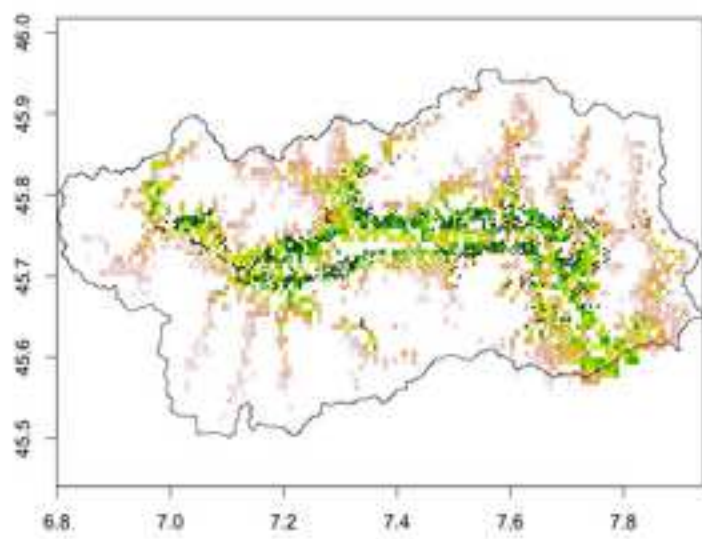


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(b)

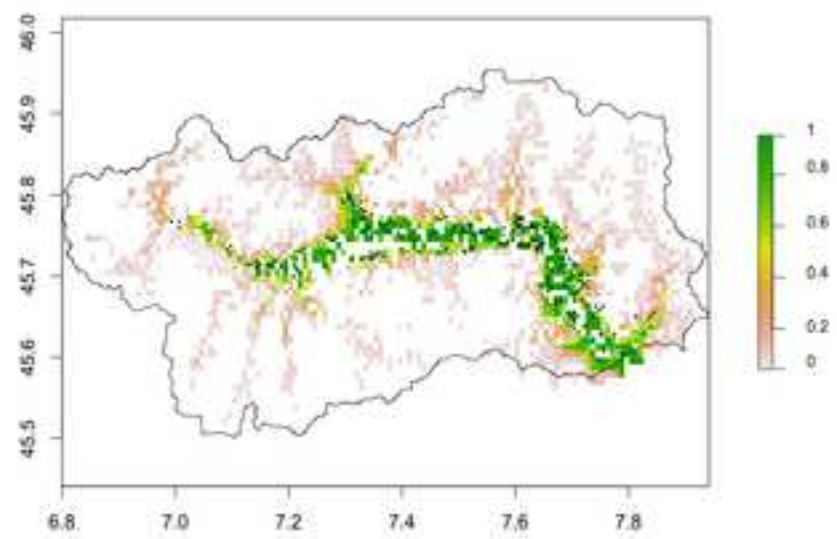
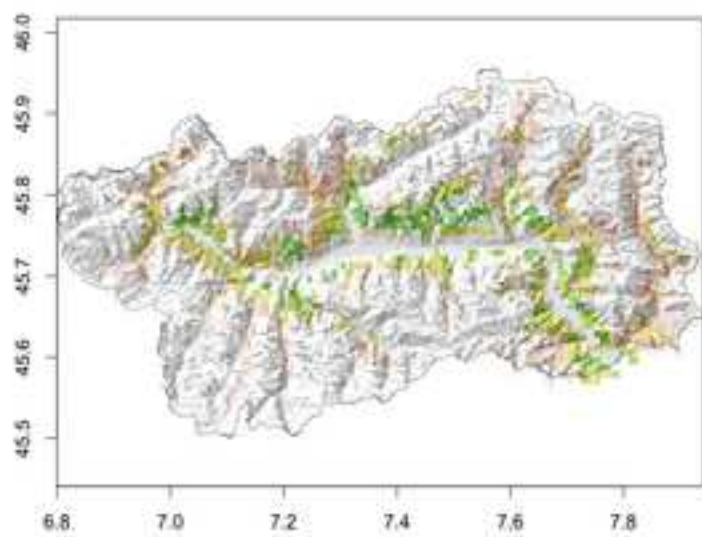




figure 3  
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(a)



(b)

