MAPPING HIGH MOUNTAIN VEGETATION USING HYPERSPECTRAL DATA

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ABSTRACT

The paper presents the methods and first results of vegetation mapping, using field and hyperspectral airborne data in high mountain ecosystems. The research also aims at a comparison of different remote sensing methods of vegetation classification and at creating a map of actual vegetation.

The study was carried on in the Tatra National Park – encompassing subalpine, alpine and subnival belts of the Tatra Mountains. The results of the ground mapping and different image classification approaches were compared.

Maximum likelihood classification method is widely used in many remote sensing applications and can be considered one of the most popular and reliable techniques. Neural network classification is based on training during a training phase, and the proper classification. The training process is based on determining the neural connection weights to make the output signal from the network as close as possible to the expected result. One of the goals was to verify the usefulness of neural networks for classification and to obtain the best results in vegetation recognising using airborne hyperspectral imagery.

For validation of the DAIS and ROSIS image classifications, a detailed large-scale vegetation map was prepared, using traditional field mapping.

Keywords: DAIS/ROSIS, hyperspectral, vegetation mapping, classification

INTRODUCTION

Vegetation cover is a perfect indicator of environmental conditions and should be well recognised and mapped. This is possible using hyperspectral data, which provides high spectral, spatial and radiometric resolution. Furthermore, the application of such data in inaccessible mountainous environments is much more effective than traditional field mapping.

Mountain plants have developed specific adaptations to survive at the fringe of life e.g.: pigment content, plant tissue structure, etc. These adaptations have direct impact on reflectance, which can be quantified using hyperspectral imagery (1,2).

This paper presents the method and first achievements of vegetation mapping, using field and hyperspectal airborne data of the DAIS 7915 and ROSIS sensors. The research aims at a comparison of different remote sensing vegetation classification methods. For validation of hyperspectral imagery 14 key areas with different plant communities, located in different topographic situations, were prepared to allow a detailed, large-scale actual vegetation map to be made at a scale of 1:10 000. The map was prepared in a traditional way using field mapping and typological Braun-Blanquet approach (3).

The test area encompasses subalpine, alpine and subnival belts of the High Tatra Mountains in the eastern part of the Tatra National Park in Poland.

Imagery used in the study was acquired by two sensors. The first sensor, DAIS, covers the spectral region from 400 to 12600 nm, using 79 narrow bands. Depending on flight altitude, the pixel size of the image can be from 3 to 20 metres. The second spectrometer, ROSIS, acquires data in 115 spectral bands ranging from 430 to 850 nm. Spatial resolution can vary from 1 to 6 metres depending on the flight altitude (4).

Hyperspectral data can be used to precisely identify many objects. This can be achieved using many classification approaches, like different types of supervised classification or neural network approach. Some of the methods are described in this paper.

Study area

The Tatra Mountains (the Tatras), although relatively small, constitute the highest part of Carpathian range, and are the highest mountain range between the Alps and the Caucasus. The total area of the Tatras is 785 km^2, of which 22.3% is located in Poland (5). The Tatras are divided into two main parts: West and High Tatras. The first part is built of igneous rocks (mainly granitoids), and is therefore higher than the second part which is built of softer, mainly calcareous rock (6).

The study area is located in one of the main valleys of the High Tatras – Dolina Gasienicowa (Figure 1). It includes subalpine, alpine and subnival vegetation belts, where geological substratum (calcareous or silicate rocks) together with climatic changes connected with altitude, determine the differentiation of plant communities (7). The subnival belt is characterised by bare rocks and very sparse vegetation, composed mainly by lichens (e.g. *Rhizocarpon geographicum*) and sparse swards (*Oreochloetum distichae subnivale*). In the alpine belt, on the siliceous rocks, *Oreochloo distichae-Juncetum trifidi* has developed as the climax association. Swards belonging to the *Festuco versicoloris-Seslerietum tatrae* community grow in a small part of the area on calcareous rocks. In both vegetation belts, scree vegetation and snow-bed vegetation are represented as well. Avalanche meadows (*Calamagrostietum villosae tatricum*) occur on steep slopes. In the subalpine belt, *Pinetum mughi carpaticum* is the main community. Depending on the geological substratum two subassociations can be distinguished: *Pinetum mughi carpaticum silicicolum* on siliceous rocks and *Pinetum mughi carpaticum calcicolum* in the calcareous biotopes (7).

