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Mapping a priori defined plant associations using remotely sensed vegetation characteristics

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ABSTRACT

Incorporation of a priori defined plant associations into remote sensing products is a major challenge that has only recently been confronted by the remote sensing community. We present an approach to map the spatial distribution of such associations by using plant indicator values (IVs) for salinity, moisture and nutrients as an intermediate between spectral reflectance and association occurrences. For a 12 km^2 study site in the Netherlands, the relations between observed IVs at local vegetation plots and visible and near-infrared (VNIR) and short-wave infrared (SWIR) airborne reflectance data were modelled using Gaussian Process Regression (GPR) (R^2 0.73, 0.64 and 0.76 for salinity, moisture and nutrients, respectively). These relations were applied to map IVs for the complete study site. Association occurrence probabilities were modelled as function of IVs using a large database of vegetation plots with known association and IVs. Using the mapped IVs, we calculated occurrence probabilities of 19 associations for each pixel, resulting in both a crisp association map with the most likely occurring association per pixel, as well as occurrence probability maps per association. Association occurrence predictions were assessed by a local vegetation expert, which revealed that the occurrences of associations situated at frequently predicted indicator value combinations were over predicted. This seems primarily due to biases in the GPR predicted IVs, resulting in associations with envelopes located in extreme ends of IVs being scarcely predicted.
Although the results of this particular study were not fully satisfactory, the method potentially offers several advantages compared to current vegetation classification techniques, like site-independent calibration of association probabilities, site-independent selection of associations and the provision of IV maps and occurrence probabilities per association. If the prediction of IVs can be improved, this method may thus provide a viable roadmap to bring a priori defined plant associations into the domain of remote sensing.

1. Introduction

Mapping the characteristics and extent of natural vegetation using remote sensing has been the subject of many studies in recent years (see for a review: Ustin & Gamon, 2010). A common challenge is to simplify and generalize the complex interactions in natural vegetation so that meaningful information on abiotic and biotic conditions can be derived (Janssen, 2004; Küchler, 1984; Küchler & Zonneveld, 1988; Sanders, Dirkse, & Slim, 2004). A typical method for this is to define vegetation units for the specific site and subsequently delineate those using the remote sensing data and a classification technique (Belluco et al., 2006; Kokaly, Despain, Clark, & Livo, 2003; Oldeland, Dorigo, Lieckfeld, Lucieer, & Jürgens, 2010; Thomas et al., 2003). The vegetation units are often based on vegetation properties that are typically well discernible by remote sensing techniques, such as vegetation structure, biochemistry and phenology (Ustin & Gamon, 2010). Other approaches ignore the concept of crisp vegetation units and visualize the continuous properties of vegetation, such as position on floristic gradients (Feilhauer, Faude, & Schmidtlein, 2011), forest diversity (Feilhauer & Schmidtlein, 2009), plant strategies (Schmidtlein, Feilhauer, & Bruelheide, 2011) or fractional cover of vegetation and soil (Asner & Heidebrecht, 2002). Other studies aim to isolate a particular feature of interest, such as nonnative species (Underwood, Ustin, & DiPietro, 2003) or invasive woody species (Hantson, Kooistra, & Slim, 2012). Discrimination and identification of individual tree or shrub species is currently feasible in some ecosystems (Cho et al., 2010; Clark, Roberts, & Clark, 2005; Dennison & Roberts, 2003; Roth, Dennison, & Roberts, 2012; Xiao, Ustin, & McPherson, 2004) and may benefit from combining LiDAR and hyperspectral data (Asner & Martin, 2009).

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The capacities of remote sensing might be more comprehensively exploited when remote sensing products reach potential end users such as nature managers and policy makers. However, such professional nature management and conservation agencies often employ a specific – and different from above – definition of vegetation units to describe their assets. Instead, these vegetation units are commonly created using a phytosociological approach, where species abundance data are used in cluster analysis and ordination to create discrete vegetation units (Dengler, Chytrý, & Ewald, 2008) that are differentiated by the presence or absence of diagnostic species (Verrelst, Geerling, Sykora, & Clevers, 2009). Current sensors are not suited to detect diagnostic species, all the more since they usually are sparse and have a low abundance (Verrelst et al., 2009). Therefore, incorporation of phytosociological vegetation units has only recently been confronted by the remote sensing community, but not without complications. For example, Schmidt et al. (2004) found that phytosociological units could only be successfully mapped after consulting expert knowledge in addition to hyperspectral and LiDAR data. Verrelst et al. (2009) chose to map clusters of phytosociological vegetation units because the individual vegetation units could not be differentiated directly. Given such difficulties, a comprehensive method that translates remote sensing data to vegetation units that are defined a priori and based on species composition, like phytosociological units, is desired.

