Hyperspectral data for classification of selected vegetation species above tree-line in the Krkonoše mts. National Park

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Abstract. The paper is focused on the classification of vegetation above the tree-line in the Krkonoše Mts. National Park (KRNAP) using hyperspectral data (APEX). The vegetation above tree-line (altitude above 1350 m) is the unique ecosystem which is characterized by mosaic of subalpine meadows with Nardus stricta and Pinus mugo growths, subalpine peat-bog, rocks and another areas of the lichen tundra in the highest parts in the Krkonoše Mts. Studying of Pinus mugo and competitive strong grasses (Molinia caerulea and Calamagrostis villosa) expansion to the original meadows with Nardus stricta is very important issue for environmental protection. The aim of this study is to classify two species Nardus stricta and Calluna vulgaris spatial distribution in the western part of tundra in the Krkonoše Mts. National Park. Different classification methods (e.g. support vector machine, spectral information divergence or spectral angle mapper) are used and evaluated. The goal is to find best classification method providing the most accurate outputs. The detailed abundance maps of Nardus stricta and Calluna vulgaris are also produced.

Keywords. hyperspectral data, classification, grasslands, subalpine, Krkonoše Mts.

1. Introduction

The vegetation above tree-line (altitude above 1,350 m) is the unique ecosystem which is characterized by mosaic of subalpine meadows with *Nardus stricta* and *Pinus mugo* growths, subalpine peat-bog, rocks and other areas of the lichen tundra in the highest parts in the Krkonoše Mts. There are biotopes hosting valuable threatened species of plants and animals. Some of them are endemic for the Krkonoše Mts., and another show the relation with Nordic tundra. Preservation of this valuable ecosystem needs knowledge of the development of species and communities abundance. The remote sensing methods enable repeatable and reliable mapping of these large areas. They are widely used for monitoring different precious areas [1], [2], [3], [4], [5], [6], [7]. Hyperspectral remote sensing with high spectral resolution provides great potential to accurately identify and map the constituents of the earth's surface [8]. That is a reason why are the hyperspectral data so valuable input for classification of heterogeneous associations. Precision identification of objects on the ground can be achieved by different classification methods. It is possible to use commonly used methods for multispectral data and also methods designed especially for hyperspectral data, e. g. Spectral Angle Mapper (SAM) [9], Spectral Linear Unmixing (SLU), Spectral Information Divergence (SID) [9] etc. Some of the methods are described in this paper.

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The classification of heterogeneous vegetation is a very difficult task [6], [10]. The main question in the process of vegetation classification is which classification technique will be chosen. The statistically based classifications like fuzzy classification are the best for heterogeneous association with the high variability inside the pixel. For homogeneous vegetation the convection hard classifiers are used [7]. Traditional classification methods (like maximum likelihood) may not capture difficulty of ecosystems characterized by variable structure of vegetation [11]. It is the reason why the alternative approaches for classification of vegetation arise. On contrary, Zagajewski et al. (2005) [12] mapped vegetation in Vysoké Tatry Mts. using hyperspectral airborne data and maximum likelihood classifier. He achieved the overall accuracy of 78 % (kappa coefficient 0.745). The studies focused on land cover analyses now often use support vector machine (SVM) classification method [5], [13]. The SVM provides more accurate results then other algorithms (decision trees, neural net) [13]. SID and SAM classification methods are designed especially for hyperspectral data e.g. Qin et al. (2009) [14] used SID classification to classify citrus crops based on hyperspectral data. Petropoulos et al. (2012) [15] used SAM classifier for mapping land use/cover characteristics using Hyperion imagery. One of the first studies dealing with the spectral characteristics of plant associations in mountains area was Kokaly et al. (2003) [4]. They acquired spectral characteristics of plant associations of Yellowstone National Park and also hyperspectral imagery from AVIRIS scanner. As in this study, Feng et al. (2013) [16] deal with classification of vegetation above tree line – they classified land cover in grazing areas using SAM and hyperspectral data HJ-1A. Müllerová (2004) [17] classified subalpine vegetation in the Krkonoše Mts using multispectral data from 1986, 1989 and 1997. Also Král (2009) [18] presented study about alpine vegetation classification in Czech Republic.

In this paper we will focus on two specific objectives: 1) to classify two species *Nardus stricta* and *Calluna vulgaris* spatial distribution in the western part of tundra in the Krkonoše Mts. National Park based on APEX data and 2) to compare the results of different classification methods.

2. Methods

2.1 Study Area

The study area is situated in the western part of the Krkonoše Mts. National Park near Labská bouda, Vosecká bouda and Martinova bouda (Figure 1). Ones of the most precious ecosystems of the Krkonoše Mts. National Park (KRNAP) are the biotopes above tree line in height above 1,350 m [19], [20], [21], [22], [23]. There is a unique and varied ecosystem characterized by mosaic of subalpine grasses with dominant *Nardus stricta* and *Pinus mugo*, peat bogs and other areas of lichen tundra in Krkonoše Mts. [19]. Studying *Pinus mugo* and competitive strong grasses (*Molinia caerulea* and *Calamagrostis villosa*) expansion to the original meadows with *Nardus stricta* is very important issue for environmental protection [24]. Biotopes are very sensitive for different changes so changes may be very quick. For example expansion of ruderalized vegetation near the paths took 2.5% of tundra in 1986 in 1997 it was 7.6% [17].