Figure 1: The study area of the High Tatras

METHODS

Field vegetation mapping

Vegetation mapping in field demands application of complementary research methods from both phytocenology and geoecology. This includes an initial phytocenological reconnaissance on the basis of existing materials, and then determination of the list of dominant plant species and communities. Vegetation units delimited on the maps comply with the Braun-Blanquet approach and include associations, subassociations, local forms and spatial complexes of communities. Usually the rank of association is at the basic level, but in case of zonal communities occurring on large surfaces, it can be at a level of subassociations or local forms and spatial complexes of communities. Smaller, heterogeneous areas were joined into higher classification units (alliance, order or class). After that a detailed vegetation map was prepared at a scale of 1:10 000. The key legend of the actual vegetation map (8) consists of 42 units. They are assembled into ecological groups:

- cryptogamic plant communities on scree - initial phase;
- epilitic lichen communities (*Rhizocarpetalia*);
- scree communities (*Androsacetalia alpinae*);
- snow-bed communities (*Luzuletum alpino-pilosae*, *Salicetum herbaceae*);
- subnival swards (*Oreochloo distichae-Juncetum trifidi* subnivale form);

- alpine swards on silicate substrate (*Oreochloo distichae-Juncetum trifidi*) differentiated into some subassociations and forms: *typicum*, *cetrarietosum*, *sphagnetosum*, *salicetosum herbaceae*, *salicetosum kitaibelianae*, *caricetosum sempervirentis*, subalpine anthropogenic form, scree form with *Juncus trifidus* and spatial complexes with other communities
- alpine swards on mylonite and limestone substrate (*Festuco versicoloris-Agrostietum alpinae)*;
- peaty and boggy communities (*Caricetum fuscae subalpinum*, *Sphagno-Nardetum*, *Polytricho-Nardetum*);
- avalanche meadows (*Calamagrostietum villosae tatricum*);
- tall herb communities (*Adenostylion*);
- grassland communities after grazing (*Festuca picta* community, *Deschampsia flexuosa* community, *Hieracio alpini-Nardetum*);
- mountain pine shrubs (*Pinetum mugho carpaticum*)

Preprocessing

Data used in this study was acquired on the 4th of August 2002 at 10:30 a.m. At this time of the day the sun elevation was 38° and sun azimuth was 145°. During the overflight 6 lines of DAIS and ROSIS images were acquired, of which 2 were taken additionally due to unfavourable atmospheric conditions. One line of ROSIS data was lost after some unexpected technical problems. Finally, 4 lines of DAIS and 3 lines of ROSIS data were used.

Each line of DAIS data covers an area of approximately 25 km^2 (2.5 km x 10 km). Due to large overlap areas the images cover about 35 km^2 (3.5 km x 10 km) in total. A line of ROSIS data is smaller and covers an area of 5.6 km^2 (0.8 km x 7 km) approximately. In the study a mosaic was used, composed of 3 ROSIS images covering an area of about 15 km^2.

For the geometric correction of image data the PARGE (PARametric GEocoding) software was used. The software, developed at the University of Zurich specially for correcting airborne imaging spectrometer data, applies parametric geocoding using high precision flight parameters (like an exact position of the aircraft and its attitude angles) for every line. If used with a digital elevation model of high accuracy, PARGE can give very accurate results (9).

DAIS data used in this study was geometrically corrected using all required parameters: GPS (Global Positioning System), INS (Inertial Navigation System), DEM (Digital Elevation Model) created from digitised contour lines, and several GCPs (Ground Control Points) of high accuracy. During this process the data was registered to the UTM coordinate system using the Nearest Neighbour resampling method that retains original data values. The resulting pixel size is 3 metres, with a geometric accuracy within 2 pixels.

Unfortunately, the procedure described above could not be applied to ROSIS data because of technical problems during data acquisition and missing parameters. Another approach had to be used employing polynomial transformation based on the large number of GCPs and the Digital Elevation Model. The data was also registered to UTM coordinate system using the same resampling method. Pixel size of the final image is 1 m. Since the geometric correction of ROSIS was not done by the authors themselves, the accuracy was not investigated thoroughly. Nevertheless, a comparison with DAIS and topographic data does not show any unacceptable geometric errors, which could prevent further analysis.

Atmospheric correction was performed on the DAIS data using ATCOR4 (ATmospheric CORrection) software, which includes a database of correction functions based on the MODTRAN4 radiative transfer code (10). During this process the data values were changed from radiance to reflectance, removing in this way the influence of the atmosphere on the data.

ROSIS data were not atmospherically corrected and were used as recorded.