We explore a method that uses vegetation characteristics such as plant traits (i.e., morphological, physiological or phenological features measurable at the individual plant level, Violle et al., 2007) or indicator values (IVs, Diekmann, 2002, see Section 2.1 for definition), as an intermediate between spectral reflectance and vegetation units. Such vegetation characteristics relate directly to plant biochemical, biophysical and phenological properties; properties that are also observable with remote sensing techniques (Asner & Martin, 2008; Asner et al., 2011; Schmidtlein, 2005; Ustin & Gamon, 2010; Verrelst, Muñoz, et al., 2012). In addition, it has been demonstrated that variation in vegetation characteristics is constrained by local environmental conditions and that plants themselves have limited ability in adapting their characteristic values upon a change in environmental conditions (Ackerly & Cornwell, 2007; Bello et al., 2009). Consequently, different vegetation units may be distributed along an *n*-dimensional vegetation characteristic space. This holds true for a priori defined vegetation units; their occurrence probability can be calculated for a given set of plant traits (Douma, Aerts, et al., 2012) or IVs (Witte, Wójcik, Torfs, De Haan, & Hennekens, 2007). This means that vegetation characteristics as predicted by remote sensing may be used to calculate vegetation unit occurrence probability.

This paper evaluates this hypothesis by using plant IVs to differentiate between a priori defined vegetation units that are often used among ecologists in the Netherlands. Two key concepts, IVs and the vegetation units, are described in detail first. Following this, a case study is presented where 19 representative vegetation units have been mapped. The resulting maps were validated by expert judgement and by comparison with a pre-existing vegetation map.

2. Method & materials

2.1. General methodology

A well-known method for determining a priori defined vegetation units is the school of Braun-Blanquet, also called 'phytosociology'. Here, discrete vegetation units, collectively called syntaxa, are clustered hierarchically into (from low to high ranks) associations, alliances, orders and classes. The integral hierarchical tree of these syntaxa is referred to as a syntaxonomical system (Weber, Moravec, & Theurillat, 2000). The association is the basic unit and defined as 'a plant community of definite floristic composition which presents a uniform physiognomy and which grows in uniform habitat conditions' (Weber et al., 2000). Plant associations are defined by the presence of diagnostic species (in particular: 'character' species and 'differential' species). As a showcase for the proposed method, we mapped plant associations according to the Dutch standard work of phytosociology 'De Vegetatie van Nederland' (DVN, the vegetation of the Netherlands, Schaminée, Stortelder, & Westhoff, 1995). This system defines 228 associations which are grouped into 89 alliances, 58 orders and 43 classes. In addition to the syntaxon names, the syntaxa in DVN are labelled with a 6 digit code from which their position in the hierarchical structure can be derived; the first two numbers indicate the class, the third and fourth characters indicate the order and alliance respectively, while the final two numbers determine the association. In this paper, the relevant associations are introduced once with their name and code and subsequently identified with their code only.

The method investigated in the paper pivots on the concept of using vegetation characteristics as an intermediate between spectral reflectance and occurrence of plant associations. In this case study, we use IVs as vegetation characteristics that couple the remote sensing data to associations. Originally introduced by Ellenberg et al. (1991), IVs use rankings of plant species occurrences to identify the most common occurrence of a species along a normalised environmental gradient (Schmidtlein, 2005). IVs are widely used in plant and systems ecology, but their use is also criticized due to supposed subjectivity and potential circular reasoning (Diekmann, 2002; Klaus et al., 2012; Schaffers & Sykora, 2000; Zelený & Schaffers, 2012). It is important to note that an IV is not a physical quantity that can be measured on a plant, but rather an artificially constructed property of a plant species. Another important aspect of our approach is that we did not use Ellenberg IVs. Instead, we employed IVs that are designed specifically for the Netherlands and that have non-integer values for individual species. This continuous representation is based on direct field observations (instead of expert knowledge) and allows for more reliable calculation of vegetation plot mean IVs. We used an already existing list of IVs per plant species that was compiled earlier; refer to Witte et al. (2007) for a detailed explanation on how this list has been compiled.

The general methodology is represented in Fig. 1. Firstly, in order to map IVs for the whole site, observed IVs of local vegetation plots were related to top of canopy reflectance values derived from airborne optical remote sensing imagery using Gaussian Process Regression (GPR) (step 1, Fig. 1). GPR model accuracy was assessed using an independent validation set of local vegetation plots. Secondly, Gaussian Mixture Density Modelling (GMDM) was used to define Probability Density Functions (PDFs) from a national database of vegetation plots (step 2, Fig. 1). Each PDF describes the Bayesian probability of association occurrence at a given combination of IVs. Finally, based on predicted IVs (step 1, Fig. 1) and the PDFs of the associations (step 2, Fig. 1), Bayesian occurrence probabilities were calculated for each association at each pixel (step 3, Fig. 1), visualizing the occurrence probability per association. In addition, the association corresponding to the highest occurrence probability was assigned to each pixel, creating a crisp classification of associations (step 3, Fig. 1). The certainty of the predicted association was represented as the maximum occurrence probability per pixel. A local vegetation expert assessed the accuracy of the predicted association occurrence. In addition, we compared the predicted distribution patterns per association with a pre-existing vegetation map of the study site.

2.2. Study site

The island of Ameland, located in the Dutch part of the Wadden Sea, was selected as study area. The Wadden Sea is located southeast of the North Sea, stretching from the Netherlands to Denmark; it is an intertidal zone of great ecological importance, as is reflected by its assignment as a Natura 2000 area and as an UNESCO world heritage site. Ameland (60 km^2, 53.45°N, 5.684°E, Fig. 2) is the third largest Dutch island in the Wadden Sea and has a large variety of ecosystems, ranging from dry and wet dunes, to tidal salt marshes, heath lands and fresh water