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Niklaus E Zimmermann

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### Modelling plant species distribution in alpine grasslands using airborne imaging spectroscopy

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# Modelling plant species distribution in alpine grasslands using airborne imaging spectroscopy

## Abstract

Remote sensing using airborne imaging spectroscopy (AIS) is known to retrieve fundamental optical properties of ecosystems. However, the value of these properties for predicting plant species distribution remains unclear. Here, we assess whether such data can add value to topographic variables for predicting plant distributions in French and Swiss alpine grasslands. We fitted statistical models with high spectral and spatial resolution reflectance data and tested four optical indices sensitive to leaf chlorophyll content, leaf water content and leaf area index. We found moderate added-value of AIS data for predicting alpine plant species distribution. Contrary to expectations, differences between species distribution models (SDMs) were not linked to their local abundance or phylogenetic/functional similarity. Moreover, spectral signatures of species were found to be partly site-specific. We discuss current limits of AIS-based SDMs, highlighting issues of scale and informational content of AIS data.

## Keywords

species distribution, reflectance, hyperspectral data, alpine grasslands

## Disciplines

Medicine and Health Sciences | Social and Behavioral Sciences

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1 **Title:**

2 MODELLING PLANT SPECIES DISTRIBUTION IN ALPINE GRASSLANDS USING  
3 AIRBORNE IMAGING SPECTROSCOPY.

4

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7 Schaepman<sup>3</sup>, Philippe Choler<sup>6,7,8</sup>, Wilfried Thuiller<sup>6,7\*</sup>, Antoine Guisan<sup>1\*</sup>, and Niklaus E.  
8 Zimmermann<sup>5\*</sup>

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23 **Number of figures: 2**

24

25 **Electronic supplementary material:**

26 ESM1: Details on data acquisition, processing and modelling.

27 ESM2: Complementary results.

28

29 **Abstract:**

30 Remote sensing using airborne imaging spectroscopy (AIS) is known to retrieve fundamental  
31 optical properties of ecosystems. However, the value of these properties for predicting plant  
32 species distribution remains unclear. Here, we assess whether such data can add value to  
33 topographic variables for predicting plant distributions in French and Swiss alpine grasslands.  
34 We fitted statistical models with high spectral and spatial resolution reflectance data and  
35 tested four optical indices sensitive to leaf chlorophyll content, leaf water content and leaf  
36 area index. We found moderate added-value of AIS-data for predicting alpine plant species  
37 distribution. Contrary to expectations, differences between species distribution models were  
38 not linked to their local abundance or phylogenetic/functional similarity. Moreover, spectral  
39 signatures of species were found to be partly site-specific. We discuss current limits of AIS-  
40 based species distribution models, highlighting issues of scale and informational content of  
41 AIS-data.

42

43 **Keywords:**

44 species distribution, reflectance, hyperspectral data, alpine grasslands.

45

46 1. INTRODUCTION

47 Spatial modelling of species distributions is commonly used to forecast environmental change  
48 effects, detect biodiversity hotspots or predict species' invasions [1]. As fine-grained  
49 environmental descriptors are difficult to obtain, coarse-grained (from hundred of metres to  
50 kilometres) topo-climatic descriptors are usually used. Recent advances in airborne imaging  
51 spectroscopy (AIS) have allowed the acquisition of images with high spectral and sub-metre  
52 spatial resolution [2]. Spectral information provided by remotely-sensed reflectance is  
53 influenced by phenology, variations in morphological, structural and biochemical properties

54 of species [3], as well as by local environmental conditions (e.g. hydric stress, soil properties  
55 or productivity [4,5]) that determine species habitat suitability [6]. Nevertheless, previous  
56 attempts to predict species distributions with hyperspectral data have generated mixed results  
57 [7,8]. Sub-metre resolution allows the targeting of small plants and micro-habitats where  
58 species find refuge, highlighting potential benefits of hyperspatial remote sensing for  
59 biodiversity monitoring [9]. However, despite increased spatial and spectral resolution of  
60 airborne data, little is known about its value in modelling species' distributions in species-rich  
61 ecosystems characterised by fine-scale heterogeneity.

62 Here, we explore the predictive power of AIS-data for modelling plant species distributions in  
63 alpine grasslands in two distinct regions. Specifically, we aim to: i) identify key remotely-  
64 sensed spectral information for predicting the distribution of grassland species; and ii) assess  
65 whether AIS-data substantially improves model predictions. We also test for any phylogenetic  
66 or functional dependency of model characteristics among species.

67

## 68 2. MATERIAL AND METHODS

### 69 (a) Study sites and species data

70 The study was conducted in the Western French (FR) and Western Swiss (CH) Alps (Electronic  
71 Supplementary Material (ESM) 1). The French site included 103 vegetation plots of 2-5m in radius,  
72 located between 2000 and 2830 metres above sea level (m.a.s.l.). The Swiss site included 68 quadrats  
73 (2 by 2 m) located between 1650 and 2150 m.a.s.l. Species cover was visually estimated using the  
74 Braun-Blanquet abundance scale. In total 160 species were selected for species distribution analysis  
75 (119 species in FR, 78 in CH). Thirty-seven species were common to both sites (see ESM 1 for the  
76 details on selection criteria).

77

### 78 (b) Remote sensing data

79 AIS-data were acquired with the dual Airborne Imaging Spectroradiometer for Applications (AISA;  
80 Specim Ltd., Finland). Raw AISA images contained 359 spectral bands between 400 and 2450 nm  
81 with spectral resolution ranging from 4.3 to 6.3 nm, and a pixel size of 0.8 m. After image processing,  
82 we extracted two types of AIS-predictors: i) reflectance in 75 spectral bands (avoiding bands with  
83 noisy radiometric response), and ii) four vegetation indices. Vegetation indices characterized leaf  
84 chlorophyll (TCARI/OSAVI and ANCB) [10], leaf water content (SIWSI) [11] and leaf area index  
85 (MTVI2) [12] (for details see ESM 1). Removal of poorly-vegetated plots resulted in datasets with 70  
86 FR and 53 CH plots.

87

#### 88 (c) Topographic predictors

89 We computed five predictors derived from digital elevation models at 50 m resolution for FR and 25  
90 m resolution for CH, representing meso-scale habitat conditions : i) elevation (metre), ii) slope  
91 (degree), iii) aspect (degree), iv) topographic position index (unitless), and v) topographic wetness  
92 index (unitless) (see ESM 1).

93

#### 94 (d) Species distribution modelling

95 Species distribution models (SDMs) were fitted with five different sets of variables: i) topographic  
96 predictors only, ii) reflectance predictors only, iii) vegetation indices only, iv) topographic and  
97 reflectance predictors combined, and v) topographic predictors and vegetation indices combined. We  
98 first used a conditional Random Forest algorithm to estimate the unbiased relative importance of  
99 predictors in the case of multi-colinearity, then ran final models based on selection of the most  
100 important predictors [13] (see ESM 1). Their predictive accuracy was evaluated within each study site  
101 separately using a repeated split-sample procedure (100 iterations). 70% of the sample points were  
102 used for model calibration and 30% for model evaluation in each iteration.

103

#### 104 (e) Model differences among species



105 The relative importance of AIS-predictors and the predictive accuracy of SDMs were tested against 1)  
106 species' phylogenetic relatedness, 2) species' functional similarity, including a set of morphological  
107 and physiological traits that are well correlated with the reflectance of canopy stands [14] (see ESM 2,  
108 section 5), and 3) species' abundance patterns within plots. Phylogenetic and functional tests were  
109 computed as described in [15] (see ESM 2, section 5).

110

### 111 3. RESULTS

112 When fitting SDMs with reflectance data the analysis of predictor importance indicated  
113 similarities in the selected spectral bands among sites (Figure 1). The most important spectral  
114 bands were located between 500 and 900 nm for both sites, but site-specific differences in  
115 important spectral bands were also apparent (1500-1800 nm in FR, 1200-1500 nm and 2000-  
116 2500 nm in CH). These site differences existed for species present at only one or both sites  
117 (ESM 2, Figure 1). On average, all vegetation indices showed similar importance for SDM  
118 fitting (ESM 2, Figure 2).

119 The prediction accuracy of SDMs based solely on topographic predictors, reflectance data or  
120 vegetation indices did not differ significantly. However, SDMs including both AIS and  
121 topographic predictors tended to be more accurate (Figure 2 and ESM 2, Table 1). The  
122 improvement was marginally significant for vegetation indices (Wilcoxon rank sum test,  $p$   
123 =0.079) but non-significant for reflectance in FR. Conversely, CH showed significant  
124 improvement when using reflectance (Wilcoxon rank sum test,  $p = 0.012$ ), but non-significant  
125 effects when using vegetation indices. Improvements when including AIS-predictors differed  
126 among species, with few species showing  $\geq 10\%$  improved predictions and many showing  
127 reduced predictive accuracy (ESM 2, Figure 3). These variations were independent of species'  
128 abundance patterns and species' phylogenetic or functional similarity (ESM 2, Figures 4-13).

129

### 130 4. DISCUSSION

131 Overall, topographic and AIS-based SDMs revealed similar predictive accuracies in both  
132 sites. Model accuracy was on average higher in FR than in CH, while the topographical and  
133 spectral ranges observed in CH were much narrower than in FR (ESM 1, Figures 2, 4, 5). This  
134 agrees with previous studies where accuracy of SDMs derived from satellite images increased  
135 with steepness of ecological gradients [6]. Unlike vegetation indices, we found that  
136 importance of spectral bands differed between sites. Site-specific differences may partly  
137 reflect canopy differences due to nutrient status or soil chemistry since reflectance in these  
138 spectral regions is sensitive to light absorption by water [12], biochemical constituents [14]  
139 and scattering by plant architecture [11]. Additional field measurements of vegetation  
140 properties could probably improve ecological understanding of these spectral regions in  
141 SDMs.

142 The distribution models fit differed between species. Overall, models including both  
143 topographic and AIS-predictors tended to be more accurate, even though significant  
144 improvements were confined to a limited number of species. This contrasts with results  
145 reported for invasive weeds [16], but agrees with results from meadows [7] where plant  
146 assemblages are inextricably mixed at the fine scale. Benefits of high spatial resolution of  
147 remote-sensing data is a subject of debate [17]. Although our methodology considers the  
148 existence of geometric misalignment between AIS-images and plot georeferencing, it still  
149 represents a source of uncertainty for matching reflectance of small pixels with local species  
150 occurrence. The significance of this uncertainty for species distribution modelling remains to  
151 be assessed.

152 We expected that differences between species models in terms of predictive accuracy and  
153 relative importance of AIS-predictors would be linked to i) abundance of species within-plots  
154 since locally-dominant species contribute more to canopy reflectance, and ii) phylogenetic or  
155 functional similarity, assuming that similar species show either comparable spectral signatures

156 or similar habitat requirements as reflected by AIS-data. These hypotheses were not  
157 supported. We suggest two possible explanations for such idiosyncrasy. Firstly, accurate  
158 estimation of species' similarity may be limited by uncertainties in phylogenetic trait  
159 conservatism or availability of plant functional trait data. Phylogenies can often contribute to  
160 the integrated comparison of plant functional and life-history traits among species. However,  
161 the evolution of traits is characterized by both conservatism and diversification, and close  
162 links between functional similarity and phylogenetic relatedness are not always found [18]. In  
163 the present study, we described species' functional similarity using morphological and  
164 ecophysiological traits that are recognized as key canopy reflectance drivers [14]. However,  
165 biochemical traits such as leaf nitrogen, chlorophyll or phosphorus content were not available  
166 for all species, and should be included wherever possible. Secondly, AIS-based SDMs may  
167 reflect both species' spectral signature and micro-habitat suitability [19] (contrary to  
168 topography-based models which reflect solely habitat suitability at meso-scales). These two  
169 factors may differ in importance when fitting AIS-variables across species and sites. This  
170 would explain why AIS-based models of both locally-dominant (species detection scenario,  
171 e.g. *Dryas octopetalla*), and low-abundance species (habitat suitability scenario, e.g.  
172 *Helictotrichon sedense*) show equivalent accuracy despite very different species contributions  
173 to canopy characteristics and functional traits. Future research should focus on discriminating  
174 between species detection and habitat suitability for an array of species and ecosystem types  
175 (of varying degree of vegetation complexity), to better assess the ecological relevance of  
176 imaging spectroscopy for species' distribution modelling.

177

178 Data accessibility:

179 Data available from the Dryad Digital Repository: doi:10.5061/dryad.n13hn

180

181

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190 version of the manuscript.

191

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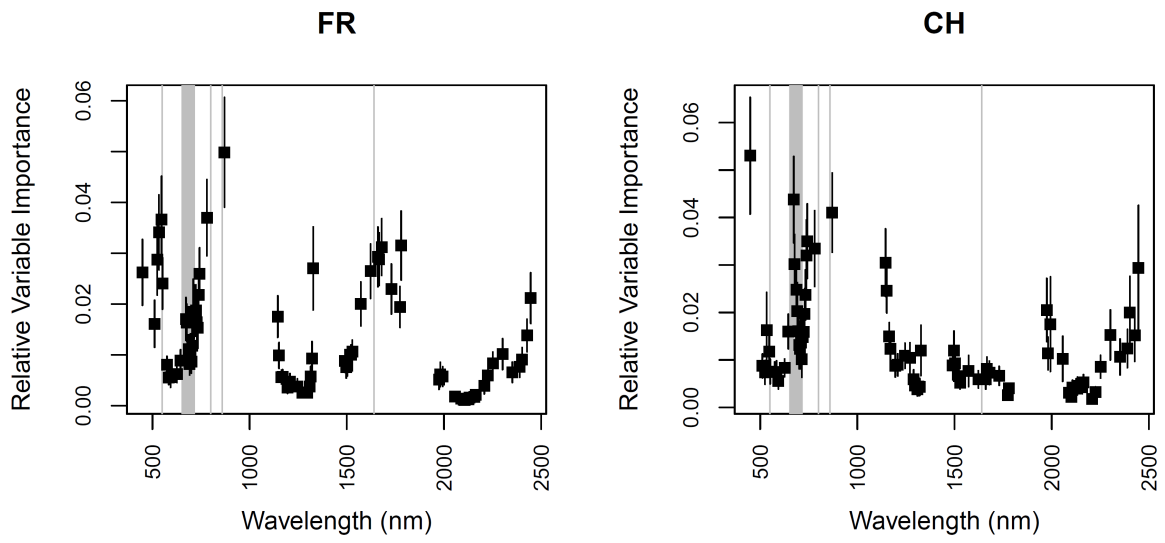
253 **Figure 1:** Relative importance of reflectance intensity in spectral bands for predicting species  
254 distributions at study sites in France (FR) and Switzerland (CH). Variable importance was  
255 assessed using conditional inference in Random Forest models. Gray areas represent bands  
256 used for the calculation of vegetation indices.

257

258 **Figure 2:** Prediction accuracy of species distribution models (based on the area under the  
259 curve of a receiver-operating characteristic plot: AUC) built with Random Forest models at  
260 study sites in France (FR) and Switzerland (CH). Topo indicates topographic-predictors, BS  
261 indicates reflectance recorded in the spectral bands and VI indicates vegetation indices.

