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Report

An Enhanced Classification Approach using Hyperspectral Image Data in Combination with in situ Spectral Measurements for the Mapping of Vegetation Communities

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Summary: This paper shows the potential of a method using field spectral measurements as independent training data for the classification of airborne hyperspectral imagery of a natural preserve in Germany, using two different machine learning algorithms. The spectral reflectance of different *dry grass*- and *heathland* vegetation communities was measured with field spectrometers (350 nm – 2500 nm) in August 2009. Additionally, hyperspectral imagery was acquired by the airborne scanner aisaEAGLE (390 nm – 970 nm). The developed normalization technique was proven to be a suitable method to make image and field spectra comparable for classification. A support vector machine (SVM) and random forest (RF) classifier trained with normalized field spectra were applied to normalized image data to classify *dry grass*- and *heathland* communities in different levels of detail. SVM (overall accuracy (OAA) 89.13%) provided significantly better classification results compared to RF (OAA 71.74%) in the second level of detail. Consequently, only SVM was used for classification in the highest level of detail (third level), which also led to high classification accuracy (OAA 77.27%). The results indicate the potential of the developed approach classifying airborne hyperspectral image data with field spectral measurements for the spatial assessment and separation of *dry grass*- and *heathland* communities.

Zusammenfassung: *Ein kombinierter Ansatz zur Klassifizierung hyperspektraler Bilddaten mit im Gelände erfassten spektralen Punktmessungen zur räumlichen Erfassung von Vegetationsgesellschaften.* Im vorliegenden Beitrag wurde das Potenzial einer Methode untersucht, bei der spektrale Punktmessungen eines Feldspektrometers als unabhängige Trainingsdaten zur Klassifizierung hyperspektraler Flugzeugscanneraufnahmen verwendet wurden. Dabei kamen zwei Algorithmen des maschinellen Lernens zum Einsatz, deren Performanz unter Betrachtung verschiedener Genauigkeitslevels getestet wurde. Im August 2009 wurden spektrale Signaturen von Trockengras- und Heidekrautgesellschaften mit einem Geländespektrometer (350 nm – 2500 nm) erfasst. Zusätzlich fand eine flächendeckende Befliegung des Untersuchungsgebietes mit dem hyperspektralen Flugzeugscanner aisaEAGLE (390 nm – 970 nm) statt. Um eine Vergleichbarkeit beider Datensätze herzustellen, wurde eine Methode zur Normalisierung der Gelände- und Bilddaten entwickelt. Die Klassifizierung der Trockengras- und Heidekrautgesellschaften erfolgte mit den Algorithmen Support Vector Machine (SVM) und Random Forest (RF). Beide Algorithmen wurden mit den normalisierten Geländespektren trainiert und dann die Klassifizierung der normalisierten Bilddaten durchgeführt. SVM (Gesamtgenauigkeit (OAA) 89,13%) lieferte im Vergleich zu RF (OAA 71,74%) das bessere Klassifizierungsergebnis im zweiten Genauigkeitslevel. Aus diesem Grund erfolgte die Klassifizierung des höchsten Genauigkeitslevels (drittes Genauigkeitslevel) ausschließlich mit dem Algorithmus SVM, wobei erneut eine hohe Klassifizierungsgüte (OAA 77,27%) erzielt wurde. Als Ergebnis konnte eine genaue räumliche Erfassung und Trennung von

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Trockengras- und Heidekrautgesellschaften erzielt werden, wodurch das Potenzial der entwickelten Methode zur Klassifizierung hyperspektraler Bilddaten mit spektralen Geländemessungen verdeutlicht wurde.

1 Introduction

One of the main applications of remote sensing is the classification of different land cover types. In general, classification of airborne or satellite images is conducted by training a classification algorithm with spectral data directly extracted from the same image. Subsequently, the trained model is applied to the image data. However, there is often no information about the location of suitable training areas for the classification algorithm, which leads to inaccurate classification results. The rising number of libraries containing field or laboratory spectral measurements of different land cover classes can be used as an alternative to train classification algorithms without extracting spectral information directly from the image data. At present only a few studies using spectral data collected in the field or the laboratory exist as independent training data for the classification of airborne hyperspectral images for mapping minerals (e.g. Kokaly et al. 2008, Swayze et al. 2009), soils (e.g. Brown 2007) and especially vegetation (e.g. Birger et al. 1998, Nidamanuri et al. 2007, Nidamanuri & Zbell 2011, Zomer et al. 2009).

