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The use of airborne hyperspectral data for tree species classification in a species-rich Central European forest area

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ABSTRACT

The success of remote sensing approaches to assess tree species diversity in a heterogeneously mixed forest stand depends on the availability of both appropriate data and suitable classification algorithms. To separate the high number of in total ten broadleaf tree species in a small structured floodplain forest, the Leipzig Riverside Forest, we introduce a majority based classification approach for Discriminant Analysis based on Partial Least Squares (PLS-DA), which was tested against Random Forest (RF) and Support Vector Machines (SVM). The classifier performance was tested on different sets of airborne hyperspectral image data (AISA DUAL) that were acquired on single dates in August and September and also stacked to a composite product. Shadowed gaps and shadowed crown parts were eliminated via spectral mixture analysis (SMA) prior to the pixel-based classification. Training and validation sets were defined spectrally with the conditioned Latin hypercube method as a stratified random sampling procedure. In the validation, PLS-DA consistently outperformed the RF and SVM approaches on all datasets. The additional use of spectral variable selection (CARS, "competitive adaptive reweighted sampling") combined with PLS-DA further improved classification accuracies. Up to 78.4% overall accuracy was achieved for the stacked dataset. The image recorded in August provided slightly higher accuracies than the September image, regardless of the applied classifier.

1. Introduction

Various studies have shown the potential of active and passive remote sensing to characterise forest stands in terms of species composition (e.g. Dalponte et al., 2013; Immitzer et al., 2012), structural parameters (e.g. Duncanson et al., 2014; Gwenzi and Lefsky, 2014), age classes (e.g. Buddenbaum et al., 2013) and chemical compounds (e.g. Asner et al., 2015) at different spatial scales. Tree species diversity and composition is a key parameter to describe forest ecosystems as it expresses, for example, the sustainability of management practices, is intrinsically linked to the provision of forest ecosystems services and positively related to the biodiversity of other taxa (Immitzer et al., 2012; Gamfeldt et al., 2013; Lindenmayer et al., 2000).

Developing tools for quantifying and detecting changes in tree diversity and composition at large scales and with high temporal resolution is therefore a crucial task for ecosystem service inventories and for the analysis of changes induced by anthropogenic or natural disturbances (Gong, 1997). Standard field-based forest inventories are costly and unable to provide information with a high spatial and temporal resolution (Immitzer et al., 2012). To operationalise tree diversity monitoring by means of remote sensing tools acceptable classification accuracies have to be reached, which is challenging in case of a complex horizontal and vertical stand structure and a high tree species number with a small-scale mixture. In addition, high spectral within-class variability, that can exceed the between-class variability (Debba et al., 2009) due to phenological effects and differences in tree age, openness of trees, natural variability, shadowing effects and differences in crown health (Clark et al., 2005; Waser et al., 2010), restricts tree species

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separability. A promising concept to overcome these limitations to some extent, is to use multi-temporal image analysis (Elatawneh et al., 2013; Pipkins et al., 2014; Somers and Asner, 2013), as it profits from the spectrally meaningful species specific annual variations of leaf chemistry or flowering and fruiting. However, the number of predictor variables highly increases with the number of considered images.

The choice of the appropriate sensor strongly depends on the classification task. Areas with a high diversity of spectrally similar tree species for example require a higher spectral and spatial resolution (Dalponte et al., 2013). Hyperspectral sensors ("imaging spectrometers") have thus been found to be usually more effective for tree species discrimination than multispectral sensors (e.g. Govender et al., 2008).

Yet, hyperspectral data comes with the disadvantage of large data volumes, multicollinearity of narrow wavelengths with an associated redundancy of information and sometimes noise (Fassnacht et al., 2014). An improvement of classification accuracies is thus not achieved by simply increasing the number of available spectral information (Bajcsy and Groves, 2004). For a supervised classification one of the main difficulties arises from the often low ratio of the number of training samples to the number of spectral bands (Melgani and Bruzzone, 2004), also known as Hughes phenomenon (Hughes, 1968). Classification accuracies may be increased if this problem can be overcome. Two main strategies to handle the problem of a huge number of predictors are: (i) variable reduction and (ii) variable selection algorithms. While variable reduction strategies aim to find latent factors for data compression, variable selection uses a subset of the most promising variables from the original dataset (Fassnacht et al., 2014). Partial Least Squares (PLS) regression in combination with variable selection is able to perform both strategies simultaneously (Li et al., 2009) and is therefore a standard procedure for regression tasks (Menze et al., 2009; Feilhauer et al., 2015). PLS Discriminant Analysis (PLS-DA) is a classification method based on components (latent variables or factors) that are defined in a classical PLS regression with categorical response variables. Using PLS to solve classification problems was proposed for the first time by Berntsson and Wold (1986). In the field of remote sensing the potential of PLS-DA for tree species separation has been recently reported (Peerbhay et al., 2014; Peerbhay et al., 2013 and Hobro et al., 2010). Peerbhay et al. (2014) classified three coniferous and one deciduous tree species with PLS-DA combined with a backward variable elimination procedure. A variety of variable selection methods, partly as ensembles, have been combined with PLS mainly in regression tasks (for a detailed review see Mehmood et al., 2012). Some of these methods consider the interaction of spectral variables in the selection process, whereas computationally more efficient methods ignore these effects (Yun et al., 2014). In our study, we combined PLS-DA with the computationally efficient "competitive adaptive reweighted sampling" (CARS, Li et al., 2009) and a backward variable selection procedure (Li et al., 2009). We performed repeated runs and finally decided about the class membership as majority vote.