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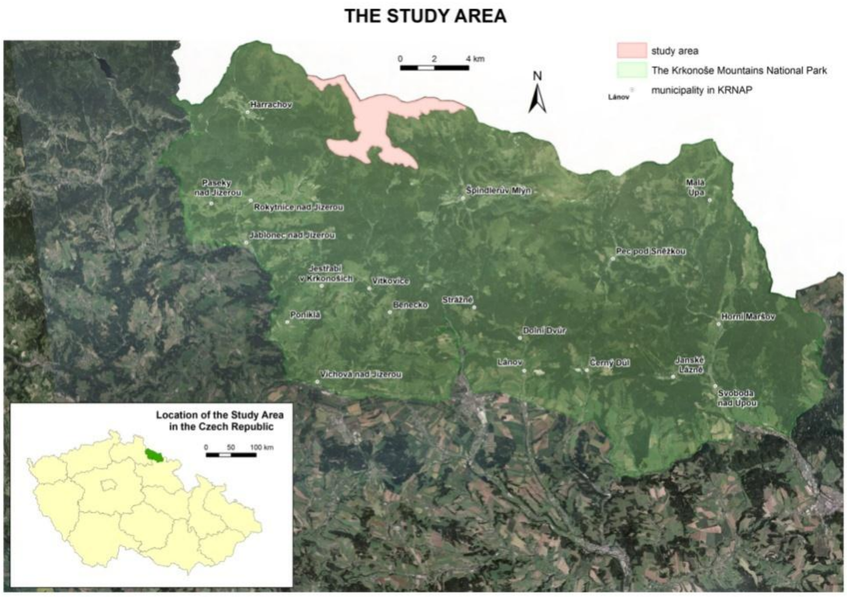

Figure 1: Study area

2.2 Data

The hyperspectral image data were acquired on 10th September 2012 using the APEX (Airborne Prism Experiment) airborne imaging spectrometer. The flight campaign was realized by project HyMountEcos. Hyperspectral images consist of 288 bands with wavelength range between 400 nm and 2500 nm and ground spatial resolution of 2 to 5 m. The preprocessing was made by Belgian VITO. Data covers both Czech and Poland part of the Krkonoše/Karkonosze Mts.

Field campaign for the training data acquisition was realized a year after the flight campaign in the same time period (17th September 2013). Polygons of the vegetation classes were obtained using the Trimble Geoexplorer 3000 Geo XT GPS device and then prepared in ArcGIS software for the classification purposes.

2.3 Data processing

Three different classification methods were performed in this study: Spectral Angle Mapper, Spectral Information Divergence and Support Vector Machine. All 288 bands of APEX data were used for these classification methods. By SAM and SID two classes were classified *Nardus stricta* and *Calluna vulgaris* and by SVM four classes were classified *Nardus stricta, Calluna vulgaris, Pinus mugo* and area without vegetation (AWV) (Figure 2) because this algorithm don't provide good classification results for just two classes.

2.3.1 SAM

The SAM is a supervised classification algorithm, which utilizes spectral angular information for classification of hyperspectral data. It treats each pixel in a hyperspectral image as a n-dimensional vector, where *n* equals the number of spectral bands. The algorithm measures similarity of target spectrum to a reference spectrum by calculating spectral angles between them. A smaller angle represent a closer match to the refer spectrum [25].

2.3.2 SID

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The spectral information divergence calculates the distance between the probability distribution produced by the spectral signatures of two pixels [9]. This method uses a divergence measure to match pixels to reference spectra. The smaller the divergence is, more likely the pixels are similar. Pixels with a measurement greater than the specified maximum divergence threshold are not classified [26].

2.3.3 SVM

Support Vector Machine is one of the recent developments in the field of machine learning. SVM is a universal learning machine for solving classifications. It's strange is in the ability to model complex, non-linear class boundaries in high dimensional feature space through the concept of kernel function and regularization [27]. SVM is classification system derived from statistical learning theory. It separates the classes with a decision surface that maximizes the margin between the classes. The surface is often called the *optimal hyperplane*, and the data points closest to the hyperplane are called *support vectors*. The support vectors are the critical elements of the training set [26].

2.3.4 Data processing

For improving SAM and SID based mapping using hyperspectral data the reference spectra for each class were chosen from three polygons of *Nardus stricta* and two polygons of *Calluna vulgaris* (polygons were obtained using the GPS during the field campaign). Reference spectra of *Nardus stricta* and *Calluna vulgaris* were extracted from region of interest (ROI) in hyperspectral image data using ENVI 4.7 software (Figure 2). In the SAM classification properties the threshold (maximum angle) value of 0.1 radians was selected. ENVI does not classify pixels with an angle larger than this value. The threshold for SID classification was set to 0.02, the value means minimum allowable variation between the endmember spectrum vector and the pixel vector [26].