Detection of occurring plant species and mapping of different vegetation communities in the field is very time consuming and expensive. In this context, airborne and spaceborne hyperspectral remote sensing data with its high spectral information content increases the possibility for a highly accurate detection of different types of vegetation (Fauvel et al. 2013). Especially for hyperspectral data many classification methods have been developed and refined in recent years (Camps-Valls et al. 2014, Lunga et al. 2014). Therefore, hyperspectral data provides an alternative for fast and area-wide classification of different vegetation communities and species in order to locate and protect areas with endangered species which have to be preserved, e.g. in the context of the European habitats directive (European Union 1992).

Several studies have shown the potential of hyperspectral remote sensing data for separating vegetation communities or even single species (Artigas & Yang 2006, Chan & Paelinckx 2008, Cochrane 2000, Schmidt & Skidmore 2003). The high information content of hyperspectral data is well suited for a data basis for area-wide mapping of vegetation habitats and for vegetation monitoring over long time periods. However, acquisition of appropriate spectral reflectance signatures directly from hyperspectral image data for each class as representative training data for the classification of natural vegetation is still a challenge because of the heterogeneous character of the plant communities and their patchy stand density. In this context, field reflectance spectra of areas where species composition was botanically determined can serve as an alternative to generate suitable training data of an area wide image classification.

The main objective of this paper is the classification of dry land vegetation communities at different levels of detail from airborne hyperspectral images using field spectral measurements as representative reference data for the different classes. The classification was also conducted comparatively using the two classification algorithms support vector machine (SVM) and random forest (RF).

2 Study Area and Data

2.1 *Study Area*

The study area (52°30‘ N, 13°3‘ E) was the natural preserve Döberitzer Heide, located in the federal state of Brandenburg, west of the German capital Berlin (Fig. 1). From the early 18th century till 1994 the area was used as a military training area. After this long period of military usage large parts were protected by the German Federal Nature Conservation Act in 1996. The Döberitzer Heide has a size of about 5000 ha and is characterized by wet

biotopes in the western and dry biotopes in the middle and eastern parts (Rutschke 1997). The study area is situated in the transition area between maritime and continental climates. For that reason the region has a mean annual precipitation of 590 mm and 8.8 °C mean annual temperature (Hendl 1996). Over 50% of the Döberitzer Heide is covered by deciduous and coniferous forest, while other parts are characterized by heathland, sandy grassland, mesophile grassland, seminatural humid meadows, wetland and wasteland.

The four test sites are located in the northwest (test site A), the northeast (test site B), the east (test site C) and the south (test site D) of the study area (Fig. 1). The test sites are dominated by dry vegetation communities, especially different types of *dry grassland*, *heathland*, *broom*, *sand pioneer corridors* and *browse bristle*.

2.2 *Data*

Hyperspectral data of the airborne imaging system aisaEAGLE (Specim Ltd.) was used for classification of *dry grass*- and *heathland* vegetation. The aisaEAGLE imagery of the study area was acquired on August, 19, 2009 with a geometric resolution of 2 m in 252 spectral bands covering the wavelength range 390 nm – 970 nm. Thirteen flight stripes – alternately scanned in north-south and south-north directions – were recorded during flyover. The ROME de-striping algorithm was used to reduce the sensor mis-calibration effects of deficient lines along tracks in the images (Rogass et al. 2011). Atmospheric correction was performed using software developed at the University of Valencia (Guanter et al. 2009). Additionally, empirical line correction was applied including spectral ground measurements of different dark and bright targets collected in the test site during aisaEAGLE overpass (Smith & Milton 1999). aisaEAGLE data geometric correction was realized with the software CaliGeo and orthorectification was performed with the software ENVI.

Furthermore, 46 vegetation plots (1 m^2 size each) in areas with homogenous plant populations were defined in the study area. Colour infrared airborne data of previous years was evaluated for identifying suitable locations of the plots in field and for allowing a representative sampling of the investigated vegetation communities (Neumann et al. 2013). Spectral reflectance measurements of all plots were collected in the study area between August, 15 and 24, 2009 by different ASD FieldSpec Pro spectroradiometers recording spectral reflectance in 2151 spectral bands in the wavelength range 350 nm – 2500 nm. For each plot, 25 spectral measurements were taken. In addition, the height of vegetation was measured, photos were taken for documentation and plot positions were located by a handheld GPS.

