Modelling plant species distribution in alpine grasslands using airborne imaging spectroscopy

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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.

1. Introduction

Spatial modelling of species distributions is commonly used to forecast environmental change effects, detect biodiversity hotspots or predict species’ invasions [1]. As fine-grained environmental descriptors are difficult to obtain, coarse-grained (from hundreds of metres to kilometres) topo-climatic descriptors are usually used. Recent advances in airborne imaging spectroscopy (AIS) have allowed the acquisition of images with high spectral and sub-metre spatial resolution [2]. Spectral information provided by remotely sensed reflectance is influenced by phenology, variations in morphological, structural and biochemical properties of species [3], as well as by local environmental conditions (e.g. hydric stress, soil properties or productivity [4,5]) that determine species habitat suitability [6]. Nevertheless, previous attempts to predict species distributions with hyperspectral data have generated mixed results [7,8]. Sub-metre resolution allows the targeting of small plants and microhabitats where species find refuge, highlighting potential benefits of hyperspatial remote sensing for biodiversity monitoring [9]. However, despite increased spatial and spectral resolution of airborne data, little is known about its value in modelling species’ distributions in species-rich ecosystems characterized by fine-scale heterogeneity.

Here, we explore the predictive power of AIS data for modelling plant species distributions in two distinct regions. Specifically, we aim to
Variable importance was assessed using conditional inference in random forest models. Grey areas represent bands used for the calculation of vegetation indices.

2. Material and methods

(a) Study sites and species data
The study was conducted in the Western French (FR) and Western Swiss (CH) Alps (electronic supplementary material, S1). The French site included 103 vegetation plots of 2–5 m in radius, located between 2000 and 2830 metres above sea level (m.a.s.l.). The Swiss site included 68 quadrats (2 × 2 m) located between 1650 and 2150 m.a.s.l. Species cover was visually estimated using the Braun–Blanquet abundance scale. In total, 160 species were selected for species distribution analysis (119 species in FR, 78 in CH). Thirty-seven species were common to both sites (see electronic supplementary material, S1).

(b) Remote sensing data
AISA data were acquired with the dual Airborne Imaging Spectro-radiometer for Applications (AISA; Specim Ltd., Finland). Raw AISA images contained 359 spectral bands between 400 and 2450 nm with spectral resolution ranging from 4.3 to 6.3 nm, and a pixel size of 0.8 m. After image processing, we extracted two types of AIS predictors: (i) reflectance in 75 spectral bands (avoiding bands with noisy radiometric response) and (ii) four vegetation indices. Vegetation indices characterized leaf chlorophyll (TCARI/OSAVI and ANCB) [10], leaf water content (SIWSI) [11] and leaf area index (MTVI2) [12] (for details see the electronic supplementary material, S1). Removal of poorly vegetated plots resulted in datasets with 70 FR and 53 CH plots.

(c) Topographic predictors
We computed five predictors derived from digital elevation models at 50 m resolution for FR and 25 m resolution for CH, representing mesoscale habitat conditions: (i) elevation (metre), (ii) slope (degree), (iii) aspect (degree), (iv) topographic position index (unitless) and (v) topographic wetness index (unitless; see the electronic supplementary material, S1).

(d) Species distribution modelling
Species distribution models (SDMs) were fitted with five different sets of variables: (i) topographic predictors only, (ii) reflectance predictors only, (iii) vegetation indices only, (iv) topographic and reflectance predictors combined and (v) topographic predictors and vegetation indices combined. We first used a conditional random forest algorithm to estimate the unbiased relative importance of predictors in the case of multicollinearity, then ran final models based on selection of the most important predictors [13] (see electronic supplementary material, S1). Their predictive accuracy was evaluated within each study site separately using a repeated split-sample procedure (100 iterations). Seventy per cent of the sample points were used for model calibration and 30% for model evaluation in each iteration.

(e) Model differences among species
The relative importance of AIS predictors and the predictive accuracy of SDMs was tested against (i) species’ phylogenetic relatedness, (ii) species’ functional similarity, including a set of morphological and physiological traits that are well correlated with the reflectance of canopy stands [14] (see electronic supplementary material, S2 and §5), and (iii) species’ abundance patterns within plots. Phylogenetic and functional tests were computed as described in [15] (see the electronic supplementary material, S2 and §5).

3. Results
When fitting SDMs with reflectance data, the analysis of predictor importance indicated similarities in the selected spectral bands among sites (figure 1). The most important spectral bands were located between 500 and 900 nm for both sites, but site-specific differences in important spectral bands were also apparent (1500–1800 nm in FR, 1200–1500 nm and 2000–2500 nm in CH). These site differences existed for species present at only one or both sites (electronic supplementary material, S2 and figure S1). On average, all vegetation indices showed similar importance for SDM fitting (electronic supplementary material, S2 and figure S2).

The prediction accuracy of SDMs based solely on topographic predictors, reflectance data or vegetation indices did not differ significantly. However, SDMs including both AIS and topographic predictors tended to be more accurate (figure 2 and the electronic supplementary material, S2 and table S1). The improvement was marginally significant for vegetation indices (Wilcoxon rank-sum test, \(p = 0.079\)) but non-significant for reflectance in FR. Conversely, CH showed significant improvement when using reflectance (Wilcoxon rank-sum test, \(p = 0.001\)).

Figure 1. Relative importance of reflectance intensity in spectral bands for predicting species distributions at study sites in France (FR) and Switzerland (CH).


8. Lawrence RL, Wood SD, Sheley RL. 2006 Mapping invasive plants using hyperspectral imagery and Breiman Cutler classifications (randomForest).