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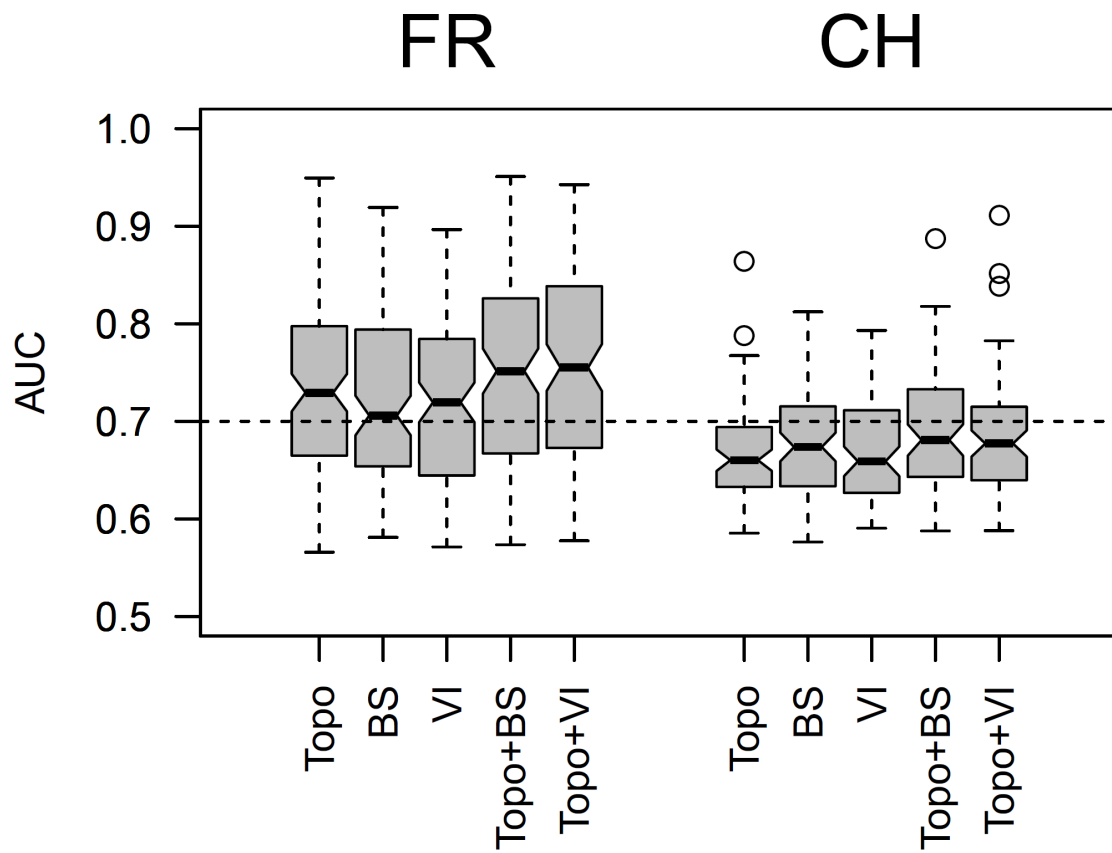
263 **Figure 1**



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266 **Figure 2**



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269 **Electronic Supplementary Material 1:**  
270 **Details on data acquisition, processing and modelling.**

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274 **1) The study sites**

275

276 **ESM 1 Table 1: Topographic, environmental and floristic characteristics of the two study**  
277 **areas.**

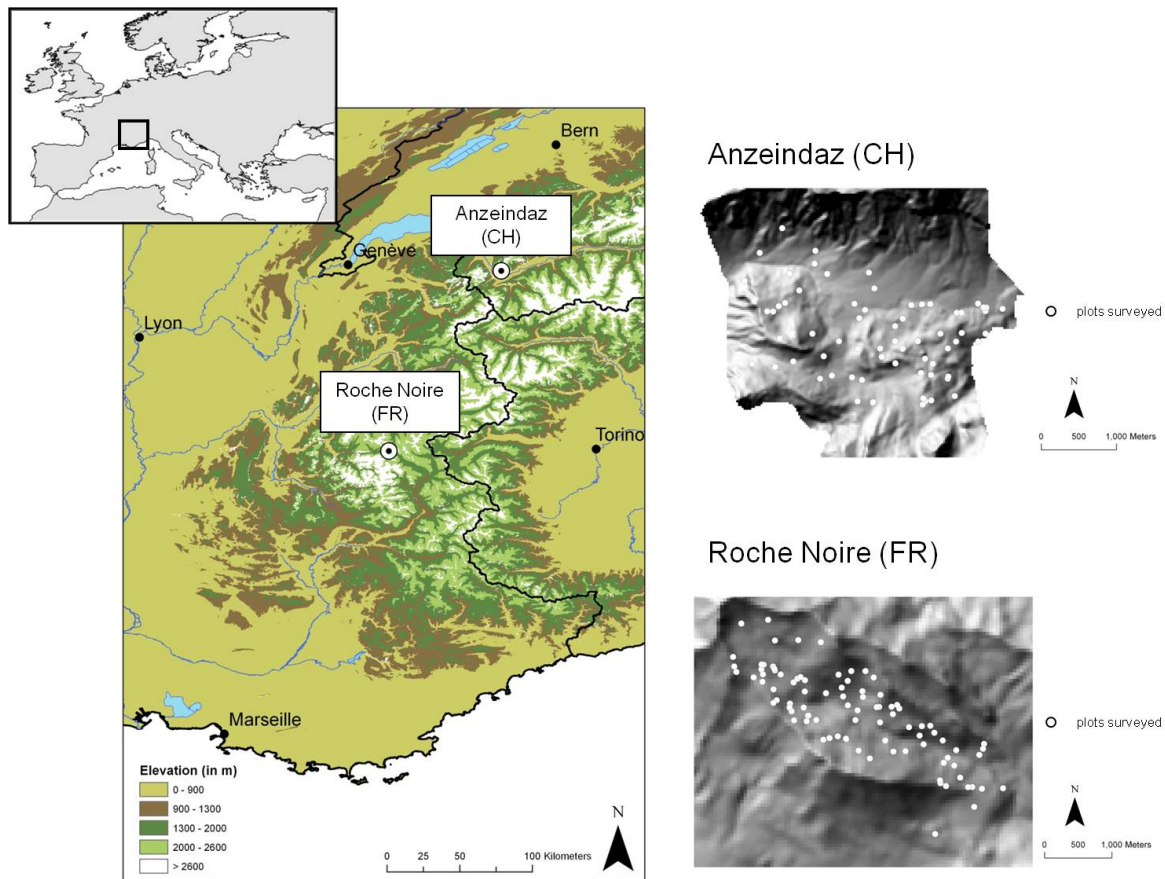
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	French site (FR)	Swiss site (CH)
Location name	Roche Noire	Anzeindaz
Geographic coordinates	45°2.3' to 45°4.2'N 6°21.6' to 6°25.2'E	46°15' to 46°18'N, 7°07' to 7°11'E
Elevation range	1900 m to 3000 m	1650 m to 2150 m
Mean annual temperature	4.8°C	1.3 °C
Mean summer precipitation	180 mm	485 mm
Bed rock	Flysch	Calcareous
Number of inventoried plots	103	68

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## 2) Floristic data

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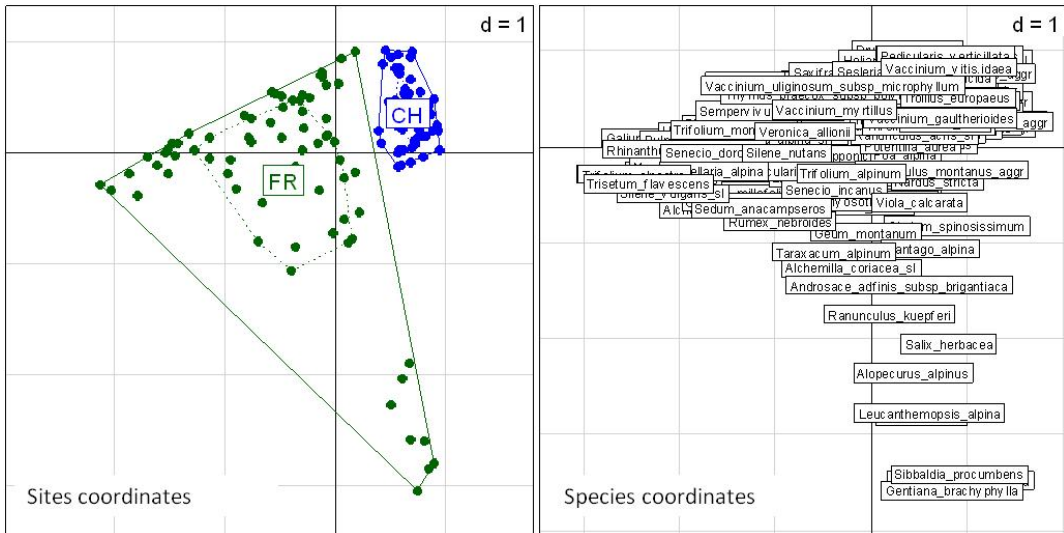
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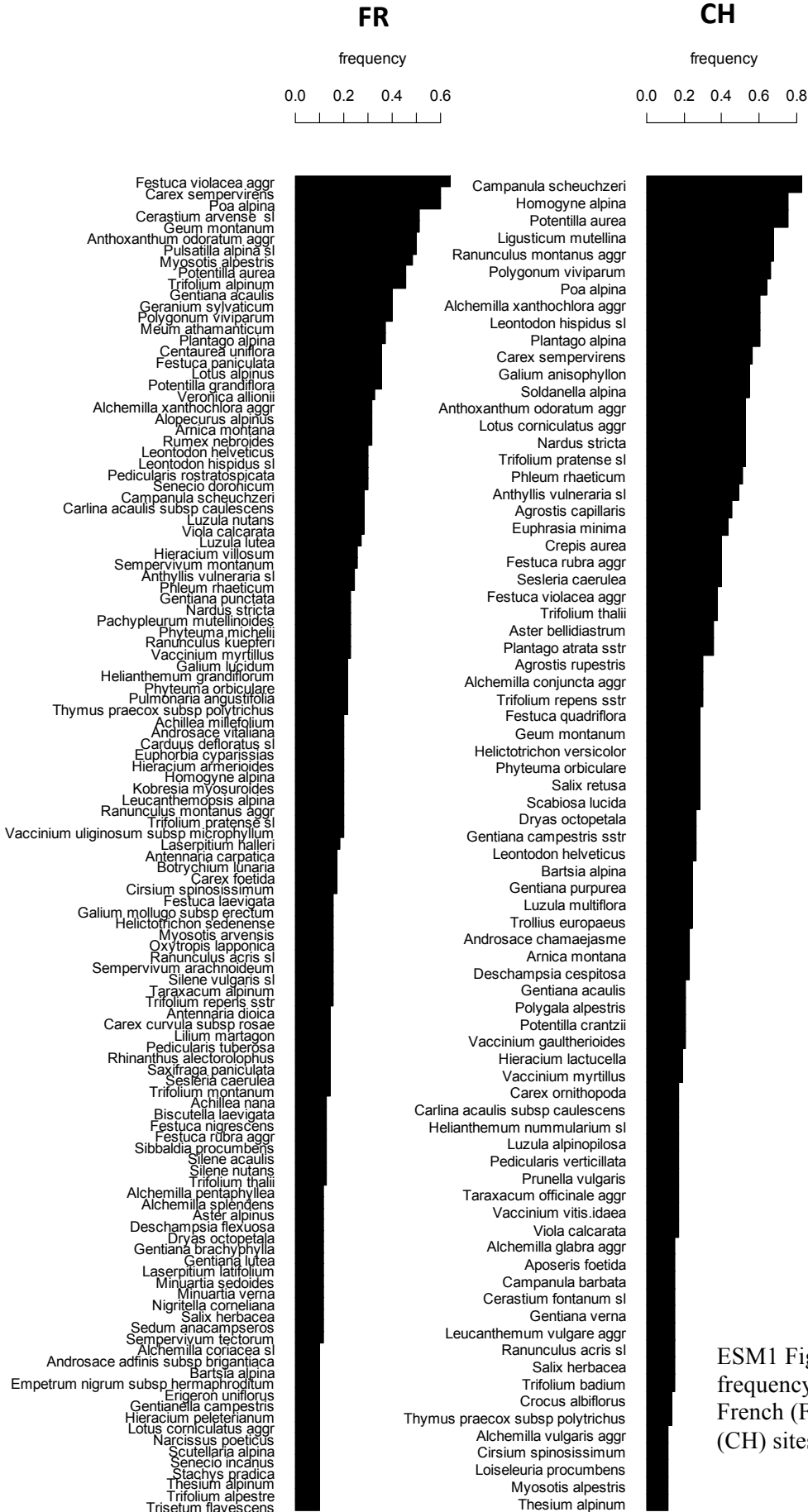
ESM 1 Fig. 1: Location of the two study areas. The minimum distance between vegetation plots is 21.91 m (mean of 1327.71 m) for FR and 12.67 m (mean of 1307.44 m) for CH.

Vegetation sampling was based on random stratified sampling designs to ensure covering equally well the different vegetation types of both FR and CH. Size of vegetation plots was chosen to approach exhaustive recording of the species. As vegetation structure differed between both sites, 2 m quadrat was chosen for CH and plots of 5 m in radius for FR. In addition, few plots of 2 m in radius were chosen in FR for sampling snowbelts. In such habitats species coexist at very fine scale so that reduced plot size still allow exhaustive sampling of the species of local vegetation patches. However, snowbelts are also characterised by fine scale vegetation changes in space. Thus, plots of 2 m in radius, compare to 5 m in radius, avoided bias in sampling associated vegetation type by edge effects.



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ESM1 Fig 2: Correspondence analysis of floristic data. Between site inertia ratio = 0.06 with  $Pvalue < 0.001$  (Permutation test with 9999 permutations, alternative is greater).



ESM1 Fig 3: Species rank-frequency curves for the French (FR) and Swiss (CH) sites.

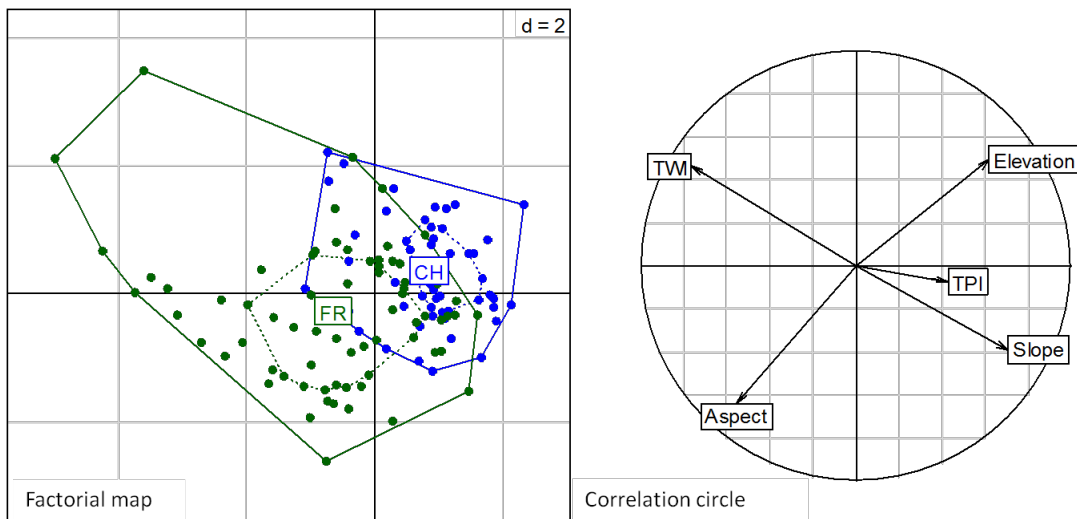
306 **3) Topographic predictors**

307

308 We computed five predictors derived from digital elevation models at 50 m resolution for FR  
309 and 25 m resolution for CH, providing useful information on meso-scale habitat conditions in  
310 species distribution models [1]. Topographic predictors were: 1) elevation (in meters); 2)  
311 slope (in degrees); 3) aspect (in degrees from north); 4) Topographic Position Index (TPI), an  
312 integrated measure of topographic exposure (unitless) [2]; 5) Topographic Wetness Index  
313 (TWI), which quantifies topographic control on soil moisture (unitless), [3]. The last is  
314 calculated as follows  $TWI = \ln(a / \tan(b))$  where  $a$  is the area of the upstream contribution  
315 (flow accumulation) and  $b$  is the slope in radians .

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322 ESM1 Fig 4: Principal component analysis of the topographic predictors. Between site  
323 inertia ratio = 0.14 with  $Pvalue < 0.001$  (Permutation test with 9999 permutations,  
324 alternative is greater). This result shows that topographical conditions of vegetation  
325 plots differ between the French (FR) and Swiss (CH) sites.

324

325

326 **4) Remote sensing predictors**

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328 a. Airborne image acquisition and processing

329 The airborne imaging spectroscopy (AIS) data were acquired with an AISA Dual system  
330 (Specim, Ltd. Finland). Images of the French study site (FR) were collected on 23<sup>rd</sup> July 2008

331 and for the Swiss study site (CH) on 24<sup>th</sup> July 2008 under clear sky and sunny conditions.  
332 Images were acquired in a high spectral and spatial resolution mode, which resulted in a  
333 spectral image data cube with 359 narrow spectral bands between 400 and 2450 nm and the  
334 ground pixel size of 0.8 m.