2.3 *Vegetation Mapping*

During vegetation mapping, open land habitats with low vegetation growth were de-

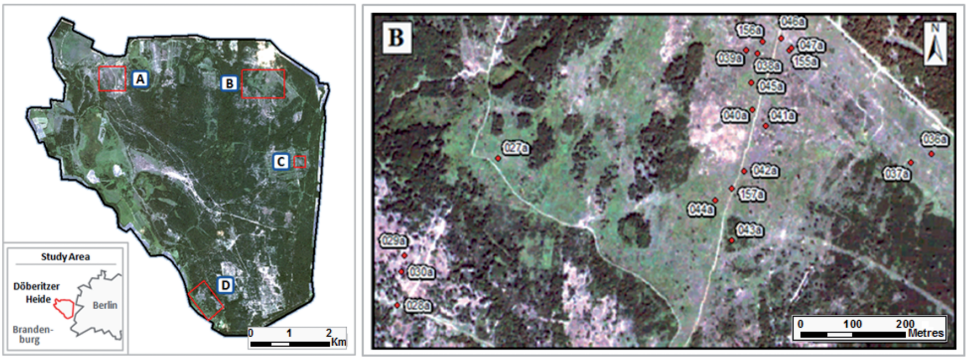

Fig. 1: Location of the study area and the test sites within the study area (left) and test site B in detail (right).

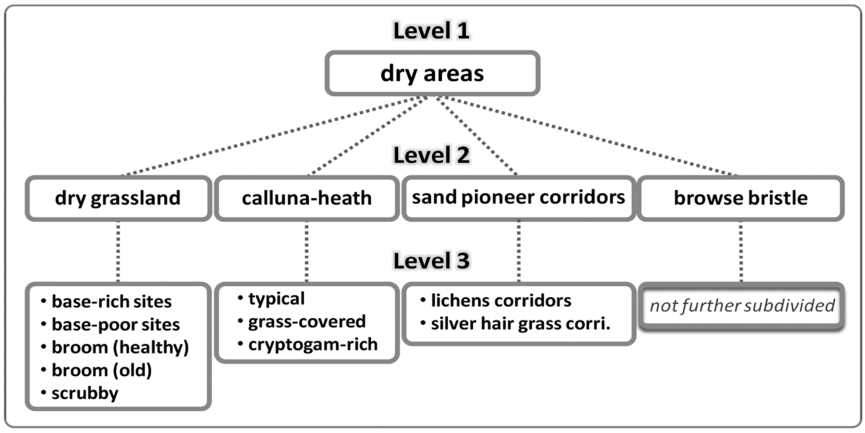

Fig. 2: Division of dry grass- and heathland habitats in different level for classification.

termined in detail. Wooden areas and shrub lands were not the focus of the investigations except broom heath, which was mapped and classified, too. The vegetation mapping scheme was finally structured in a hierarchical division of open land habitats with different levels (Fig. 2).

3 Methods

3.1 *Spectral Pre-Processing*

At the beginning of spectral pre-processing the inner fence (IF) was calculated for the 25 spectral field measurements of each plot. The IF is a statistical method to find outliers in a dataset. First, the inter-quartile range (IQR) has to be computed (1), and then the upper (IF_{upper}) and lower inner fence (IF_{lower}) is determined (2) (Tukey 1977). $Q_{0.25}$ and $Q_{0.75}$ represent the first and the third quantile.

$$IQR = Q_{0.75} - Q_{0.25} \quad (1)$$

$$IF_{upper} = (Q_{0.75} + 1.5 * IQR) \text{ and}$$
$$IF_{lower} = (Q_{0.25} - 1.5 * IQR) \quad (2)$$

In this study, for every spectral band the upper and lower IF was calculated from the 25 spectral field measurements of each plot. As a result, an inner fence range (IFR) was created limited by two artificially generated spectral signatures. Consequently, all spectral measurements of a plot outside the IFR were excluded from further processing and from final classification (Fig. 3). For classification of the aisaEAGLE image data with all selected spectral measurements of each plot, the data had to be spectrally prepared because spectral attributes of the training (ASD field measurements) and classification datasets (aisaEAGLE image data) showed significant spectral differences. Therefore, field spectra were resampled to aisaEAGLE spectral resolution and spectral range, making both datasets comparable.

