



# Estimating leaf functional traits by inversion of PROSPECT: Assessing leaf dry matter content and specific leaf area in mixed mountainous forest

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## ABSTRACT

Assessments of ecosystem functioning rely heavily on quantification of vegetation properties. The search is on for methods that produce reliable and accurate baseline information on plant functional traits. In this study, the inversion of the PROSPECT radiative transfer model was used to estimate two functional leaf traits: leaf dry matter content (LDMC) and specific leaf area (SLA). Inversion of PROSPECT usually aims at quantifying its direct input parameters. This is the first time the technique has been used to indirectly model LDMC and SLA. Biophysical parameters of 137 leaf samples were measured in July 2013 in the Bavarian Forest National Park, Germany. Spectra of the leaf samples were measured using an ASD FieldSpec3 equipped with an integrating sphere. PROSPECT was inverted using a look-up table (LUT) approach. The LUTs were generated with and without using prior information. The effect of incorporating prior information on the retrieval accuracy was studied before and after stratifying the samples into broadleaf and conifer categories. The estimated values were evaluated using  $R^2$  and normalized root mean square error (nRMSE).

Among the retrieved variables the lowest nRMSE (0.0899) was observed for LDMC. For both traits higher  $R^2$  values (0.83 for LDMC and 0.89 for SLA) were discovered in the pooled samples. The use of prior information improved accuracy of the retrieved traits. The strong correlation between the estimated traits and the NIR/SWIR region of the electromagnetic spectrum suggests that these leaf traits could be assessed at canopy level by using remotely sensed data.

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## 1. Introduction

Components of biodiversity that influence ecosystem dynamics, stability, productivity, nutrient balance and other aspects of ecosystem functioning are collectively referred as functional diversity (e.g., Tilman et al., 1997; Tilman, 2001). Most ecologists now agree that a major determinant of ecosystem functioning is functional diversity, rather than number of species per se (Díaz and Cabido, 2001). By quantifying functional diversity in natural communities, researchers gain additional understanding of the spatial and temporal distribution of biodiversity, ecosystem services and

plant community productivity (Cadotte et al., 2009; Lavorel et al., 2011). It is believed that better conservation and restoration decisions can be made by measuring and understanding functional diversity (Cadotte et al., 2011). This realization has underpinned the shift in focus of biodiversity research from species diversity to functional diversity (Tilman, 2001).

Like species diversity, functional diversity is quantified on the basis of trait values of organisms (Petchev and Gaston, 2006; Zhang et al., 2012). A trait is any measurable morphological, physiological or phenological feature of an organism (Violle et al., 2007). In plants, a trait is called a functional trait (e.g., specific leaf area) when it affects plant fitness indirectly via its impacts on plant growth, reproduction, and survival (Violle et al., 2007). It is the combination of plant functional traits that determines how plants respond to environmental factors, affect other trophic levels, and influence

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ecosystem processes and services (Zhang et al., 2012). For instance, plants growing in a resource-rich environment will have a relatively high specific leaf area and low dry matter content, whereas for plants growing in a resource-poor environment the opposite is true (Wilson et al., 1999). Traits also provide a link between ecosystem functional diversity and species richness (Carlson et al., 2007; Gregory, 2008). The functional traits are increasingly used to investigate community structure and ecosystem functioning, as well as to classify species into functional types (Smith et al., 1997) or for to validate global vegetation models (Albert et al., 2010).

In general, plant traits can be categorized into four groups (Cornelissen et al., 2003): whole-plant traits (e.g., growth form and height), stem and belowground traits (e.g., stem specific density and specific root length), regenerative traits (e.g., seed mass and dispersal mode) and leaf functional traits. Two fundamental leaf functional traits that are of central interest for researchers are Leaf Dry Matter Content (LDMC) and Specific Leaf Area (SLA) (Wilson et al., 1999; Asner et al., 2011). The LDMC, sometimes referred to as tissue density, is the dry mass of a leaf divided by its fresh mass, commonly expressed in mg/g (Cornelissen et al., 2003). It reflects plant growth rate and carbon assimilation and is a better predictor of location on an axis of resource capture, usage and availability (Wilson et al., 1999). The SLA is defined as the leaf area per unit of dry leaf mass usually expressed in  $\text{m}^2/\text{kg}$  (Cornelissen et al., 2003). It is referred to as leaf mass per unit area, as specific leaf mass, as well as leaf specific mass. SLA links plant carbon and water cycles, and provides information on the spatial variation of photosynthetic capacity and leaf nitrogen content (Pierce et al., 1994). According to the latter, “SLA is indicative of plant physiological processes such as light capture, growth rates and life strategies of plants”. A worldwide foliar dataset indicates that 82% of all variation in photosynthetic capacity can be explained by SLA and nitrogen (Wright et al., 2004). SLA is species-specific, but significant plasticity exists within and between individual plants of the same species (Pierce et al., 1994; Asner et al., 2011).