335

336 The basic processing of AISA Dual images comprised of radiometric, geometric, and  
337 atmospheric correction. The radiometric correction that converted image digital numbers into  
338 radiance values [ $\text{W}\cdot\text{m}^{-2}\cdot\text{sr}^{-1}\cdot\mu\text{m}^{-1}$ ] was performed in the CaliGeo software (CaliGeo v.4.6.4 -  
339 AISA processing toolbox, Specim, 2007) using the factory delivered radiometric calibration  
340 coefficients. Images were geometrically corrected using the onboard navigation data from the  
341 Inertial Navigation System and a local digital elevation model (spatial resolution of 2.5 m for  
342 FR and 1 m for CH site). Images were further orthorectified into the Universal Transverse  
343 Mercator (UTM, Zone 32N) map projection. An accuracy of the geometric correction was  
344 evaluated by calculating an average root mean square error (RMSE) between distinct image  
345 displayed and ground measured control points. Assessment resulted into an average RMSE of  
346 about 2.04 m for the French site and about 1.25 m for the Swiss site. Atmospheric corrections  
347 were combined with vicarious radiometric calibrations in the ATCOR-4 software [4]. To  
348 eliminate random noise, spectra of the atmospherically corrected images were smoothed by a  
349 moving average filter with the window size of 7 bands. Accuracy of the atmospheric  
350 corrections was evaluated by comparing image surface reflectance with a set of ground  
351 measured reference spectra. An average reflectance RMSE between the image and the ground  
352 target spectra was equal to 2.1% for the French and 1.6% for the Swiss site. As the final step  
353 of the image processing we applied a fully constrained linear spectral unmixing algorithm [5]  
354 to identify pixels with high vegetation fraction. Only pixels with vegetation fraction higher  
355 than 75% were included into further analysis of species distribution modelling.

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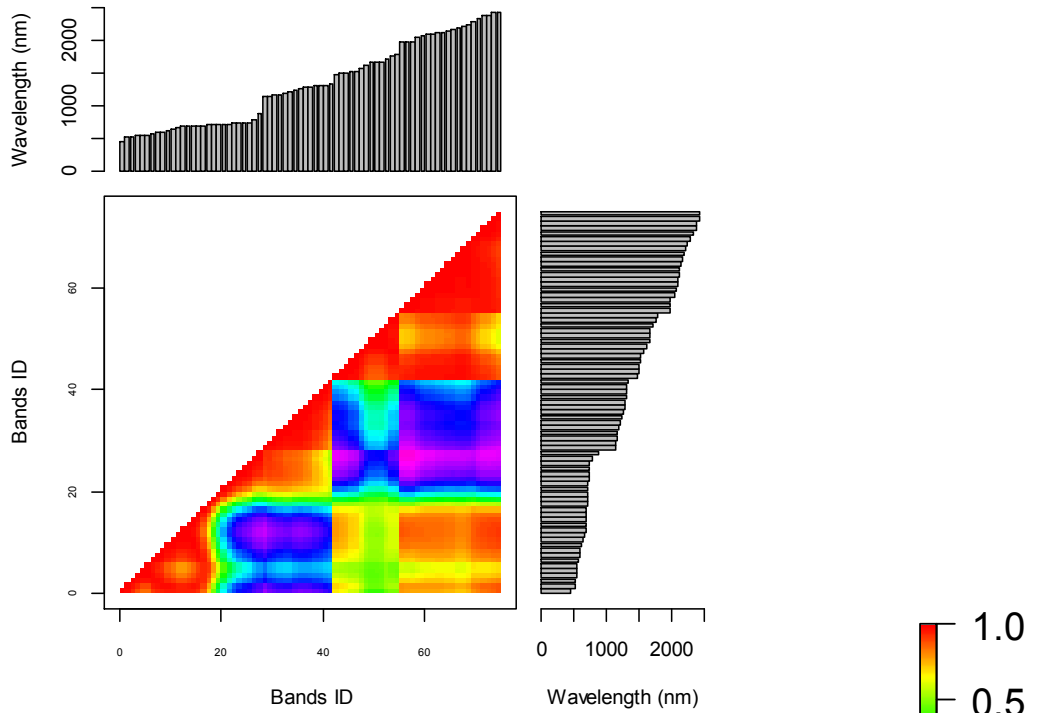
357 We paired the AISA image data with the georeferenced plots, where floristic species  
358 composition was investigated in-situ. Their geographical locations were superimposed over  
359 the AISA images and the reflectance function of each a research plot was averaged. Plots with  
360 high proportion of non-vegetated pixels (i.e. pixels with vegetation fraction lower than 75%  
361 due to the occurrence of stones or bare soil patches) were excluded. After this selection, we  
362 retained 70 plots at the French site and 53 plots at the Swiss site. Two types of remote sensing  
363 predictors were tested for the species distribution modelling: i) reflectance intensity of 75  
364 noise-free bands and ii) four vegetation indices (summarized in Table 2).

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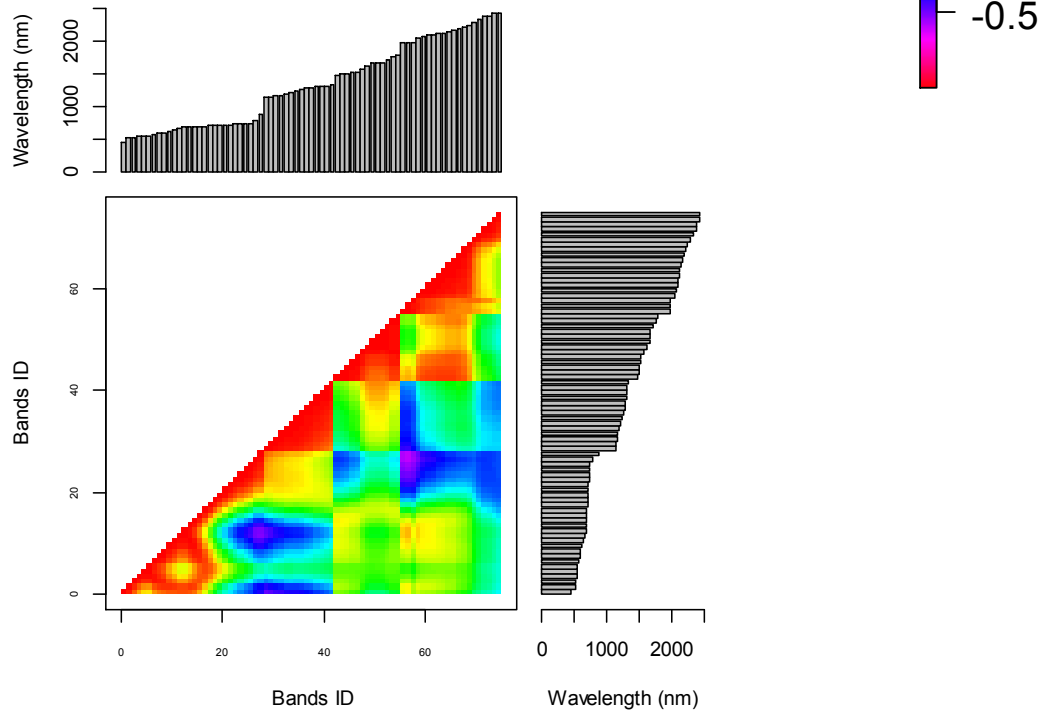
366                   b. Removal of spectral bands with low signal quality

367 Only 75 spectral bands out of 359 were included in the species distribution analysis. We  
368 removed bands with poor signal quality due to the low radiometric sensitivity at the edges of  
369 both sensor spectral ranges (401-444, 876-1140 and around 2450 nm), bands strongly  
370 influenced by atmospheric water vapor absorption (i.e., 1334-1485 and 1786-1968 nm) and  
371 adjacent bands of near infrared wavelengths between 752 and 771 nm, which are highly  
372 correlated and contain redundant spectral information.

FR



CH

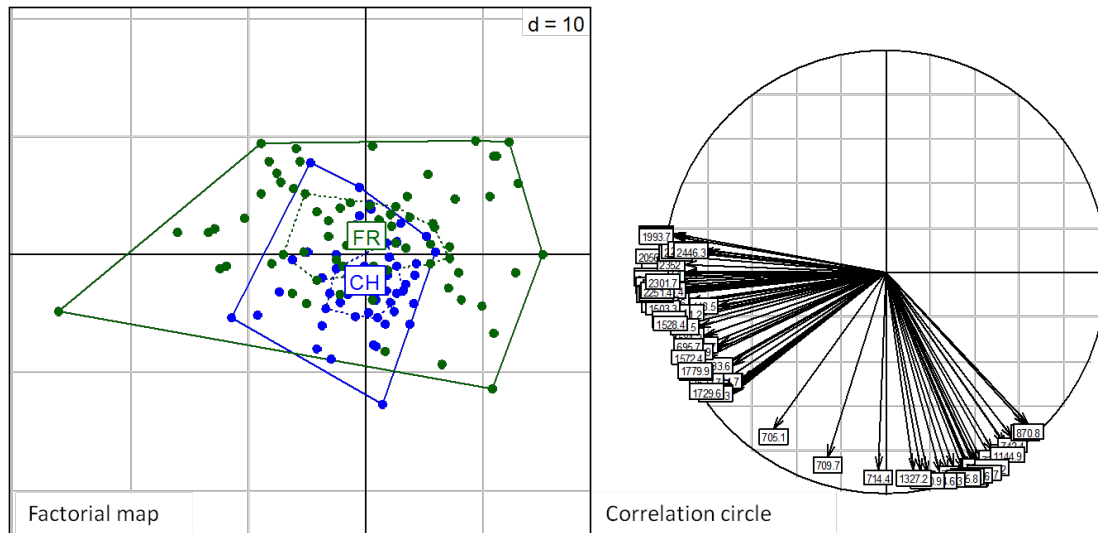


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ESM1 Fig 5: Between reflectance bands correlation patterns for the French (FR) and Swiss (CH) sites. Although band selection (75 out of 359) led to the removal of highly correlated adjacent bands, many non-adjacent bands were strongly correlated. This justifies the use of unbiased conditional random forest in case of multicollinearity.





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### c. Calculation of vegetation indices and the between site PCA

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ESM1 Fig 6: Principal component analysis of the 75 reflectance bands. Between site inertia ratio = 0.06 with  $Pvalue < 0.001$  (Permutation test with 9999 permutations, alternative is greater). This result shows that reflectance pattern of vegetation plots differed between the French (FR) and Swiss (CH) sites.

Four vegetation optical indices, defined in Table 2, were selected as remote sensing indicators of the vegetation biochemical and biophysical properties. Two indices are highly sensitive to leaf chlorophyll content, but insensitive to the variations in amount of green biomass (TCARI/OSAVI and ANCB<sub>650-720</sub>). MTVI2 index was chosen as an indicator of green leaf area index, while suppressing negative confounding influence of leaf chlorophyll content. Finally, SIWSI index is sensitive to plant water content. The variability of the selected optical indices is expected to be species composition specific in accordance with the species-specific changes of the related biochemical and biophysical characteristics. These four indices can thus potentially discriminate key properties of the species, justifying their use for species distribution modeling.

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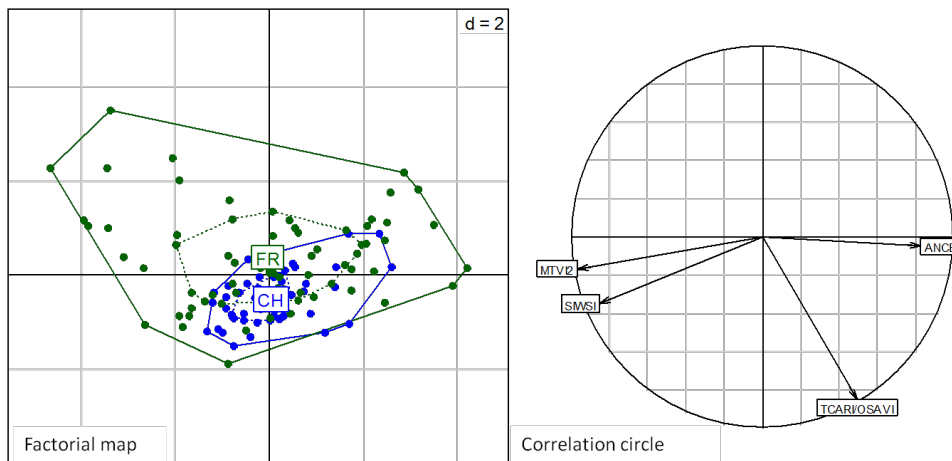
395 EMS 1 Table 2: Vegetation indices tested for species distribution modeling

396

Vegetation index	Equation	Reference
Transformed Chlorophyll Absorbance Reflectance Index / Optimized Soil-Adjusted Vegetation Index  (TCARI/OSAVI)	$TCARI = 3[R_{700} - R_{670} - 0.2(R_{700} - R_{550})(R_{700}/R_{670})]$ $OSAVI = \frac{1.16(R_{800} - R_{670})}{R_{700} + R_{670} + 0.16}$	Haboudane et al, (2002) [5]
Area under curve Normalized to the Continuum-removed Band depth (ANCB <sub>650-720</sub> )	$\frac{AUC_{650-720}}{CBD_{670}}$ <p>where AUC<sub>650-720</sub> is area under continuum removed reflectance between 650-720 nm and CBD<sub>670</sub> is continuum removed band depth at 670 nm</p>	Malenovsky et al. (2013) [6]
Modified Triangular Vegetation Index (MTVI2)	$\frac{1.5[1.2(R_{800} - R_{550}) - 2.5(R_{670} - R_{550})]}{\sqrt{(2R_{800} + 1)^2 - (6R_{800} - 5\sqrt{R_{570}}) - 0.5}}$	Haboudane et al. (2004) [7]
Shortwave Infrared Water Stress Index (SIWSI)	$\frac{R_{858.5} - R_{1640}}{R_{858.5} + R_{1640}}$	Cheng et al. (2006) [8]

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401 ESM1 Fig 7: Principal component analysis of the remote sensing predictors  
 (vegetation indices. Between site inertia ratio = 0.05 with *Pvalue*=0.003 (Permutation  
 402 test with 9999 permutations, alternative is greater). This result shows that reflectance  
 indices of vegetation plots differed between the French (FR) and Swiss (CH) sites.

403

404 d. Correlation of AIS-data with topographic predictors

405 AIS and topographical data were weakly correlated (max absolute values for Pearson  
406 correlations amounted to 0.40-0.55 between elevation and bands in the range of 2000 and  
407 2500 nm, while most of absolute values for Pearson correlation coefficients are between 0 and  
408 0.3). Absence of strong correlation allows for mixing both types of data in species distribution  
409 models, as topographic- (indicating meso-scale habitat suitability of the species) and fine-  
410 scale AIS-data may represent complementary information.

## 411 **5) Selection of spectral bands for building final species distribution models**

412 Based on the analysis performed to quantify the importance of each of the 75 spectral bands,  
413 we built final species distribution models according to the following variable selection  
414 procedure:

- 415 1. Rank bands in decreasing order of importance
- 416 2. While not all bands have been considered, select the first ranked band (with the  
417 highest relative importance) and remove all bands showing correlation  $>0.7$  with the  
418 previously selected band.

419 This procedure was performed with random forest (RF) using conditional inference trees as  
420 base learners and was implemented with the *party* library [9] for R [10]. Variable importance  
421 is measured as the mean decrease in accuracy of model predictions after permuting the  
422 predictor variables.