Data adjustment of aisaEAGLE data and selected field spectra was achieved by normalization of both datasets, dividing reflectance values of the single bands (ref_n) by the maximum reflectance value of the spectral curve (ref_{max}). This procedure was adapted to all spectral signatures in both datasets.

$$ref_{norm} = \frac{ref_n}{ref_{\max}} \quad (3)$$

As a result, all spectral reflectance signatures were scaled to a maximum value of 1. Fig. 4 shows the spectral curves of an aisaEAGLE pixel with corresponding ASD field measurements before and after normalization.

The result clearly indicates a better match of the spectral reflection curves after the normalization procedure. Furthermore, in total 122 spectral bands at the beginning and end of the datasets (390 nm – 500 nm, 800 nm – 970 nm) were deleted because of noise, leav-

ing 130 spectral bands in the range 500 nm – 800 nm for the classification (Fig. 4, right). Subsequently, normalized aisaEAGLE data and selected, resampled and finally normalized field measurements were applied for classification of *dry grass*- and *heathland* vegetation.

3.2 *Machine Learning Classification*

A requirement for classification with SVM and RF is the availability of training samples for each dataset class (Muñoz-Marí et al. 2007). In this study only *dry grass*- and *heathland* areas were in the focus of the investigations, so that all the other classes had to be masked before starting with the machine learning classification. First, subsets with the spatial extension of the four test sites were extracted from aisaEAGLE image data. Afterwards, wooded areas, areas without vegetation and shadows were classified by applying an unsupervised K-means classification algorithm. Subsequently, a mask was created from the three classes and used to reduce the aisa-

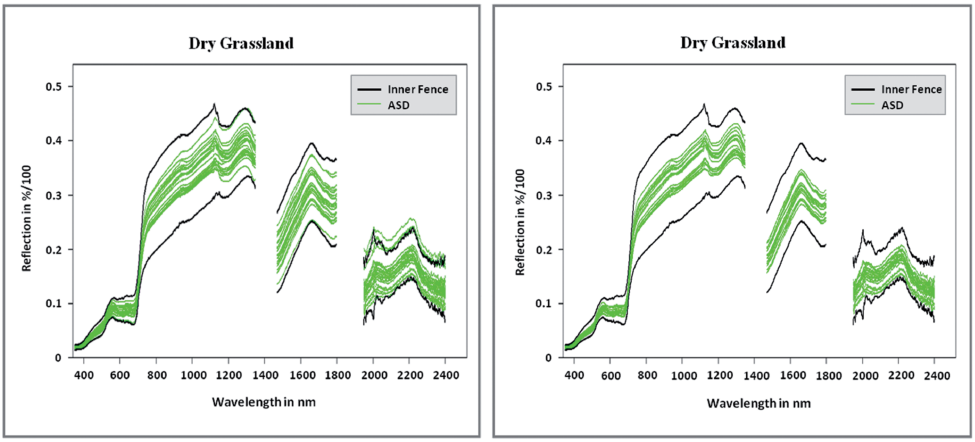

Fig. 3: Left: Spectral field measurements of a dry grassland plot before selection by inner fence. Right: Spectral field measurements of a dry grassland plot after selection by inner fence.