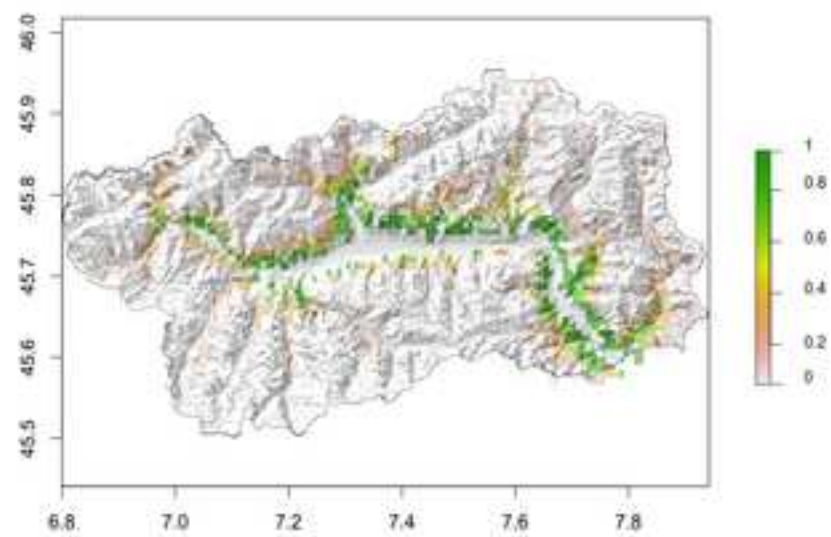
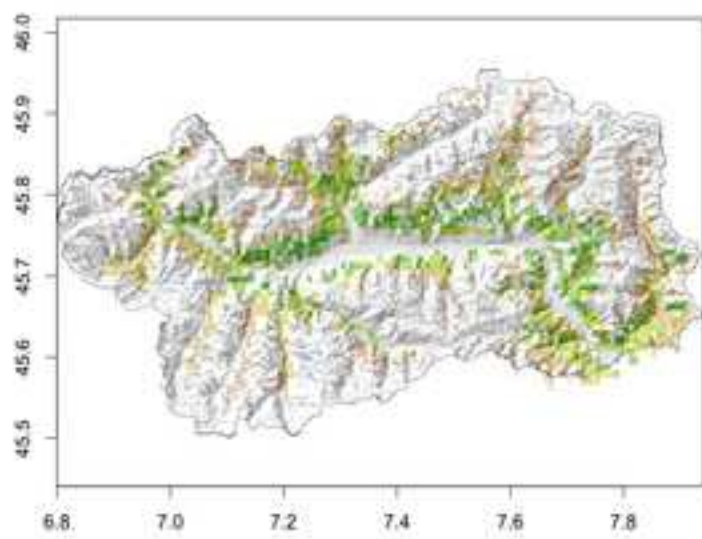


figure 4  
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(a)



(b)

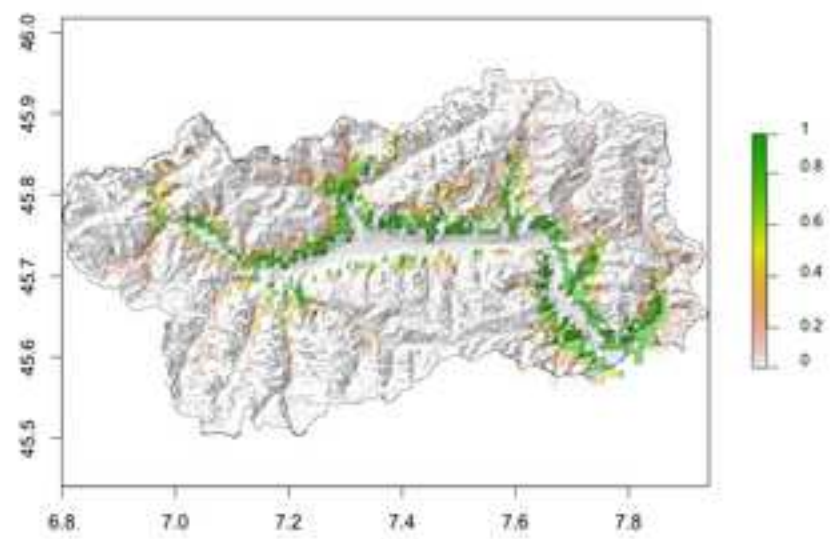




figure S1  
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