Besides their independent role as important ecological indicators, LDMC and SLA could be used to estimate leaf thickness (LT). The estimation of LT from the two traits has been investigated in detail by Vile et al. (2005). This implies SLA is a compound trait which is inversely proportional to the product of LDMC and LT. A study by Hodgson et al. (2011) found that  $\text{LDMC} \times \text{LT}$  accounted for nearly three quarters of the observed variation in SLA and that very different combinations of LT and LDMC regularly generate similar values of SLA. However, there are misconceptions in the definition of the stated traits. In many publications, leaf mass per area (LMA or  $C_m$ ), which is the inverse of SLA, is defined as LDMC.

Several trait data bases have been established worldwide through field measurements (e.g., Kleyer et al., 2008; Kattge et al., 2011). However, acquiring information on such traits purely on the basis of field measurements is labor-intensive and time-consuming, and thus expensive. Remotely sensed data can play a critical role in acquiring such data at broad spatial scales. Hyperspectral remote sensing has the advantage of providing detailed and continuous spectral information, which can potentially be used for measuring these traits. Previous studies have focused on using hyperspectral data to quantify biochemical and biophysical variables of vegetation, such as chlorophyll content, nitrogen and leaf area index (Darvishzadeh et al., 2008a; Vohland and Jarmer, 2008; Asner and Martin, 2009; Knox et al., 2010; Skidmore et al., 2010; Asner et al., 2011; Laurent et al., 2011; Ramoelo et al., 2011; Asner and Martin, 2012; Ramoelo et al., 2012). Hyperspectral remote sensing has also been used to map canopy functional and species diversity (Carlson et al., 2007; Papeş et al., 2010) and to estimate biodiversity (even simply as the number of species) (Lauver, 1997; Gould, 2000; Saatchi et al., 2008; Papeş et al., 2010; Féret and Asner, 2011; Ruiliang, 2011; Féret and Asner, 2014). However, directly

mapping individual species from remote sensing becomes difficult at larger scales and in ecosystems with very high species variability. An alternative approach to mapping species is to estimate plant functional traits, particularly those found in tree crown leaves, and to use these for assessing and monitoring biodiversity (Carlson et al., 2007; Gregory, 2008).

The methods applied to retrieve plant traits from remote sensing data can be grouped into statistical and physical (Darvishzadeh et al., 2008b; le Maire et al., 2008): statistical techniques are used to find a relation between the plant trait measured in situ and its spectral reflectance or some transformation of reflectance. Vegetation indices are widely used in this approach. When hyperspectral data are utilized, it is possible to select the most informative narrow spectrum features from the entire electromagnetic spectrum domain and use them for simple and fast assessment of vegetation properties (Broge and Mortensen, 2002). However, statistical methods are known to be site-specific and lack generalization. An alternative is to use a deductive or physical model approach (Radiative Transfer Model (RTM)) inversion, which is based on physical laws. Running an RTM enables the creation of a simulated training database covering a wide range of situations and configurations. Such forward RTM simulations allow for sensitivity studies of parameters and development of vegetation indices. This makes RTM inversion approaches more powerful than statistical methods. However, the retrieval of variables through RTMs inversion is ill-posed, since different combination of the input parameters may produce the same spectral signature. To overcome the effect of the ill-posed problem, Combal et al. (2003) recommended the use of prior information. Several studies have reported significant improvement to the accuracy of parameter retrieval after using prior information (e.g., Malenovsky et al., 2006; Dasgupta et al., 2009); others (Feret et al., 2011; Romero et al., 2012) have tried to exclude unrealistic combinations of input parameters by applying a linear regression equation derived from correlating the input parameters.

Leaf RTMs simulate leaf reflectance and transmittance by using certain input parameters derived from leaves. There are a number of leaf RTMs and each one requires a different number of input parameters. One such leaf radiative transfer model is the LIBERTY (Leaf Incorporating Biochemistry Exhibiting Reflectance and Transmittance Yields) model (Dawson et al., 1998) for conifer needles. However, it requires many input parameters which need to be obtained by intensive fieldwork and laboratory analysis (Malenovsky et al., 2006; Morsdorf et al., 2009). Another widely applied leaf radiative transfer model is PROSPECT (Jacquemoud and Baret, 1990). PROSPECT, which stands for PROPriétés SPECTrales (French for Spectral Properties). It simulates leaf reflectance and transmittance and is the most popular leaf optical properties model of all those published since 1990 (Jacquemoud et al., 2009).

Although much work has been done on estimating plant traits from remote sensing, the estimation of LDMC and SLA at all scales (i.e., leaf, canopy and landscape) is rare. To our knowledge, the use of remote sensing techniques to estimate LDMC has not yet been tested at any scale. Compared to other biophysical variables, studies conducted on SLA are also limited and have mainly been conducted using statistical methods at a canopy scale. Lyburner et al. (2000) tested several existing vegetation indices in order to estimate SLA from Landsat TM imagery and found a strong correlation between average canopy SLA and green, red, NIR and MIR reflectance of Landsat TM data. A strong correlation between leaf mass per area and reflectance in the 750–2500 nm wavelength range has been also reported for tropical rainforest leaf samples (Asner and Martin, 2008; Asner et al., 2011). Normalized indices for leaf mass per area at leaf and canopy scales have been developed only recently, by le Maire et al. (2008) and Feret et al. (2011). However, these indices need to be tested on other images, sites and canopies (le Maire

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