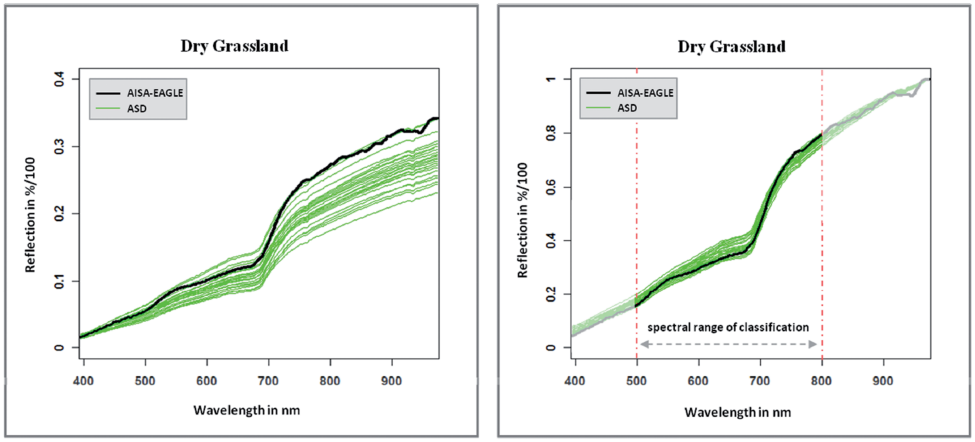

Fig. 4: Spectral reflection comparison of a dry grassland plot between the sensors aisaEAGLE and ASD FieldSpec. Left: Before normalization. Right: After normalization with the spectral range used for classification.

EAGLE data of the different test sites only to areas with *dry grass*- and *heathland*.

SVMs and RFs trace back to statistical learning theory, and some years ago they were adapted to solve classification and regression problems in the field of remote sensing. The advantage of SVMs and RFs compared with other classification algorithms, e.g. maximum likelihood and spectral angle mapper, is their capability to deal with high dimensional data. For that reason, SVMs (Braun et al. 2010, Foody & Mathur 2004, Huang et al. 2002, Pal & Mather 2006) and RFs (Chan & Canters 2007, Crawford et al. 2003, Lawrence et al. 2006) have often been used for classification of hyperspectral data in recent years.

SVM classification of dry grassland communities was realized with the software "ImageSVM" (Rabe et al. 2010), which is freely available as a part of the EnMAP-Box (www.enmap.org). In this context, a Gaussian radial basis function (RBF) kernel was used to build the SVM classification models. In order to find the optimal parameter values for C (regularization parameter) and g (Gaussian RBF kernel parameter), imageSVM uses a grid search technique based on an implementation in "libsvm" (Chang & Lin 2001). For RF classification, the free programming language R for statistical computing and graphics was used in combination with the additional R-package "randomForest", which provides a direct implementation of Breiman's RF algorithm (Breiman 2001). For classification of the vegetation communities, each RFR model was made up of 500 individual trees. Each tree was built with two thirds of the training data randomly selected (bootstrap samples), while the remaining third (out-of-bag samples) was used for a model internal validation. At each node of a tree, only a small number of features (square root of all features) were randomly selected for decision making.

The procedure to train the classification model and apply it to aisaEAGLE image data from the test sites was the same for both classification algorithms. First, the algorithms were trained with field spectra. Then, derived models were applied to the image data to classify *dry grass*- and *heathland*. Accuracy assessment was conducted by simply verifying whether a pixel corresponding to a measured plot in the field was classified in the right or in a wrong class. This approach of accuracy assessment could be performed because training data and classification data were independent datasets, so that a division between training and validation data was not necessary.

4 Results and Discussion

In level 1 the objective was to separate *dry grass*- and *heathland* vegetation from all other land cover classes. Just one of the 46 field plots was incorrectly masked in level 1 (overall accuracy (OAA) = 97.83%). This plot represented *healthy broom*, which at this growing stage had a very similar spectral reflectance compared to young trees. The subsequent classification of level 2 was conducted with the 45 remaining plots. For classification in level 2 the machine learning algorithms SVM and RF were used. The validation procedure was similar to level 1, except that at this point the classes of level 2 were intended to serve as reference for validation. While SVM classified 41 of the 46 plots (89.13%) correctly, with RF just 33 of the 46 plots (71.74%) were assigned to the correct class.

Tab. 1 shows results for SVM classification for the different classes at level 2. The *calluna heath* (CH) and *browse bristle* (BB) plots were all classified in the correct classes. The incorrect classified plot in the class *dry grassland* (DGL) was the *healthy broom* plot, which was already masked at level 1 and is consequently incorrect at level 2, too. The classification of the *sand pioneer corridor* (SPC) plots was more problematic compared to the other classes. Four of the 16 plots were assigned to wrong classes, mostly in the class CH.

Based on the substantially better results at level 2 for SVM compared to RF, at level 3 classification was only continued with SVM. At level 3, 34 of the 44 plots (77.27%) were classified to their corresponding classes. In this context, it has to be noted that the class browse bristle was not further subdivided at level 3, reducing the total number of plots to 44.