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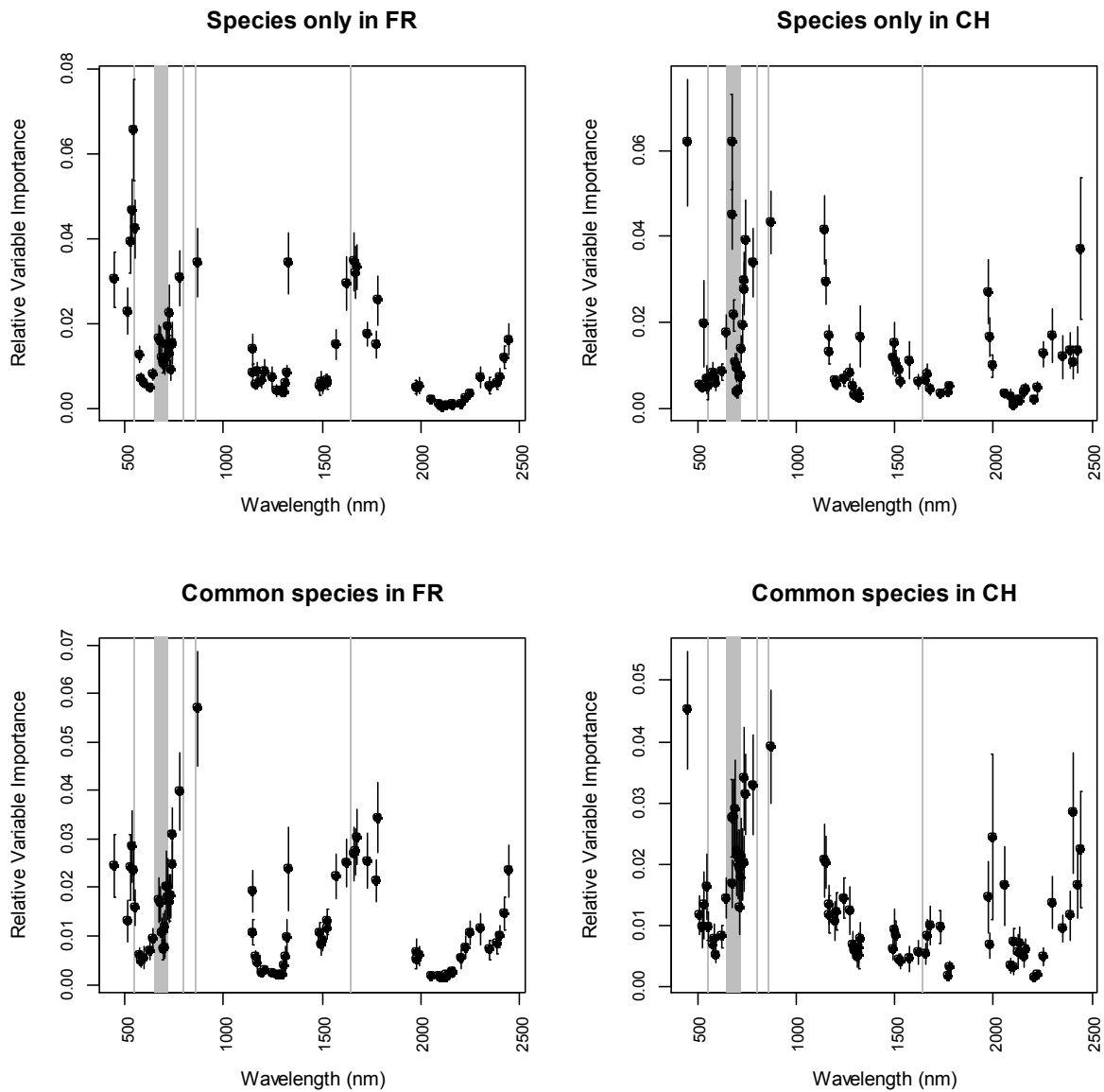
457 **Electronic Supplementary Material 2:**

458 **Complementary results.**

459

460 **1) Relative importance of reflectance intensity in spectral bands for predicting the**  
461 **distribution of species recorded only in one of the two sites or recorded in both**  
462 **sites.**

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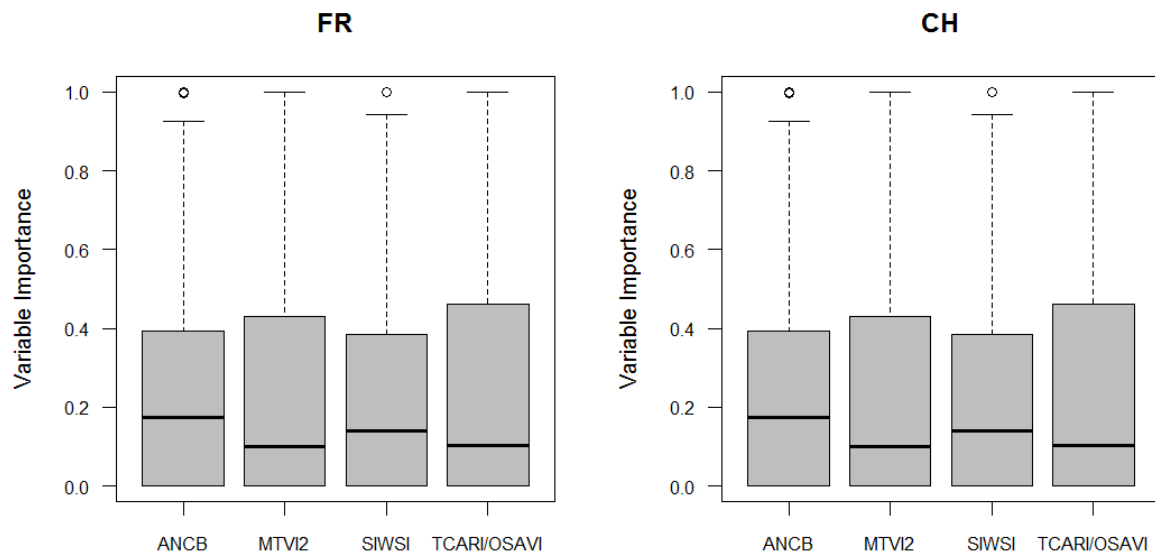


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466 **ESM2 Fig 1: Relative importance of reflectance intensity in spectral bands for predicting**  
467 **the distribution of species recorded only in the French site (FR), only in the Swiss site**  
468 **(CH), recorded in both sites but modeled in the French site and recorded in both sites but**  
**modeled in the Swiss site. Gray areas represent bands used for the calculation of the**  
**vegetation indices.**

469 **2) Variable importance of vegetation indices for the French site (FR) and the Swiss**  
 470 **site (CH).**



471 ES2 Fig 2: Variable importance of the RS-retrieved vegetation indices for modeling  
 472 species distribution. FR for the French site and CH for the Swiss site. Details on the  
 473 calculation of indices can be found in ES1.

474  
 475 **3) Detailed prediction accuracy of species distribution models.**

476  
 477 ES2 Table 1: Summary table of prediction accuracy of species distribution models assessed with  
 478 the area under the curve of a receiver-operating characteristic plot: AUC. Topo indicates models based  
 479 on topographic predictors only, BS models based on reflectance selected spectral bands. VI indicates  
 480 models based on vegetation indices only. Topo+BS and Topo+VI indicate respectively models based  
 481 on topographic predictors and reflectance or vegetation indices as predictors. Species are listed in  
 482 alphabetic order according to their occurrence in the two sites. Green highlighting indicates species  
 483 that showed at least 10% improvement of model accuracy when adding the AIS-predictors to  
 484 topographic based models in at least one of the two sites. AUC values above 0.7 can be considered as  
 485 models with good prediction accuracy.  
 486

	Topo		BS		Topo+BS		VI		Topo+VI	
	FR	CH	FR	CH	FR	CH	FR	CH	FR	CH
<i>Achillea millefolium</i>	0.686	-	0.807	-	0.811	-	0.8	-	0.827	-
<i>Achillea nana</i>	0.8	-	0.703	-	0.783	-	0.737	-	0.746	-
<i>Alchemilla coriacea</i> sl.	0.735	-	0.707	-	0.717	-	0.721	-	0.732	-
<i>Alchemilla pentaphyllea</i>	0.893	-	0.763	-	0.897	-	0.817	-	0.884	-
<i>Alchemilla splendens</i>	0.695	-	0.682	-	0.728	-	0.664	-	0.727	-
<i>Alopecurus alpinus</i>	0.742	-	0.607	-	0.704	-	0.668	-	0.733	-
<i>Androsace adfinis</i> subsp. <i>brigantiaca</i>	0.703	-	0.65	-	0.713	-	0.719	-	0.763	-

<i>Androsace vitaliana</i>	0.666	-	0.785	-	0.786	-	0.786	-	0.76	-
<i>Antennaria carpatica</i>	0.776	-	0.757	-	0.823	-	0.743	-	0.787	-
<i>Antennaria dioica</i>	0.783	-	0.675	-	0.783	-	0.639	-	0.737	-
<i>Aster alpinus</i>	0.703	-	0.689	-	0.664	-	0.662	-	0.711	-
<i>Biscutella laevigata</i>	0.795	-	0.631	-	0.722	-	0.627	-	0.755	-
<i>Botrychium lunaria</i>	0.681	-	0.704	-	0.679	-	0.722	-	0.711	-
<i>Carduus defloratus</i> sl.	0.852	-	0.796	-	0.817	-	0.751	-	0.836	-
<i>Carex curvula</i> subsp. <i>rosae</i>	0.789	-	0.803	-	0.827	-	0.82	-	0.764	-
<i>Carex foetida</i>	0.78	-	0.655	-	0.721	-	0.67	-	0.763	-
<i>Centaurea uniflora</i>	0.781	-	0.8	-	0.864	-	0.779	-	0.837	-
<i>Cerastium arvense</i> sl.	0.677	-	0.581	-	0.663	-	0.592	-	0.689	-
<i>Deschampsia flexuosa</i>	0.658	-	0.653	-	0.597	-	0.729	-	0.657	-
<i>Empetrum nigrum</i> subsp. <i>hermaphroditum</i>	0.943	-	0.843	-	0.933	-	0.897	-	0.931	-
<i>Erigeron uniflorus</i>	0.656	-	0.664	-	0.66	-	0.672	-	0.673	-
<i>Euphorbia cyparissias</i>	0.832	-	0.785	-	0.842	-	0.755	-	0.852	-
<i>Festuca laevigata</i>	0.846	-	0.681	-	0.859	-	0.702	-	0.87	-
<i>Festuca nigrescens</i>	0.607	-	0.705	-	0.658	-	0.686	-	0.62	-
<i>Festuca paniculata</i>	0.741	-	0.746	-	0.782	-	0.783	-	0.839	-
<i>Galium lucidum</i>	0.776	-	0.66	-	0.746	-	0.613	-	0.765	-
<i>Galium mollugo</i> subsp. <i>erectum</i>	0.87	-	0.756	-	0.848	-	0.73	-	0.874	-
<i>Gentiana brachyphylla</i>	0.882	-	0.664	-	0.859	-	0.736	-	0.903	-
<i>Gentiana lutea</i>	0.949	-	0.801	-	0.942	-	0.737	-	0.943	-
<i>Gentiana punctata</i>	0.709	-	0.706	-	0.708	-	0.692	-	0.71	-
<i>Gentianella campestris</i>	0.719	-	0.656	-	0.676	-	0.686	-	0.708	-
<i>Geranium sylvaticum</i>	0.775	-	0.796	-	0.801	-	0.82	-	0.821	-
<i>Helianthemum grandiflorum</i>	0.775	-	0.642	-	0.74	-	0.62	-	0.752	-
<i>Helictotrichon sedenense</i>	0.64	-	0.858	-	0.839	-	0.849	-	0.837	-
<i>Hieracium armerioides</i>	0.633	-	0.692	-	0.666	-	0.72	-	0.645	-
<i>Hieracium peleterianum</i>	0.645	-	0.692	-	0.635	-	0.673	-	0.648	-
<i>Hieracium villosum</i>	0.616	-	0.608	-	0.645	-	0.613	-	0.597	-
<i>Kobresia myosuroides</i>	0.68	-	0.695	-	0.732	-	0.738	-	0.73	-
<i>Laserpitium halleri</i>	0.73	-	0.803	-	0.771	-	0.718	-	0.701	-
<i>Laserpitium latifolium</i>	0.864	-	0.852	-	0.908	-	0.82	-	0.87	-
<i>Leucanthemopsis alpina</i>	0.734	-	0.822	-	0.861	-	0.829	-	0.858	-
<i>Lilium martagon</i>	0.819	-	0.806	-	0.789	-	0.783	-	0.839	-
<i>Lotus alpinus</i>	0.626	-	0.624	-	0.628	-	0.602	-	0.615	-
<i>Luzula lutea</i>	0.725	-	0.762	-	0.762	-	0.753	-	0.754	-
<i>Luzula nutans</i>	0.623	-	0.657	-	0.669	-	0.631	-	0.633	-
<i>Meum athamanticum</i>	0.829	-	0.919	-	0.931	-	0.881	-	0.888	-
<i>Minuartia sedoides</i>	0.783	-	0.77	-	0.806	-	0.779	-	0.767	-
<i>Minuartia verna</i>	0.753	-	0.824	-	0.817	-	0.821	-	0.896	-
<i>Myosotis arvensis</i>	0.85	-	0.859	-	0.876	-	0.822	-	0.847	-
<i>Narcissus poeticus</i>	0.935	-	0.875	-	0.951	-	0.886	-	0.942	-
<i>Nigritella corneliana</i>	0.615	-	0.592	-	0.622	-	0.631	-	0.621	-
<i>Oxytropis lapponica</i>	0.645	-	0.733	-	0.662	-	0.632	-	0.641	-

<i>Pachypleurum mutellinoides</i>	0.828	-	0.831	-	0.841	-	0.797	-	0.845	-
<i>Pedicularis rostratospicata</i>	0.64	-	0.592	-	0.647	-	0.624	-	0.642	-
<i>Pedicularis tuberosa</i>	0.748	-	0.758	-	0.786	-	0.686	-	0.765	-
<i>Phyteuma michelii</i>	0.75	-	0.686	-	0.752	-	0.66	-	0.727	-
<i>Potentilla grandiflora</i>	0.801	-	0.768	-	0.809	-	0.735	-	0.785	-
<i>Pulmonaria angustifolia</i>	0.781	-	0.781	-	0.801	-	0.779	-	0.837	-
<i>Pulsatilla alpina</i> sl.	0.566	-	0.601	-	0.574	-	0.594	-	0.584	-
<i>Ranunculus kuepferi</i>	0.727	-	0.612	-	0.693	-	0.6	-	0.698	-
<i>Rhinanthus alectorolophus</i>	0.864	-	0.869	-	0.932	-	0.847	-	0.926	-
<i>Rumex nebroides</i>	0.673	-	0.726	-	0.719	-	0.746	-	0.713	-
<b><i>Saxifraga paniculata</i></b>	<b>0.665</b>	-	0.843	-	<b>0.853</b>	-	0.861	-	<b>0.846</b>	-
<i>Scutellaria alpina</i>	0.864	-	0.777	-	0.894	-	0.777	-	0.879	-
<i>Sedum anacampseros</i>	0.691	-	0.643	-	0.676	-	0.705	-	0.693	-
<b><i>Sempervivum arachnoideum</i></b>	<b>0.707</b>	-	0.75	-	0.774	-	0.798	-	<b>0.816</b>	-
<i>Sempervivum montanum</i>	0.752	-	0.719	-	0.754	-	0.736	-	0.795	-
<i>Sempervivum tectorum</i>	0.745	-	0.645	-	0.756	-	0.623	-	0.776	-
<i>Senecio doronicum</i>	0.841	-	0.779	-	0.826	-	0.778	-	0.83	-
<i>Senecio incanus</i>	0.683	-	0.699	-	0.662	-	0.704	-	0.667	-
<i>Sibbaldia procumbens</i>	0.836	-	0.721	-	0.841	-	0.858	-	0.877	-
<i>Silene acaulis</i>	0.774	-	0.832	-	0.834	-	0.848	-	0.849	-
<i>Silene nutans</i>	0.683	-	0.678	-	0.669	-	0.642	-	0.633	-
<i>Silene vulgaris</i> sl.	0.736	-	0.813	-	0.777	-	0.711	-	0.761	-
<i>Stachys pradica</i>	0.764	-	0.669	-	0.743	-	0.672	-	0.74	-
<i>Taraxacum alpinum</i>	0.64	-	0.631	-	0.613	-	0.644	-	0.661	-
<i>Trifolium alpestre</i>	0.874	-	0.88	-	0.916	-	0.856	-	0.942	-
<i>Trifolium alpinum</i>	0.606	-	0.69	-	0.661	-	0.655	-	0.651	-
<b><i>Trifolium montanum</i></b>	<b>0.824</b>	-	0.833	-	<b>0.92</b>	-	0.836	-	<b>0.915</b>	-
<i>Trisetum flavescens</i>	0.888	-	0.871	-	0.925	-	0.886	-	0.932	-
<i>Vaccinium uliginosum</i> subsp. <i>microphyllum</i>	0.841	-	0.798	-	0.86	-	0.811	-	0.841	-
<i>Veronica allionii</i>	0.708	-	0.619	-	0.689	-	0.665	-	0.697	-
<i>Alchemilla xanthochlora</i> aggr	0.629	0.601	0.612	0.603	0.608	0.588	0.59	0.636	0.617	0.631
<i>Anthoxanthum odoratum</i> aggr	0.591	0.704	0.624	0.641	0.628	0.671	0.618	0.638	0.629	0.68
<i>Anthyllis vulneraria</i> sl.	0.681	0.75	0.624	0.66	0.666	0.727	0.616	0.65	0.662	0.75
<i>Arnica montana</i>	0.828	0.617	0.802	0.66	0.83	0.659	0.758	0.71	0.822	0.645
<b><i>Bartsia alpina</i></b>	<b>0.699</b>	0.629	0.657	0.705	<b>0.769</b>	0.658	0.641	0.643	0.71	0.645
<i>Campanula scheuchzeri</i>	0.641	0.643	0.685	0.709	0.685	0.681	0.698	0.651	0.661	0.629
<i>Carex sempervirens</i>	0.628	0.76	0.608	0.648	0.598	0.755	0.605	0.655	0.596	0.709
<i>Carlina acaulis</i> subsp. <i>caulescens</i>	0.81	0.723	0.786	0.744	0.823	0.771	0.791	0.691	0.853	0.783
<i>Cirsium spinosissimum</i>	0.681	0.671	0.629	0.681	0.7	0.71	0.688	0.686	0.742	0.735
<b><i>Dryas octopetala</i></b>	<b>0.769</b>	0.694	0.812	0.71	<b>0.847</b>	0.733	0.816	0.685	<b>0.881</b>	0.697
<b><i>Festuca rubra</i> aggr.</b>	0.681	<b>0.658</b>	0.706	0.76	0.711	<b>0.79</b>	0.709	0.716	0.693	0.706
<i>Festuca violacea</i> aggr.	0.609	0.634	0.608	0.608	0.586	0.599	0.595	0.63	0.62	0.642
<i>Gentiana acaulis</i>	0.729	0.72	0.709	0.68	0.758	0.72	0.645	0.693	0.737	0.738
<b><i>Geum montanum</i></b>	0.645	<b>0.603</b>	0.593	0.709	0.607	<b>0.68</b>	0.579	0.758	0.638	<b>0.687</b>
<i>Homogyne alpina</i>	0.896	0.615	0.799	0.625	0.878	0.656	0.81	0.605	0.901	0.623