Our goal was to evaluate the PLS-DA classification approach, for the Leipzig floodplain forest as representative of a multi-species and spatially highly variable forest site. Combined with CARS, this approach has to our knowledge not yet been applied to hyperspectral remote sensing data. As reference methods, we used two more established and conceptually different classification approaches – Random Forests (RF, Breiman, 2001) and Support Vector Machines (SVM, Vapnik, 1979). All approaches were competitively tested for their capability to correctly predict tree species identity for three differing datasets, generated on the basis of random sampling and, as alternative, a stratified random sampling procedure.

2. Materials and methods

2.1. Study area and data

The study site "Burgaue" (Fig. 1) is located in the north western part of Leipzig (Saxony, Germany). It is largely even, at an altitude of between 100 m and 140 m a.s.l and covers a total area of 2.18 km^2.

The average annual rainfall is 557 mm with a maximum in summer. The potential natural vegetation would be an oak-elm floodplain forest (*Querco-Ulmetum minoris*, Gutte and Sickert, 1998). Due to a strong reduction in the flooding frequency resulting in a lowering of the ground water level there is an on-going gradual shift to an oak-hornbeam forest (*Galium-carpinetum stachyetosum*, Gutte and Sickert, 1998). Leipzig's floodplain forest can be considered as an outstanding rare, near natural forest community due to its high number of tree species and its structural and age class diversity. The dominating tree species in decreasing order according to their abundances are European ash (*Fraxinus excelsior* L.), English oak (*Quercus robur* L.), Sycamore maple (*Acer pseudoplatanus* L.), European hornbeam (*Carpinus betulus* L.) and Small-leaved lime (*Tilia cordata* Mill.).

In the study area, 25 plots each with a size of 2500 m^2 were established. In each plot, forest inventory data were collected and tachymeter measurements performed. The forest inventory data included information about the tree species, DBH (Diameter at breast height), tree height and canopy coverage. To increase the number of rare occurring species additional field campaigns were realised using a differential GPS (Trimble Nomad® 900L, Trimble Ltd., Sunnyvale, California, U.S.).

The employed hyperspectral datasets were acquired with an AISA DUAL imaging system (SPECIM, Spectral Imaging Ltd., Oulu, Finland). The Dual system combines the Eagle and the Hawk sensors and covers a spectral range between 400.9 nm and 2497.1 nm with 367 spectral bands. Two images were acquired, one on 25 September 2011 and another on 2 August 2013; in both acquisitions a spatial ground resolution of 2 m was reached. At each date five flight stripes were recorded to cover the whole study area, with an overlap of 30% in across sensor direction. All flight stripes were pre-processed (according to Fig. 2) involving radiometric correction (CaliGeo, SPECIM), destriping (ROME, Rogaß et al., 2011), geometric correction (CaliGeo, SPECIM) and atmospheric correction (ATCOR4, Richter and Schläpfer, 2011). For all flight stripes the image registration was conducted in ENVI 5.0 (Exelis, Tysons Corner, Virginia, U.S.) using a high resolution aerial image (spatial resolution 0.2 m) as base map. Approximately 120 ground control points were manually defined per image and used for Delaunay triangulation, which resulted in a location error close to pixel size. The number of bands was reduced to 267, as bands affected by strong noise or atmospheric effects (water vapour absorption) were eliminated. In detail, the following AISA bands were removed: 1–6 (400.9 nm–422.1 nm), 190–215 (1383.6 nm–1541.0 nm), 260–300 (1819.6 nm–2083.4 nm) and 350–367 (2384.4 nm–2497.1 nm).

2.2. Pre-classification data processing

Non-forested areas (such as buildings, rivers or fields) were excluded from the image using the forest area boundaries provided by the local forestry office. Non-forest objects within those boundaries were manually masked. As it has often been found to be advantageous to use only sunlit pixels for tree species classification, various studies have included a manual delineation of non-shaded crown pixels (e.g. Dalponte et al., 2013; Ghosh et al., 2014; Immitzer et al., 2012). To overcome this time consuming, subjective and thus not fully reproducible processing step, we applied linear spectral mixture analysis (SMA) for a separation of sunlit and shaded crown parts using VIPER Tools 1.5 (Roberts et al., 2007). SMA assumes