Classification accuracies at level 3 are listed in Tab. 2. The class *caluna-heath* provided the best classification result at level 3 with 11 of 13

Tab. 1: Classification results for the different classes of level 2 with SVM (DGL = dry grassland, CH = calluna-heath, SPC = sand pioneer corridor, BB = browse bristle).

Classes (level 2)	DGL	CH	SPC	BB
Result	14/15	13/13	12/16	2/2
Accuracy	93.33%	100%	75%	100%
Overall accuracy	41/46 (89.13%)			

Tab. 2: Classification results for the different classes of level 3 with SVM.

Classes (level 3)	DGL	CH	SPC
Correct/incorrect	12/15	11/13	11/16
Accuracy	80.00%	84.62%	68.75%
Overall accuracy	34/44 (77.27%)		

correctly classified plots (84.62%). *Dry grassland* also had high accuracy, at 80%, and 12 of 16 correctly assigned plots. The accuracy for the class *sand pioneer corridors* is relatively low compared to the other classes, with only 11 of 16 plots (68.75%) correctly classified.

The presented results underline that a detailed classification of *dry grass*- and *heathland* vegetation communities with hyperspectral airborne- and field data within the study area was possible. At level 1 the masking proved to be an appropriate procedure to reduce the aisaEAGLE data to *dry grass*- and *heathland* areas, which were the focus of this study. The incorrect masking of the pixel corresponding to the *healthy broom* plot could possibly be prevented if the area were classified again with data acquired at another time in the growing season, for example during the blossoming of *broom*. Under these conditions the spectral curve of *broom* should be different from young trees because of the dominance of the yellow blossoms.

The classification at level 2 showed that SVMs are more suitable than RFs for the classification of *dry grass*- and *heathland* in the study area. The reason for this could be the small number of training spectra for some classes. Foody et al. (2006) demonstrated that SVMs can handle classification problems with a small amount of training data very well because the algorithm only needs samples from the edges of the classes, the so-called "support vectors". In contrast, RFs appear to have more problems with the small number of training samples in the presented study. A higher number of training samples could possibly solve this problem: Pal & Mather (2006) showed that the classification of hyperspectral data with more than 250 training samples per class provided nearly the same classification accuracies for SVM and RF. Furthermore, the out-of-bag error, which is an indicator for the robustness of a RF, was also very high, at 15.49%. This fact indicates that the algorithm RF already had problems to separate the processed ASD field spectra, and therefore no satisfactory results were expected before classification.

SVM results for level 2 underline the capability of the classification algorithm to separate different dry and heathland classes. There was only a problem with the classification of the *sand pioneer corridors*. This class was unique because it had numerous variations of nearly uncovered soils, from areas slightly covered with lichen to areas with increasing grass cover, which can be seen as a transitional stage to the class *dry grassland*. Especially here, mixed pixels in the aisaEAGLE data had a major impact on the classification accuracy. For future work, classification approaches including spectral unmixing techniques and gradient mapping could help to overcome the problem; data should also be used with a spatial resolution higher than 2 m ground sampling distance. At level 3, classification accuracy for the different classes of *dry grassland*

and *caluna-heath* was lower by more than 10% compared to level 2, whereas the accuracy for the *sand pioneer corridors* was lower only by 7%. At this level mixed pixels also became problematic for the separation of different *dry grassland* and *calluna-heath* classes, but with 80.00% and 84.62% correct classified plots accuracy was still high. Finally, Fig. 5 illustrates the classification results for an aisaEAGLE image data subset of test site B at all three levels. At level 3, no more accuracy improvement seems to be possible.

The already-mentioned spectral unmixing or new ordination techniques for vegetation mapping in a floristic continuum are promising approaches to map plants in even higher levels of detail. Especially the latter approach has already provided detailed mapping results for different types of natural vegetation (Feilhauer et al. 2011, Schmidtlein et al. 2007, Schmidtlein & Sassin 2004). Neumann et al. (2011, 2012, 2013) also used continuous vegetation gradients in combination with multivariate regression analysis to map heterogeneous dry vegetation communities of the Döberitzer Heide, demonstrating the potential of the method with very promising results.