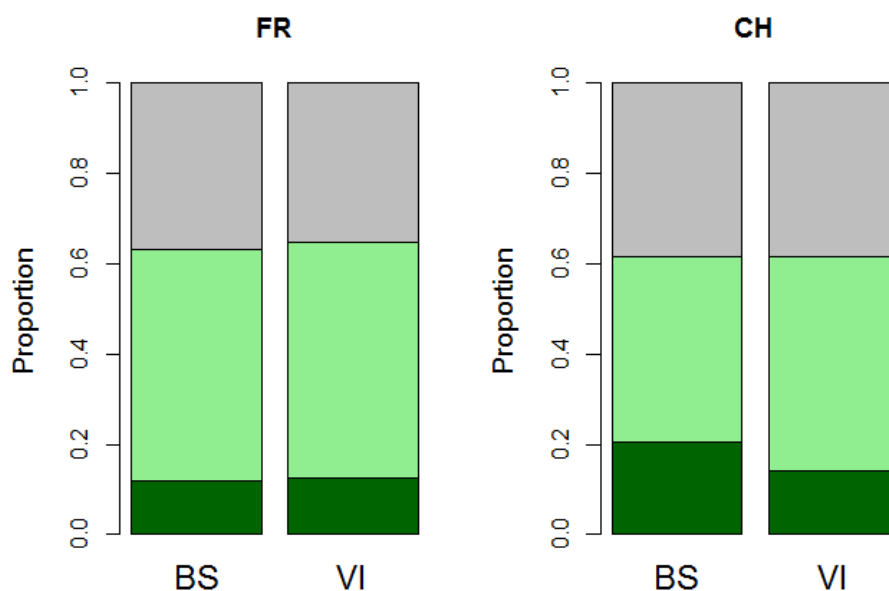
<i>Leontodon helveticus</i>	0.59	0.677	0.666	0.746	0.642	0.772	0.663	0.71	0.615	0.715
<i>Leontodon hispidus</i> sl.	0.802	0.659	0.8	0.645	0.818	0.699	0.735	0.61	0.859	0.665
<i>Lotus corniculatus</i> aggr.	0.862	0.616	0.71	0.608	0.859	0.608	0.713	0.601	0.901	0.61
<i>Myosotis alpestris</i>	0.672	0.729	0.713	0.639	0.735	0.664	0.735	0.608	0.753	0.693
<i>Nardus stricta</i>	0.654	0.613	0.624	0.659	0.644	0.655	0.625	0.667	0.641	0.647
<i>Phleum rhaeticum</i>	0.68	0.683	0.75	0.576	0.724	0.682	0.718	0.653	0.692	0.701
<i>Phyteuma orbiculare</i>	0.631	0.66	0.614	0.62	0.603	0.626	0.625	0.614	0.578	0.638
<i>Plantago alpina</i>	0.619	0.618	0.621	0.621	0.619	0.631	0.671	0.59	0.635	0.588
<i>Poa alpina</i>	0.788	0.647	0.619	0.633	0.795	0.655	0.625	0.627	0.764	0.64
<i>Polygonum viviparum</i>	0.718	0.652	0.653	0.685	0.698	0.691	0.722	0.615	0.743	0.655
<i>Potentilla aurea</i>	0.625	0.612	0.669	0.746	0.659	0.75	0.571	0.745	0.596	0.725
<i>Ranunculus acris</i> sl.	0.664	0.68	0.748	0.665	0.748	0.662	0.803	0.731	0.799	0.681
<i>Ranunculus montanus</i> aggr.	0.684	0.599	0.745	0.652	0.744	0.642	0.727	0.714	0.781	0.677
<i>Salix herbacea</i>	0.741	0.655	0.781	0.686	0.818	0.639	0.791	0.62	0.811	0.669
<i>Sesleria caerulea</i>	0.666	0.655	0.752	0.705	0.737	0.718	0.797	0.671	0.783	0.713
<i>Thesium alpinum</i>	0.71	0.66	0.793	0.781	0.791	0.747	0.84	0.718	0.788	0.678
<i>Thymus praecox</i> subsp. <i>polytrichus</i>	0.771	0.649	0.694	0.748	0.803	0.717	0.655	0.757	0.756	0.649
<i>Trifolium pratense</i> sl.	0.759	0.592	0.66	0.75	0.72	0.731	0.67	0.697	0.732	0.678
<i>Trifolium repens</i> sstr.	0.651	0.747	0.609	0.691	0.611	0.746	0.639	0.786	0.673	0.749
<i>Trifolium thalii</i>	0.623	0.606	0.66	0.612	0.612	0.607	0.635	0.606	0.634	0.616
<i>Vaccinium myrtillus</i>	0.882	0.647	0.801	0.671	0.858	0.623	0.779	0.643	0.848	0.659
<i>Viola calcarata</i>	0.627	0.68	0.613	0.614	0.624	0.616	0.624	0.737	0.622	0.628
<i>Agrostis capillaris</i>	-	0.66	-	0.771	-	0.774	-	0.793	-	0.852
<i>Agrostis rupestris</i>	-	0.685	-	0.762	-	0.721	-	0.598	-	0.666
<i>Alchemilla conjuncta</i> aggr.	-	0.599	-	0.684	-	0.697	-	0.669	-	0.629
<i>Alchemilla glabra</i> aggr.	-	0.671	-	0.736	-	0.705	-	0.619	-	0.66
<i>Alchemilla vulgaris</i> aggr.	-	0.74	-	0.634	-	0.65	-	0.655	-	0.674
<i>Androsace chamaejasme</i>	-	0.658	-	0.602	-	0.643	-	0.61	-	0.646
<i>Aposeris foetida</i>	-	0.788	-	0.714	-	0.818	-	0.692	-	0.838
<i>Aster bellidiastrum</i>	-	0.705	-	0.646	-	0.741	-	0.657	-	0.758
<i>Campanula barbata</i>	-	0.703	-	0.789	-	0.745	-	0.787	-	0.72
<i>Carex ornithopoda</i>	-	0.707	-	0.638	-	0.68	-	0.612	-	0.677
<i>Cerastium fontanum</i> sl.	-	0.682	-	0.684	-	0.706	-	0.683	-	0.685
<i>Crepis aurea</i>	-	0.634	-	0.716	-	0.639	-	0.636	-	0.597
<i>Crocus albiflorus</i>	-	0.744	-	0.733	-	0.769	-	0.727	-	0.781
<i>Deschampsia cespitosa</i>	-	0.683	-	0.715	-	0.726	-	0.773	-	0.754
<i>Euphrasia minima</i>	-	0.585	-	0.66	-	0.624	-	0.6	-	0.606
<i>Festuca quadriflora</i>	-	0.634	-	0.767	-	0.737	-	0.679	-	0.647
<i>Galium anisophyllum</i>	-	0.767	-	0.609	-	0.753	-	0.713	-	0.771
<i>Gentiana campestris</i> sstr.	-	0.705	-	0.597	-	0.665	-	0.65	-	0.673
<i>Gentiana purpurea</i>	-	0.62	-	0.81	-	0.797	-	0.788	-	0.746
<i>Gentiana verna</i>	-	0.682	-	0.681	-	0.663	-	0.674	-	0.646
<i>Helianthemum nummularium</i> sl.	-	0.631	-	0.631	-	0.627	-	0.638	-	0.624
<i>Helictotrichon versicolor</i>	-	0.627	-	0.607	-	0.615	-	0.597	-	0.605
<i>Hieracium lactucella</i>	-	0.648	-	0.755	-	0.761	-	0.771	-	0.748

<i>Leucanthemum vulgare</i> aggr.	-	0.864	-	0.756	-	0.888	-	0.707	-	0.911
<i>Ligusticum mutellina</i>	-	0.624	-	0.677	-	0.671	-	0.741	-	0.698
<i>Loiseleuria procumbens</i>	-	0.66	-	0.639	-	0.601	-	0.635	-	0.624
<i>Luzula alpinopilosa</i>	-	0.671	-	0.69	-	0.681	-	0.711	-	0.688
<i>Luzula multiflora</i>	-	0.715	-	0.582	-	0.643	-	0.608	-	0.684
<i>Pedicularis verticillata</i>	-	0.682	-	0.657	-	0.693	-	0.627	-	0.681
<i>Plantago atrata</i> sstr.	-	0.6	-	0.614	-	0.607	-	0.605	-	0.593
<i>Polygala alpestris</i>	-	0.633	-	0.643	-	0.637	-	0.702	-	0.615
<i>Potentilla crantzii</i>	-	0.639	-	0.67	-	0.635	-	0.657	-	0.625
<i>Prunella vulgaris</i>	-	0.683	-	0.622	-	0.661	-	0.63	-	0.634
<i>Salix retusa</i>	-	0.68	-	0.688	-	0.764	-	0.661	-	0.748
<i>Scabiosa lucida</i>	-	0.647	-	0.678	-	0.727	-	0.607	-	0.633
<i>Soldanella alpina</i>	-	0.642	-	0.717	-	0.717	-	0.683	-	0.677
<i>Taraxacum officinale</i> aggr.	-	0.757	-	0.627	-	0.685	-	0.761	-	0.681
<i>Trifolium badium</i>	-	0.689	-	0.696	-	0.666	-	0.695	-	0.66
<i>Trollius europaeus</i>	-	0.667	-	0.812	-	0.8	-	0.715	-	0.75
<i>Vaccinium gaultherioides</i>	-	0.633	-	0.648	-	0.641	-	0.624	-	0.647
<i>Vaccinium vitis-idaea</i>	-	0.705	-	0.666	-	0.674	-	0.644	-	0.723

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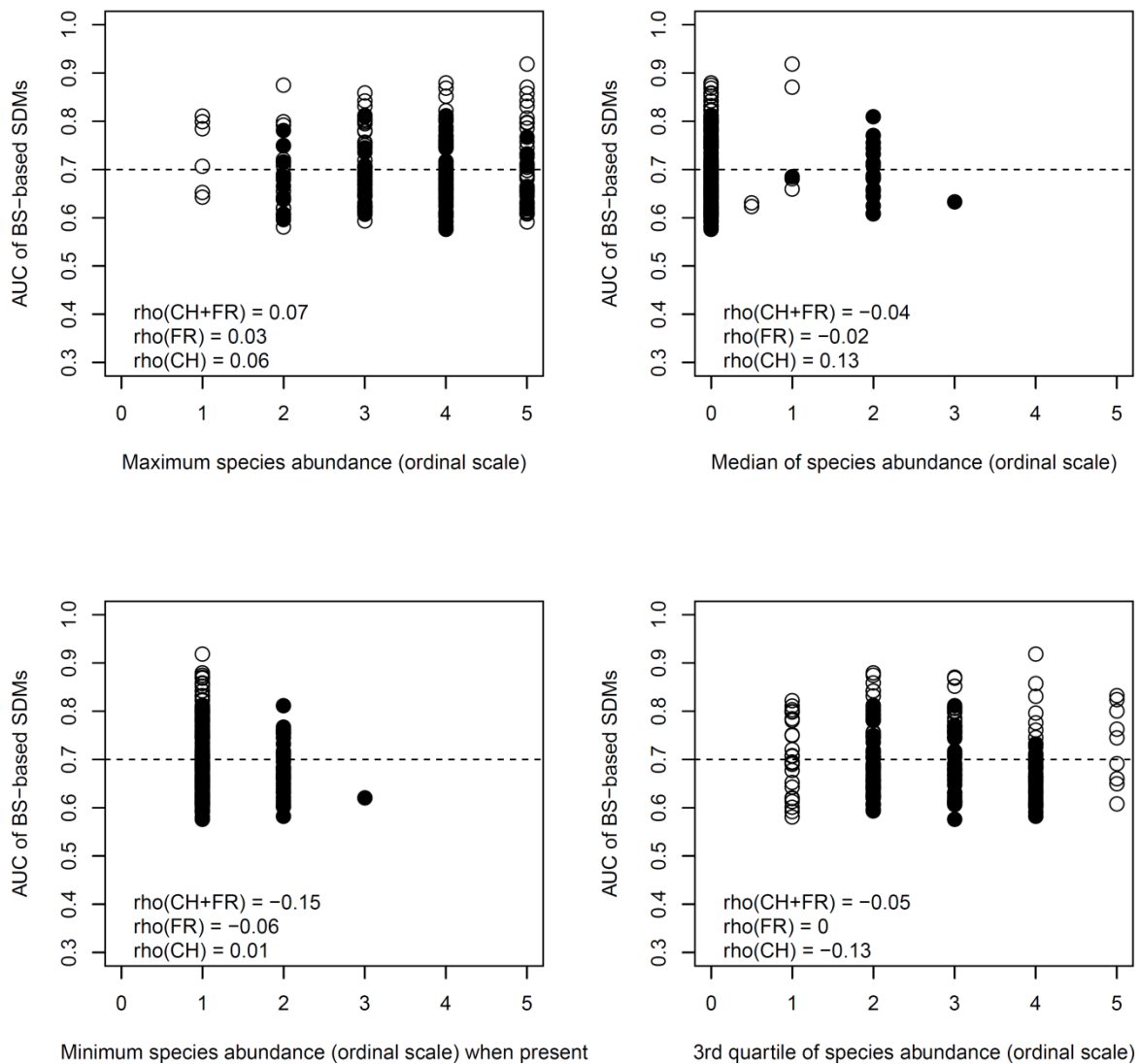
ESM2 Fig 3: Proportions of species distribution models for which accuracy was improved by 10% (dark green areas) or between 0 and 10% (light green areas) or was declined (gray areas) when adding the AIS-predictors to topographic based models. FR for the French site and CH for the Swiss site. BS indicates reflectance records in spectral bands as predictors and VI indicates vegetation indices as predictors. See ESM2 Table 1 for identity of the species that showed best model improvement.

494

495 Weak or no improvement of species distribution models, when including AIS-predictors,  
496 suggests that the ecological information represented by AIS-data was redundant to already  
497 included topography indicators. Increasing the dimensionality of the set of predictors without  
498 additional informational content may flaw the fitted statistical relationships and ultimately  
499 decrease model accuracy as we observed for many species at both sites.