For SVM classification all pixels from acquired polygons of *Nardus stricta* and *Calluna vulgaris* were used. The kernel function named Radial Basis Function was applied and the selected reclassification probability threshold was 0.75.

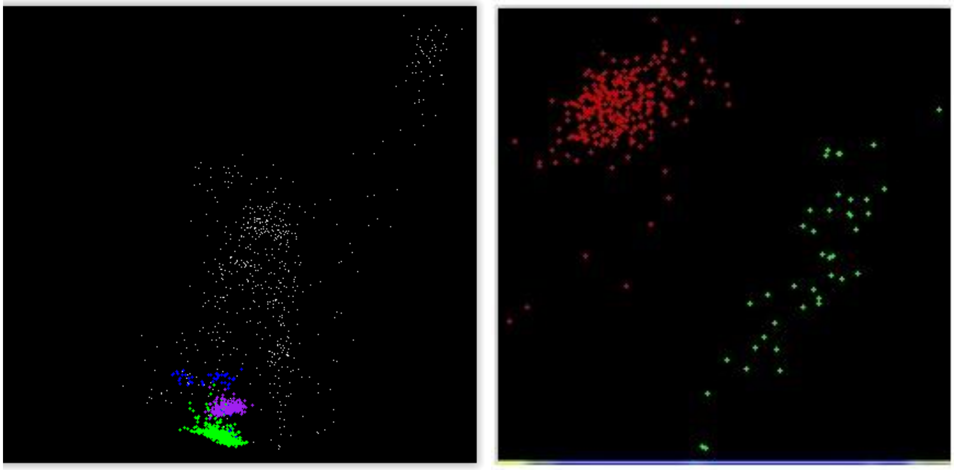

Figure 2: Left: Scatter plot of classes classified by SVM (Nardus stricta (blue), Calluna vulgaris (purple), Pinus mugo (green), AWV (white)). Right: Scatter plot of classes classified by SAM and SID (Nardus stricta (green), Calluna vulgaris (red))

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3. Results

The overall classification accuracy of 84.67% was achieved by SAM (kappa coefficient 0.86) (Figure 3) and 87.59% was achieved by SID (kappa coefficient 0.7) (Fig. 4). In comparison, Spectral Information Divergence classification method provided better results than Spectral Angle Mapper, but the both methods provided very high accuracy for two selected classes. The user and producer accuracies of SID are concluded in Table 1. The higher user accuracy was provided for *Nardus stricta* and higher produccer accuracy was provided for *Calluna vulgaris*.

The classification Support Vector Machine provided overall accuracy of 78.84% with kappa coefficient 0.72 for four selected classes (Fig. 5).

Table 1. The user and producer accuracies of SID

Class	User accuracy	Product accuracy
Calluna vulgaris	87%	95.6%
Nardus stricta	89.2%	71.7%

Figure 3: The result of the APEX image classification using the SAM algorithm

Figure 4: The result of the APEX image classification using the SID algorithm

Figure 5: The result of the APEX image classification using the SVM algorithm

4. Conclusions

Hyperspectral remote sensing methods show a potential for vegetation mapping in mountainous areas and can be used for classification of selected species because hyperspectral data enable to recognize different species of vegetation above tree line on the basis of their spectral signatures. Two classes were classified by SAM and SID classification methods and four classes were classified by SVM. Very good results were achieved using all of APEX bands for classifications. SAM and SID are specialized for hyperspectral data. For these two methods only pure pixels for each class were used. We proved that the selection of an appropriate threshold is the key factor for the final classification results. The highest accuracy was achieved by SID classification method (87.59%) with threshold value of 0.02. Qin et al. (2009) [14] achieved higher accuracy using SID classification and hyperspectral data to classify citrus crops. An overall classification accuracy of 96.2% was achieved using an optimized SID threshold value of 0.008. The overall accuracy for SAM classification method (84.67%) reached in this study is comparable with value presented by Fang et al. (2013) [16], they classified land cover in grazing areas above tree line using hyperspectral data and they achieved the overall accuracy of 85.9%. The lowest accuracy in this study was achieved by SVM classification method (78.84%) even though the accuracy was still quite high. It was caused by more classified classes. This result is comparable with study presented by Su et al. (2006) [5] they classified species in desert meadows and the overall accuracy of 76.7% was achieved by SVM classification. All methods used in this study can be considered as effective tool for determination different vegetation species above tree line. In comparison with Müllerová (2004) [17] the hyperspectral data provide more possibilities to classify vegetation above tree line more correctly then multispectral data. Müllerová (2004) [17] classified subalpine vegetation in Krkonoše Mts. but based on multispectral data she was not able to separate *Nardus stricta* and paths unlike this study.

This study confirms that all classification methods and also hyperspectral data are very useful for future work including classification on the level of vegetation associations and on the level of particular species. In final work 12 classes with some subclasses will be classified.

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