5 Conclusions

In the presented study, *dry grass-* and *heathland* communities of a dryland nature preserve in Germany were classified in different levels of detail on the basis of hyperspectral aisaEAGLE image data in combination with spectral field measurements. The normalization of image and field spectra before classification was proven to be a suitable method to make both datasets spectrally compara-

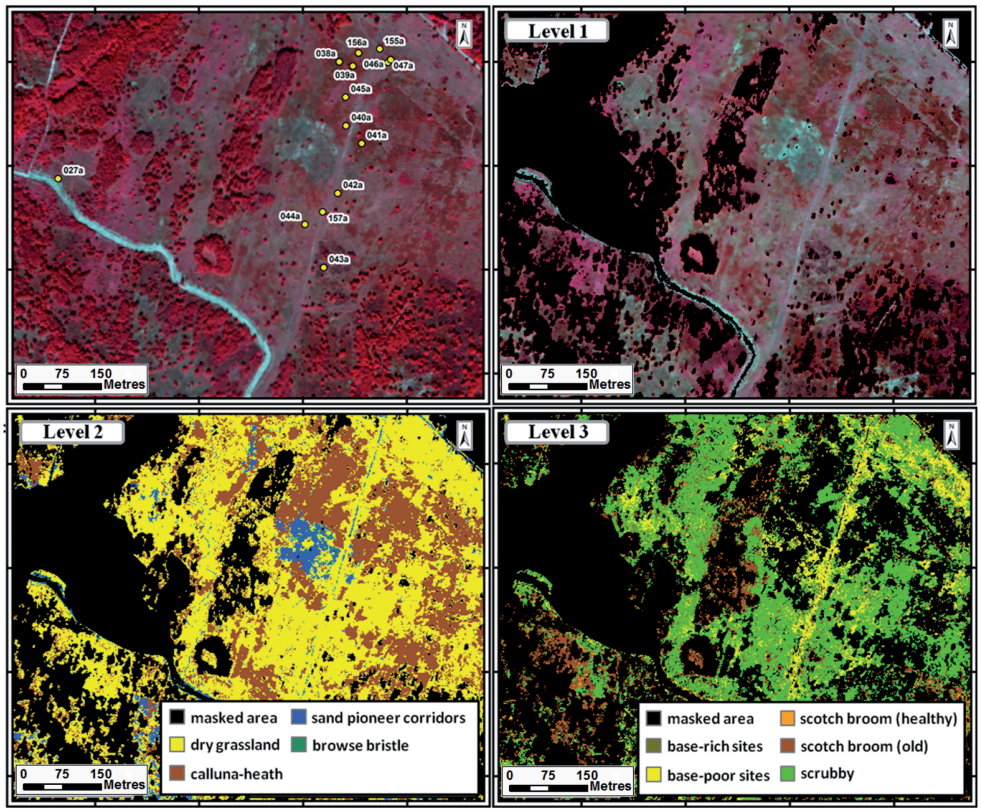

Fig. 5: Classification procedure for a subset of test site B. Top left: aisaEAGLE input image with the locations of several field plots. Top right: Masked aisaEAGLE data – level 1. Bottom left: SVM classification result – level 2. Bottom right: SVM classification result for dry grassland – level 3.

ble. The subsequent classification with the machine learning algorithms SVM (89.13% – level 2) and RF (71.74% – level 2) provided results with significantly differing classification accuracies, because SVMs can obviously deal better with training data which was not from the same source than the classification data. Therefore, the classification of the highest level of detail (level 3) was only performed with the algorithm SVM, also providing a result with relatively high classification accuracy (77.27%).

The acquired field spectral measurements of dry vegetation communities used in this study were stored in a spectral library system for the first time (*SPECTATION* www-app2.gfz-potsdam.de/spectation). This and many other spectral libraries offer open access to spectral reflectance measurements of numerous plants, soils and minerals and can be used as reference data for future classification studies in remote sensing. However, it is important that these libraries provide additional meta information about the reflectance measurements, e.g. day of acquisition, measurement conditions, for verifying their suitability for a certain classification problem. By the use of reference data from spectral libraries cost- and time intensive field campaigns to measure spectral reference data in field would no longer be necessary for every classification application.

The presented classification approach showed the potential of using field spectral reflectance measurements for the classification of hyperspectral image data with high accuracy. Furthermore, the classification procedure can easily be transferred to other classification problems where image data with high spatial resolution and suitable field reflectance measurements (possible from spectral libraries) are available.

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