500

501 **4) The effect of species abundance patterns on the prediction accuracy of remote**  
502 **sensing-based species distribution models.**



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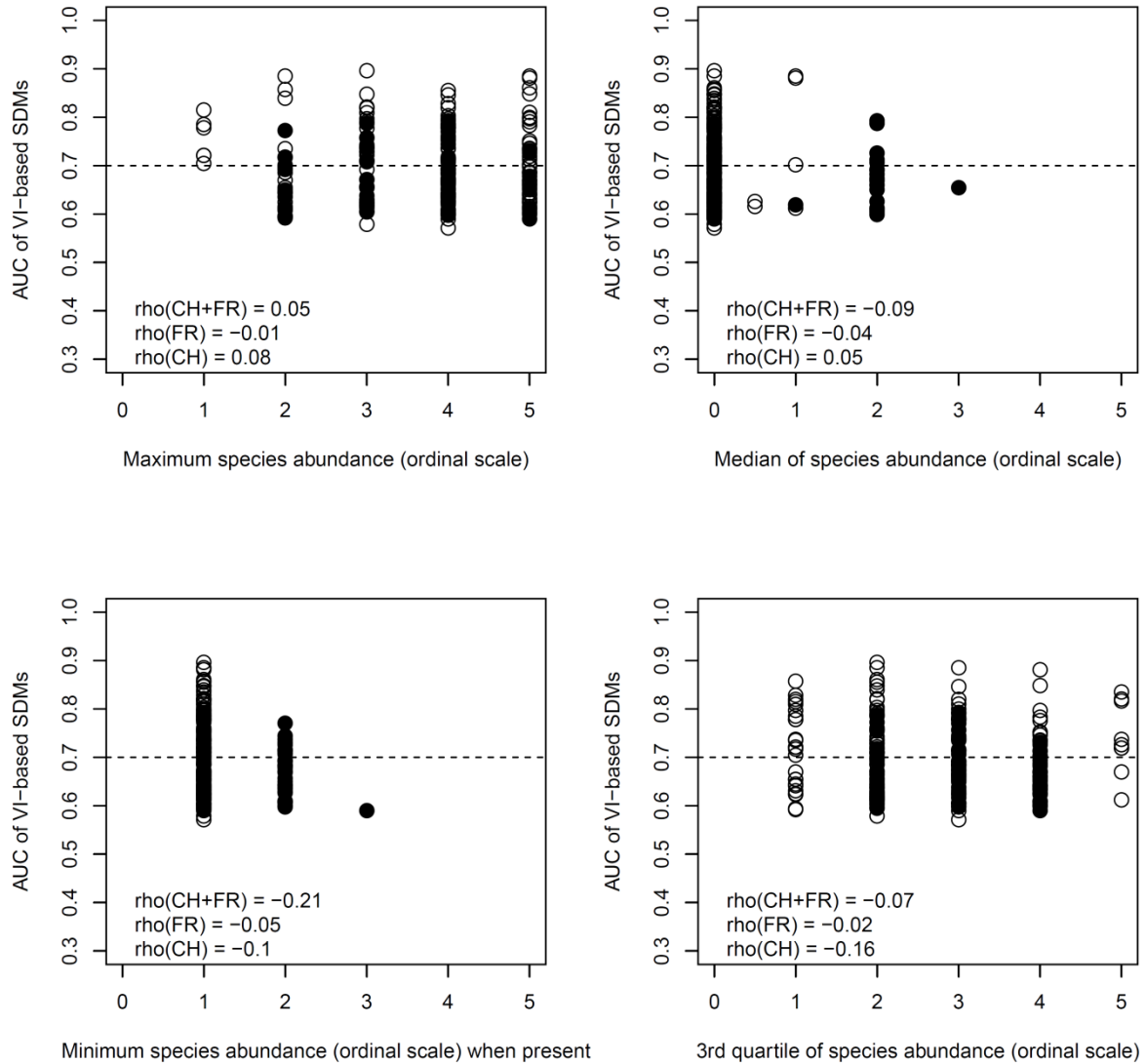
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ESM2 Fig 4: Relationships between four predictors of species abundance patterns and the accuracy of species distribution models based on the reflectance records in spectral bands (BS). White points for species from the French site (FR) and black points for species from the Swiss site (CH).

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ESM2 Fig 5: Relationships between four predictors of species abundance patterns and the accuracy of species distribution models based on the vegetation indices. White points for species from the French site (FR) and black points for species from the Swiss site (CH).

515 **5) Testing the phylogenetic and functional dependency of model features between**  
516 **the species.**

517  
518 We implemented a similar procedure as for the test of phylogenetic signal of species traits,  
519 except we considered the AUC values and AIS-predictor importance as traits and we sought  
520 for both phylogenetic and functional signals. Specifically, we implemented two  
521 complementary analyses following recommendations of Hardy and Pavoine 2012 [1]. In the  
522 first, we computed a global Mantel test contrasting dissimilarity of species distribution models  
523 (Euclidean distance between AUC values or AIS-variable importance) and phylogenetic or  
524 functional dissimilarity between the species. The randomisation procedure consisted of  
525 random reallocation of AUC values or variable importance between the species (999  
526 permutations). In the second, we computed distograms where species model dissimilarities  
527 (again as Euclidean distance between AUC values or AIS-variable importance) are plotted  
528 against classes of phylogenetic or functional distance between the species. This indicates how  
529 species models differ for functionally/phylogenetically closely related species and for  
530 dissimilar species.

531  
532 Phylogenetic information for the French site was extracted from the complete phylogeny for the  
533 Alpine flora at the genus level published in Thuiller et al. 2014 [2]. Finally, we randomly  
534 resolved terminal polytomies by applying a birth-death (Yule) bifurcation process within each  
535 genus [3]. Phylogenetic information for the Swiss site was extracted from the phylogeny for  
536 the 231 most frequent species of the Western Swiss Alps of the Canton of Vaud (a 700 km<sup>2</sup>  
537 region surrounding the Swiss site Anzeindaz). This phylogeny is based on DNA sequences  
538 extracted from collected vegetal material and built by alignment of chloroplastic DNA  
539 sequences (*rbcl* and *matK*) with GTR + gamma models of evolution under a Bayesian  
540 inference framework. Details are available in Ndiribe et al. 2013 [4].

541 All the species of the French site (i.e. 119) were included in phylogenetic tests while 69  
542 species of the Swiss site (on 78) could be accounted for.

543 The phylogenetic distance between the species was quantified using the Abouheif proximity  
544 measure for Mantel tests and the square-root of patristic distance for distograms [1].

545  
546 Traits information included morphological and physiological traits that are acknowledged to  
547 indicate plant fitness, community dynamics and ecosystem processes. Some of them are also  
548 recognized to be related to the reflectance pattern of vegetation stands [5,6]. We considered:  
549 1) specific leaf area (SLA; m<sup>2</sup>.kg<sup>-1</sup>), 2) leaf dry matter content (LDMC, mg.g<sup>-1</sup>), 3) vegetation

550 height (mm), 4) plant growth form discriminating species as graminoid, forb, legume or  
 551 shrub, 5) Leaf distribution along the stem discriminating species with leaves growing  
 552 regularly along the stem, rosette or tufted species and semi rosette species, and 6) branching, a  
 553 binary trait describing species ability to fill lateral space. SLA, LDMC and vegetation height  
 554 were measured for most species in the field within each of the two sites (89 out 119 for FR  
 555 and 71 out of 78 for CH). Leaf distribution, growth form, and branching were retrieved from  
 556 the LEDA database [7]. Since trait data covered continuous and categorical variables, the  
 557 functional dissimilarity between species was quantified using the Gower distance metric [8]  
 558 for both Mantel tests and distogram computation.

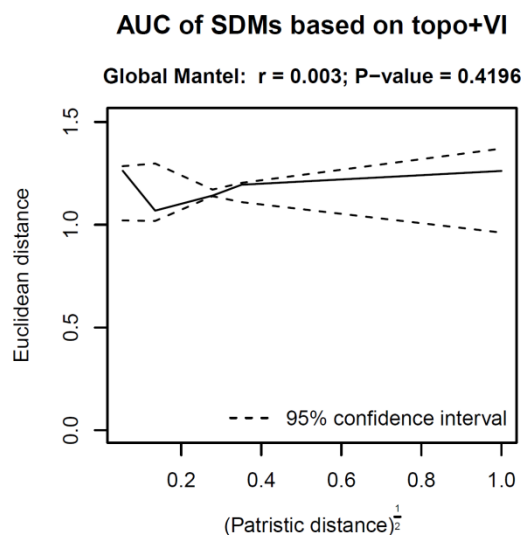
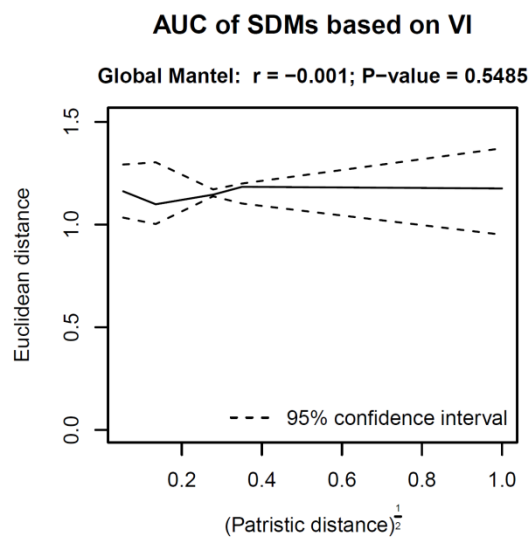
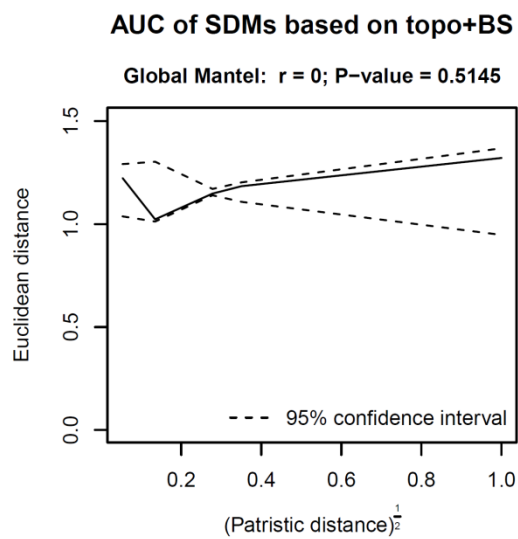
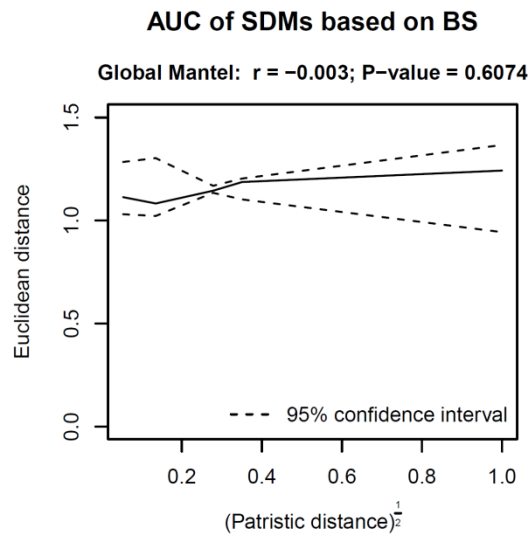
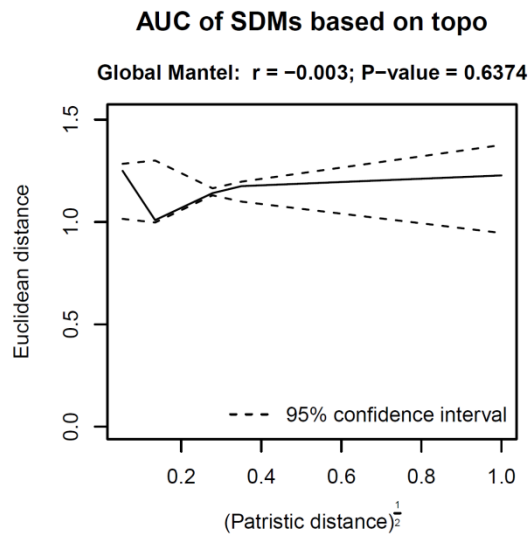
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560 Tests for phylogenetic and functional dependency of the importance of AIS-variables  
 561 considered only the species that showed distribution models with fair to good prediction  
 562 accuracy (i.e. AUC > 0.7) in order to exclude spurious estimates of variable importance from  
 563 inaccurate models. This led to analyses with reduced list of species as follows:

564

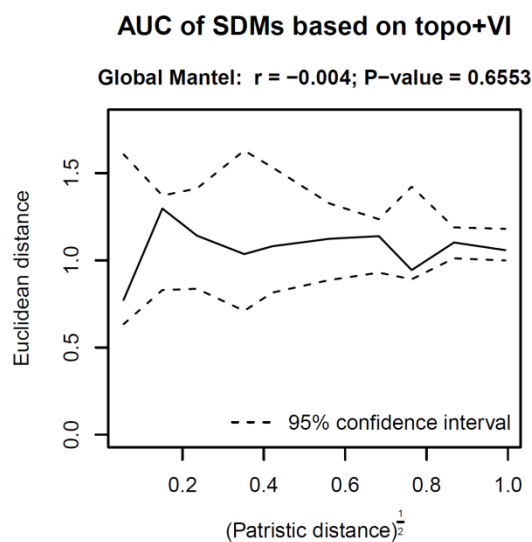
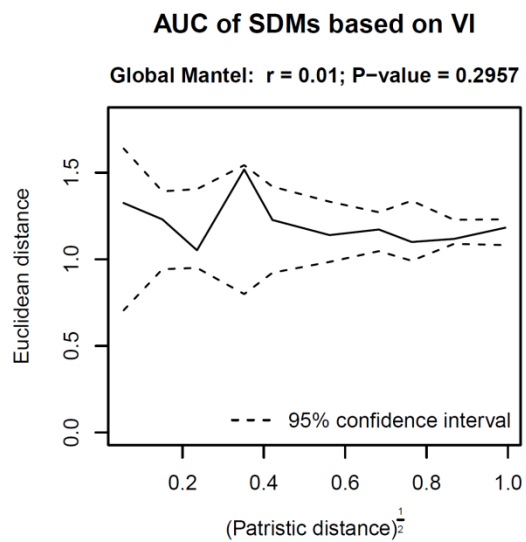
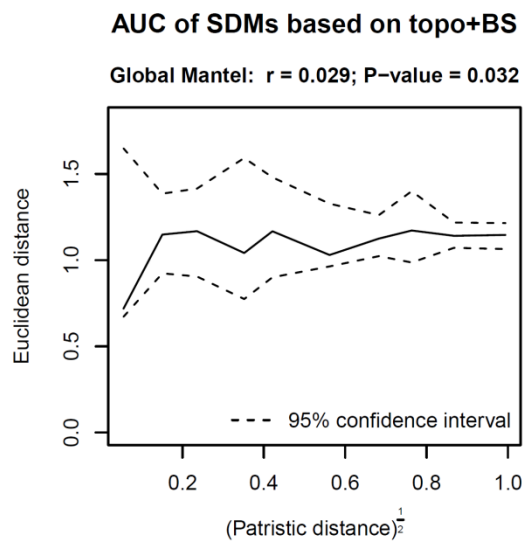
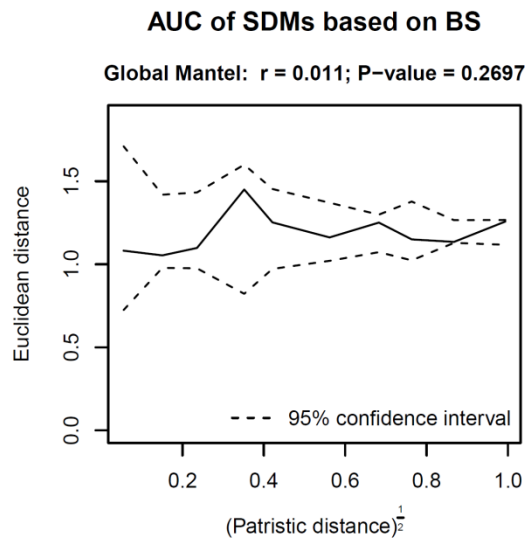
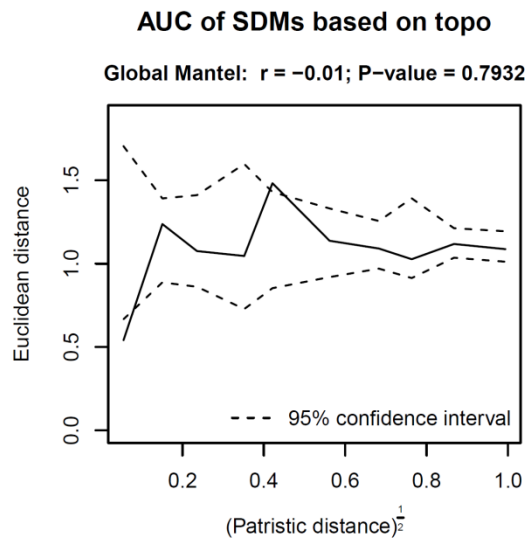
Number of species included in the analyses	FR		CH	
	Phylogenetic (119/119sp)	Functional (89/119sp)	Phylogenetic (69/78sp)	Functional (71/78sp)
Reflectance in spectral bands	64	47	25	25
Vegetation indices	68	50	19	20

565



ESM2 Fig 6: **Phylogenetic dependency of model accuracy** (AUC: the area under the curve of a receiver-operating characteristic plot) between the species for the **French site (FR)**. The x-axis represents the phylogenetic distance between the species and the y-axis differences in AUC. Topo indicates models based on topographic predictors only, BS models based on reflectance recorded in the spectral bands. VI indicates models based on vegetation indices only. Topo+BS and Topo+VI indicate respectively models based on topographic predictors and reflectance records in spectral bands or vegetation indices as predictors. Confidence intervals were computed with random re-allocation of AUC values between the species (9999 permutations)

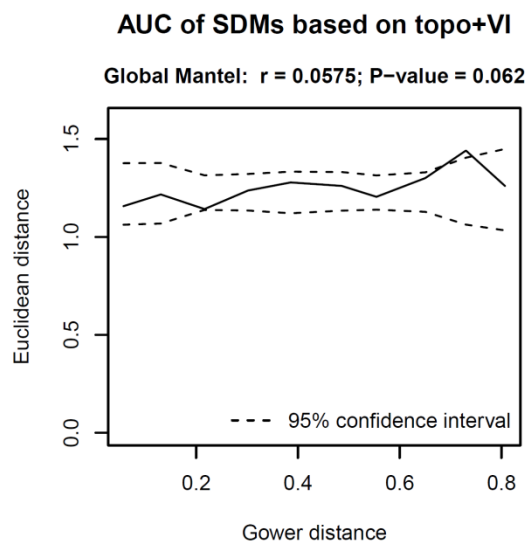
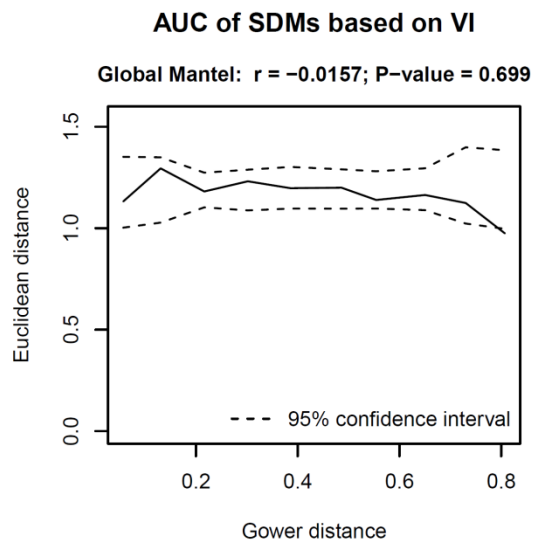
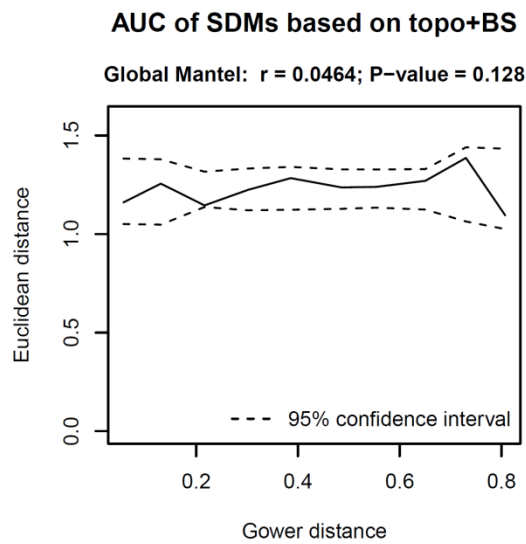
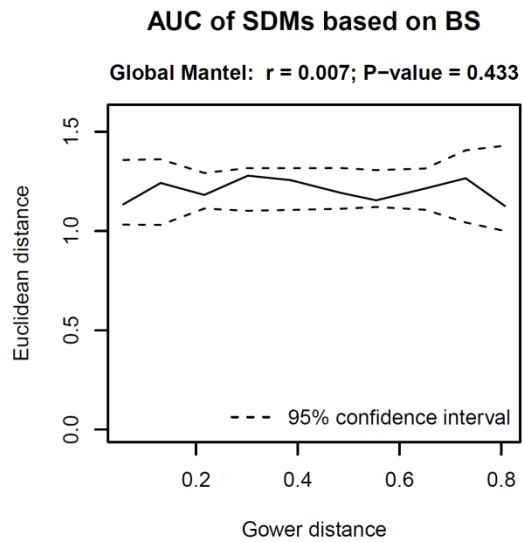
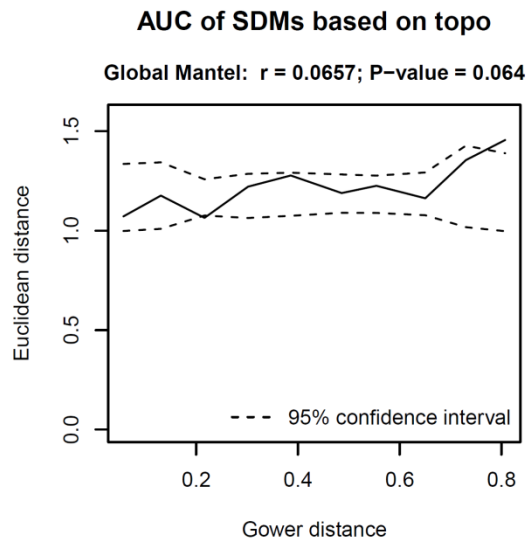
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ESM2 Fig 7: **Phylogenetic dependency of model accuracy** (AUC: the area under the curve of a receiver-operating characteristic plot) between the species for the **Swiss site (CH)**. The x-axis represents the phylogenetic distance between the species and the y-axis differences in AUC. Topo indicates models based on topographic predictors only, BS models based on reflectance recorded in the spectral bands. VI indicates models based on vegetation indices only. Topo+BS and Topo+VI indicate respectively models based on topographic predictors and reflectance records in spectral bands or vegetation indices as predictors. Confidence intervals were computed with random re-allocation of AUC values between the species (9999 permutations)

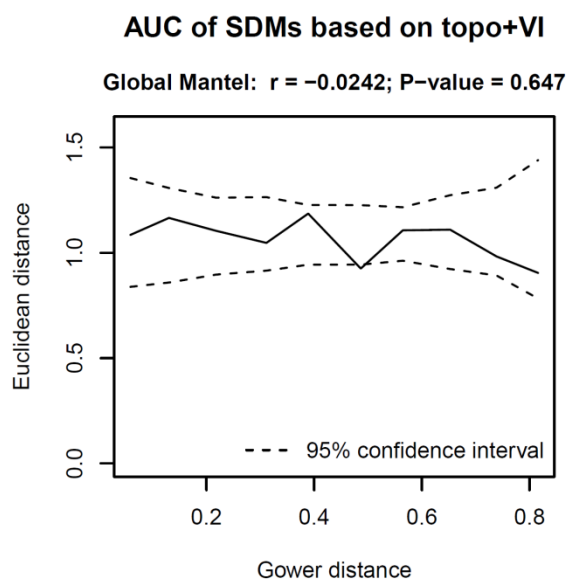
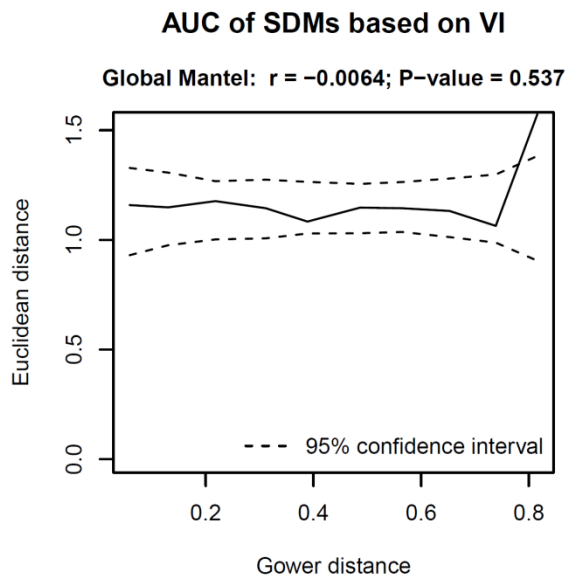
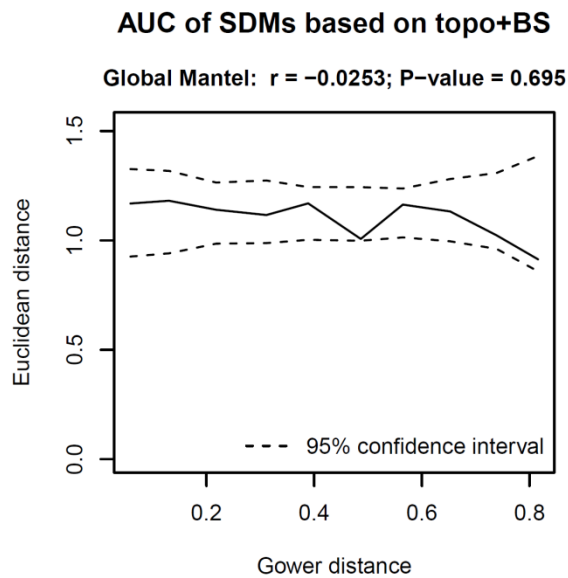
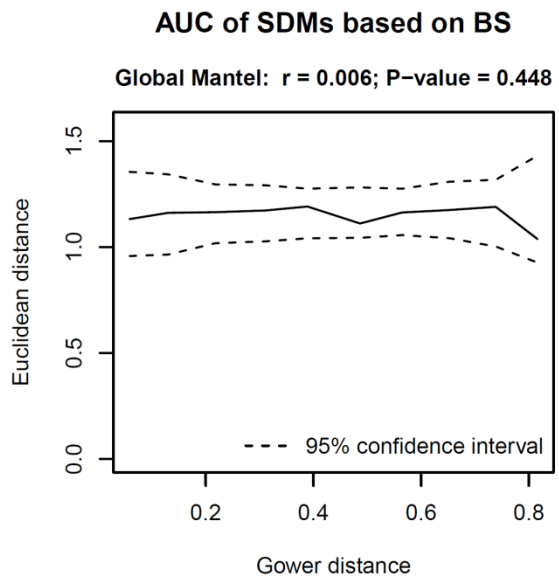
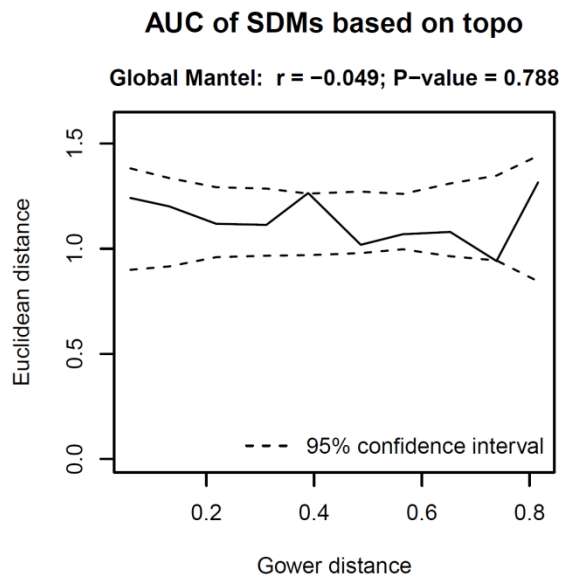
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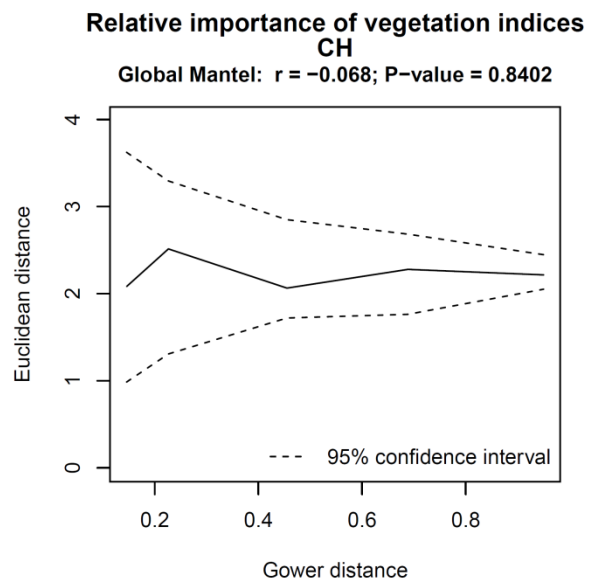
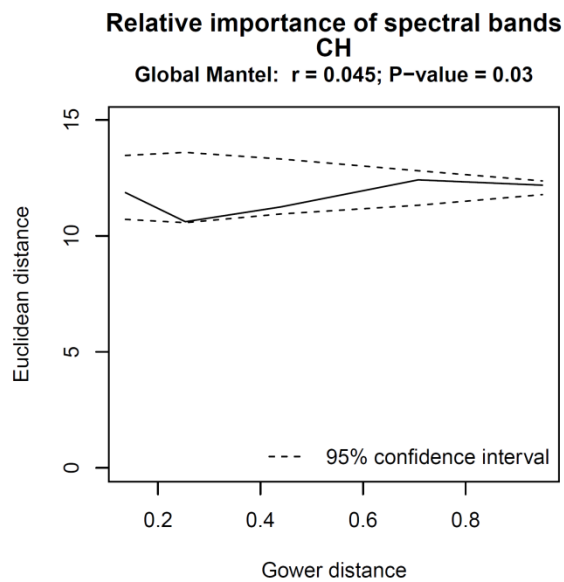
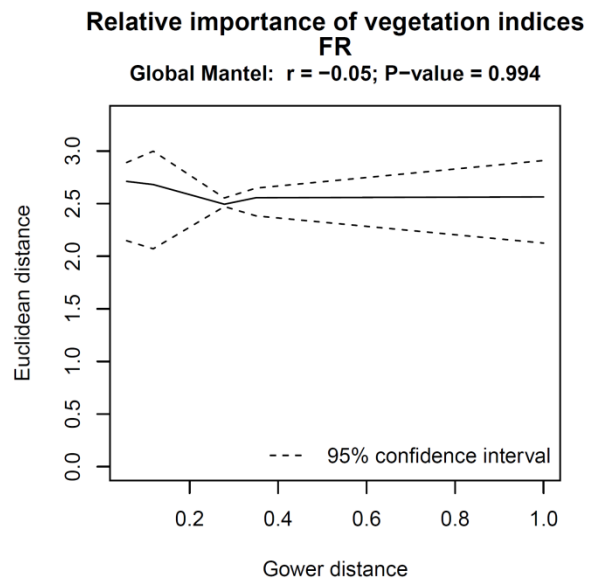
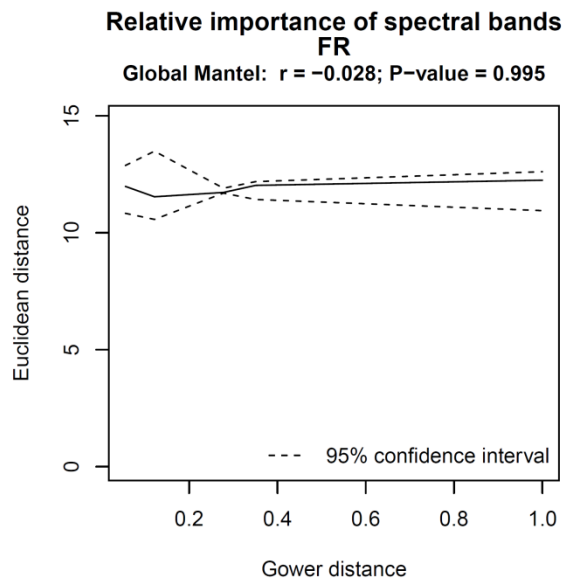


ESM2 Fig 8: **Functional dependency of model accuracy** (AUC: the area under the curve of a receiver-operating characteristic plot) between the species for the **French site (FR)**. The x-axis represents the functional distance between the species and the y-axis differences in AUC. Topo indicates models based on topographic predictors only, BS models based on reflectance recorded in the spectral bands. VI indicates models based on vegetation indices only. Topo+BS and Topo+VI indicate respectively models based on topographic predictors and reflectance records in spectral bands or vegetation indices as predictors. Confidence intervals were computed with random re-allocation of AUC values between the species (9999 permutations)

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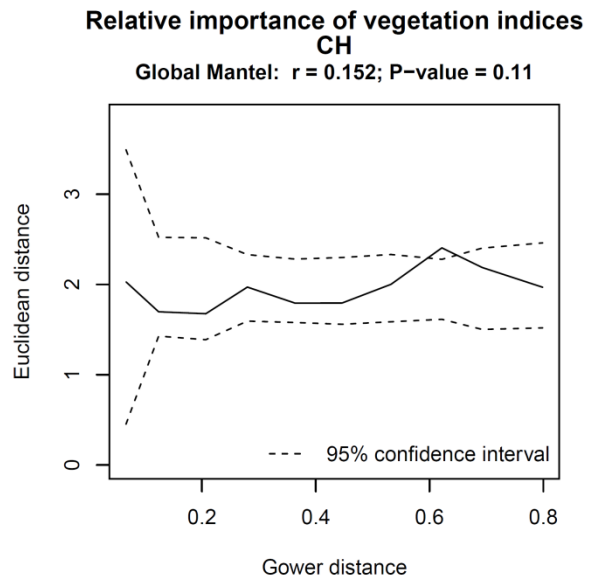
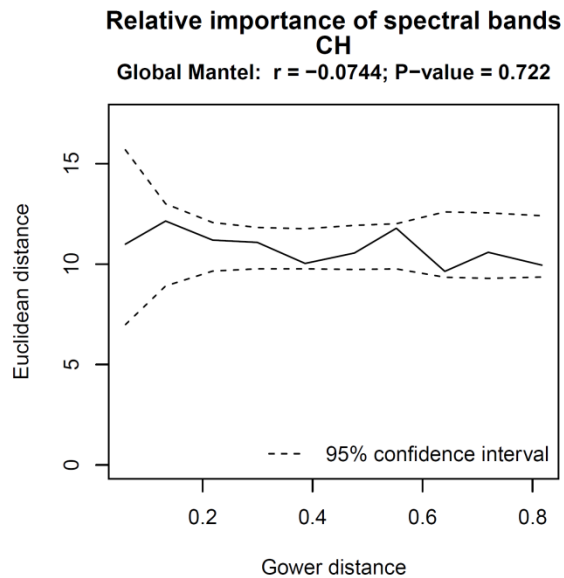
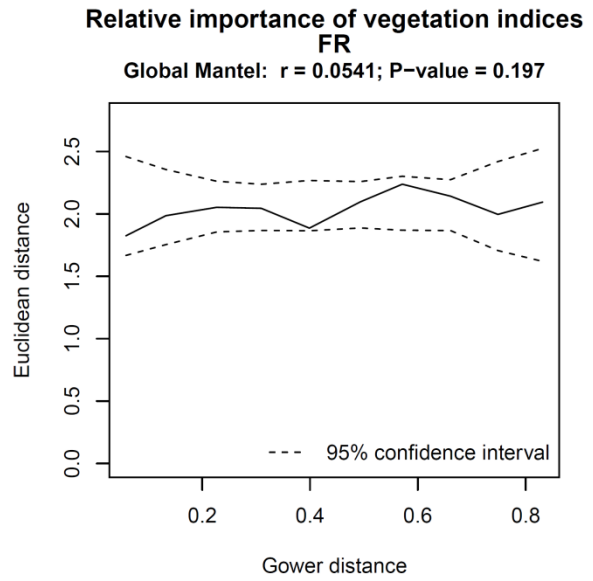
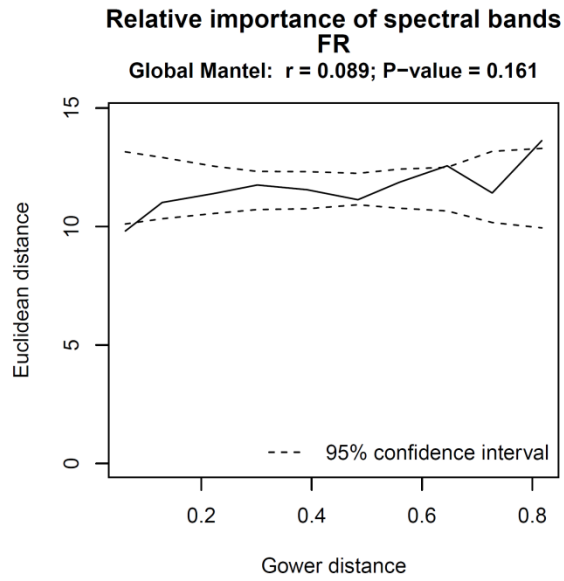


ESM2 Fig 9: **Functional dependency of model accuracy** (AUC: the area under the curve of a receiver-operating characteristic plot) between the species for the **Swiss site (CH)**. The x-axis represents the functional distance between the species and the y-axis differences in AUC. Topo indicates models based on topographic predictors only, BS models based on reflectance recorded in the spectral bands. VI indicates models based on vegetation indices only. Topo+BS and Topo+VI indicate respectively models based on topographic predictors and reflectance records in spectral bands or vegetation indices as predictors. Confidence intervals were computed with random re-allocation of AUC values between the species (9999 permutations)



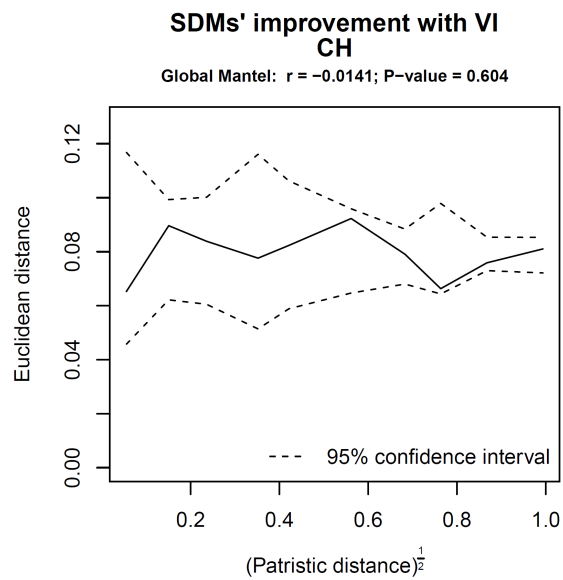
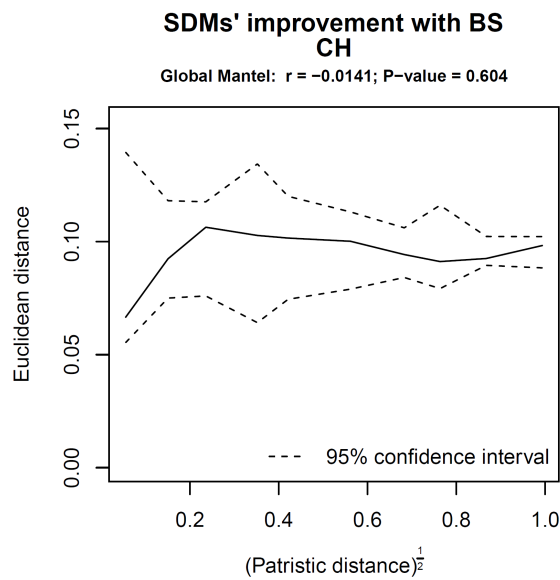
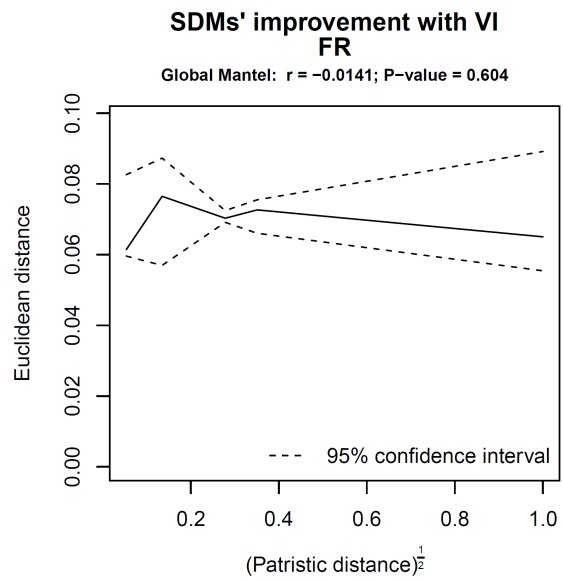
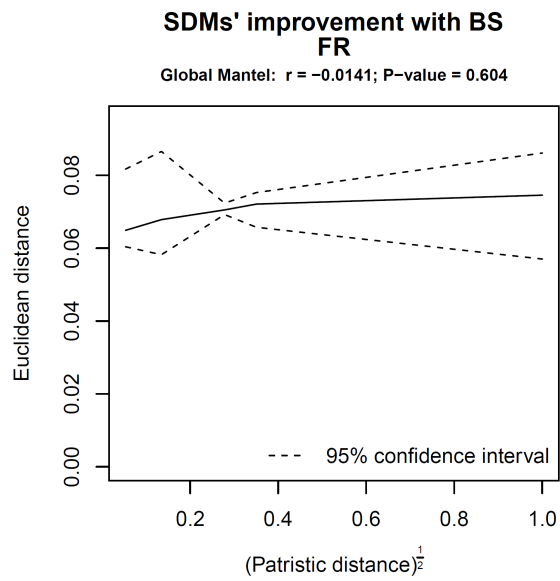
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ESM2 Fig 10: **Phylogenetic dependency of relative importance of AIS-predictors** between the species for both the French site (FR) and the Swiss site (CH). The x-axis represents the phylogenetic distance between the species and the y-axis differences in RS-predictors (either reflectance recorded in the spectral bands or vegetation indices). Only species with distribution models showing fair to good prediction accuracy ( $AUC > 0.7$ ) were considered. Confidence intervals were computed with random re-allocation of predictor importance between the species (9999 permutations)



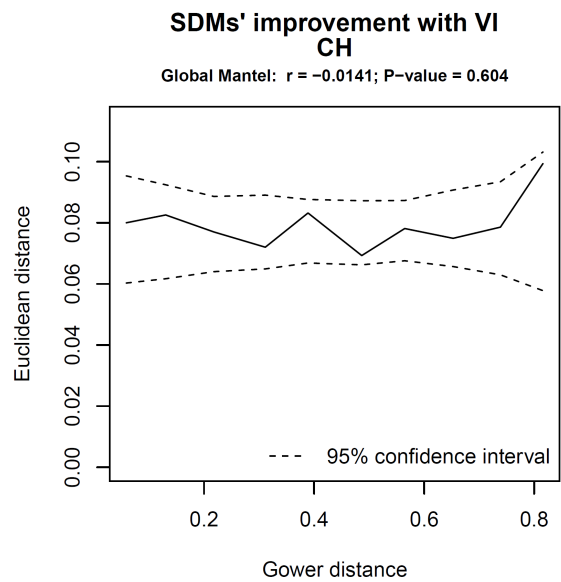
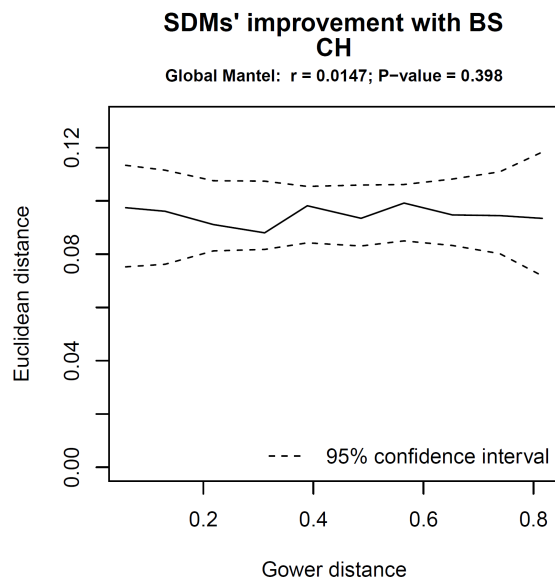
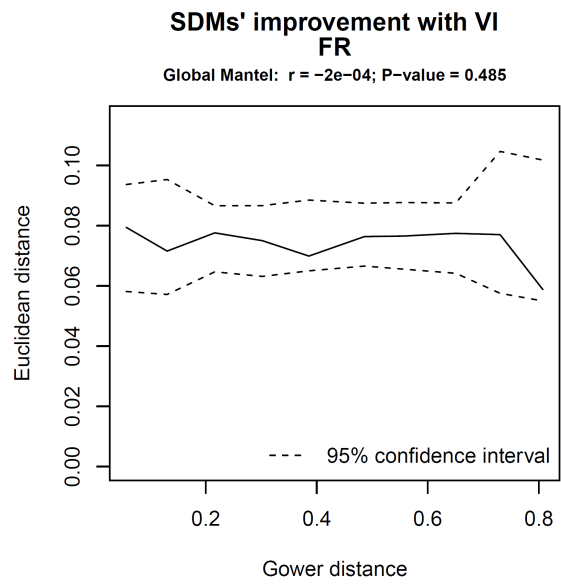
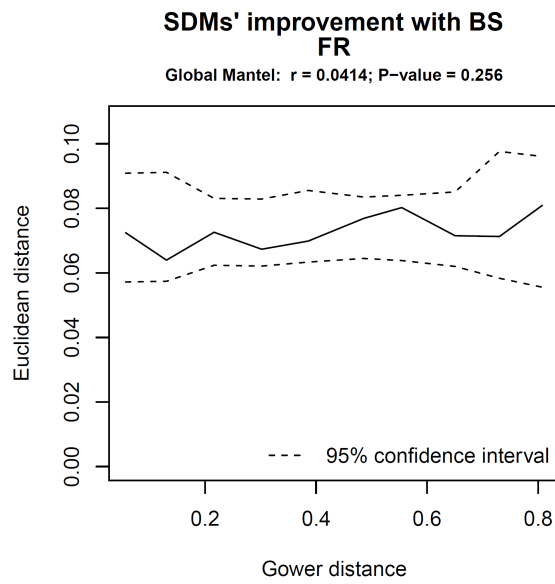
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ESM2 Fig 11: **Functional dependency of relative importance of RS-predictors** between the species for both the French site (FR) and the Swiss site (CH). The x-axis represents the functional distance between the species and the y-axis differences in AIS-predictors (either reflectance recorded in the spectral bands or vegetation indices). Only species with distribution models showing fair to good prediction accuracy ( $AUC > 0.7$ ) were considered. Confidence intervals were computed with random re-allocation of predictor importance between the species (9999 permutations)



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ESM2 Fig 12: **Phylogenetic dependency of model improvement among species with addition of AIS-predictors** for the French site (FR) and the Swiss site (CH). The x-axis represents the phylogenetic distance between the species and the y-axis differences in model improvement when adding AIS-predictors (either reflectance recorded in the spectral bands (BS) or vegetation indices (VI)) to topographic predictors. Confidence intervals were computed with random re-allocation of AUC values between the species (9999 permutations)



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ESM2 Fig 13: **Functional dependency of model improvement among species with addition of AIS-predictors** for the French site (FR) and the Swiss site (CH). The x-axis represents the functional distance between the species and the y-axis differences in model improvement when adding AIS-predictors (either reflectance recorded in the spectral bands (BS) or vegetation indices (VI)) to topographic predictors. Confidence intervals were computed with random re-allocation of AUC values between the species (9999 permutations)

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628 Airborne imaging spectroscopy (AIS) can provide remotely sensed estimates of physical and  
629 bio-chemical quantitative properties of ecosystems. However, the value of these  
630 characteristics for predicting diversity patterns has not been tested yet. We assess the added  
631 value of such data for predicting plant distributions in French and Swiss alpine grasslands. We  
632 fitted statistical models with high spectral and spatial resolution reflectance data and with four  
633 optical indices sensitive to leaf chlorophyll content, leaf water content and leaf area index. We  
634 found moderate added value of AIS-data for predicting alpine plant species distribution,  
635 revealing issues of scale and AIS-data informational content.  
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