RESULTS

Hyperspectral data consist of a high number of narrow and continuous bands and offering identification of particular features. A small range of each of them allows precise differentiation between many objects based on their unique spectral properties. A high number of channels is also the reason of between-band correlation, causing information redundancy. One of the most important stages in the analysis process is to reduce the number of bands to a minimum that will still provide optimal classification run. Choosing adequate ranges allows nuances in different land cover types to be identified and mapped. Thenkabail et al. (11) indicated 12 wavebands between 400 and 1100 nm that are quite important from the point of view of distinguishing different kinds of cereals. Some spectral ranges were indicated for identification of tree species (12) and for analysing vegetation conditions (2). Results of these studies, however, cannot be extrapolated to other areas, because specific growth conditions cause spectral characteristic changes even within the same species. Mapping of high mountains plant communities is even more challenging because of very fragmented landscapes and very diverse reliefs. This type of analysis demands an optimal spectral band set.

Spectral reflectance data adequate for classification were chosen based on the spectral curves derived from the DAIS image, which made it possible to avoid water absorption bands and channels with significant errors or noise. For further analysis 14 spectral bands were chosen. Their characteristics are listed in Table 1. Additionally, a temperature band was added as the 15th band. This band was created by converting the radiant temperature measured by the DAIS sensor to the absolute temperature in degrees Celsius. Information about surface temperature can be very useful when analysing vegetation (13).

Table 1: Spectral characteristics of DAIS bands used during the study

band number	centre wavelength /nm	band number	centre wavelength /nm
1	0.502	22	0.873
4	0.554	24	0.906
8	0.625	26	0.939
9	0.641	33	1.542
12	0.695	34	1.573
13	0.711	78	11.636
17	0.783	79	12.278

To reduce data dimensionality and avoid information redundancy, a Principal Component Analysis (PCA) procedure was applied. This is a mathematical process that transforms correlated bands into a new image set of uncorrelated principal components. All image bands that were not rejected during the previous stage, were transformed into PCA space. Upon analysis of the information contained in the new data set, only 6 first bands (i.e. from PC1 to PC6) representing about 99% of the original image information were chosen for the next step.

Image classification can be done in an unsupervised or supervised manner. Unsupervised classification is based on assigning pixels to a given number of classes that are spectrally homogeneous and not taking into account any additional information about the analysed region. Users define only the number of classes. Their names are defined after the whole process. Results of this approach depend on spectral characteristics of the data. On the contrary, supervised classification depends on the user and his knowledge. The user defines pixels representing land cover elements on the basis of different data and information available,. The class types and names have to be defined before the classification starts.

One of the characteristics of vegetation is its variable reflectance: identification of some communities may be difficult using only spectral properties. Vegetation reflectance registered by remote sensing instruments is the average of the reflectance of photosynthetically active parts, non-photosynthetically active parts (i.e. branches, dry leaves), shadow and ground. These elements, being an integral part of plant communities, impede their recognition in case of assuming their spectral properties. Thus, it is obvious, that vegetation can be characterised by a high variability of the signal and therefore the statistical distribution of reflectance differs from the normal distribution.

Supervised classification

The first step during the supervised classification process was to choose the number of classes that should be discriminated and then to create spectral signatures of land cover types under investigation. This was done based on a visual analysis of the image and on the results of unsupervised classification that was performed earlier. Seven main classes were defined: mountain pine shrubs, forests, meadows, rocks, lakes, shadows and tourist routes. Training areas for each class contained a minimum of 50 pixels and the signatures were calculated as an average of pixel values of a given cover type taken from different parts of the image.

The classification results were compared with the vegetation map of the area. The map, at scale 1:10 000, was created as an outcome of detailed terrain mapping carried out in recent years in Tatra Mountains (8). Classification results were also compared with the unclassified image. Both data sources were used for accuracy assessment and Kappa coefficient calculation.

The output of unsupervised classification that was made as the reconnaissance before the main classification process, did not show satisfactory result. Many areas of the same land cover type, even if they were spectrally very different, were assigned to improper classes. For example, some pixels that are in fact meadow pixels, were assigned to the forest class, and vice versa. These misclassifications could be a result of vegetation complexity and high fragmentation of mountain landscape. The unsupervised classification method is too simple to reveal the differences in vegetation cover, and therefore is not suitable for mountain vegetation analyses.

In case of supervised classification the results were much better. The best outcome was produced with the maximum likelihood algorithm (Figure 2). The overall accuracy was 78%: the poorest result was noted for rocks and tourist routes (about 40% accuracy), while the best results were obtained for lakes and meadows (90 – 100% accuracy).

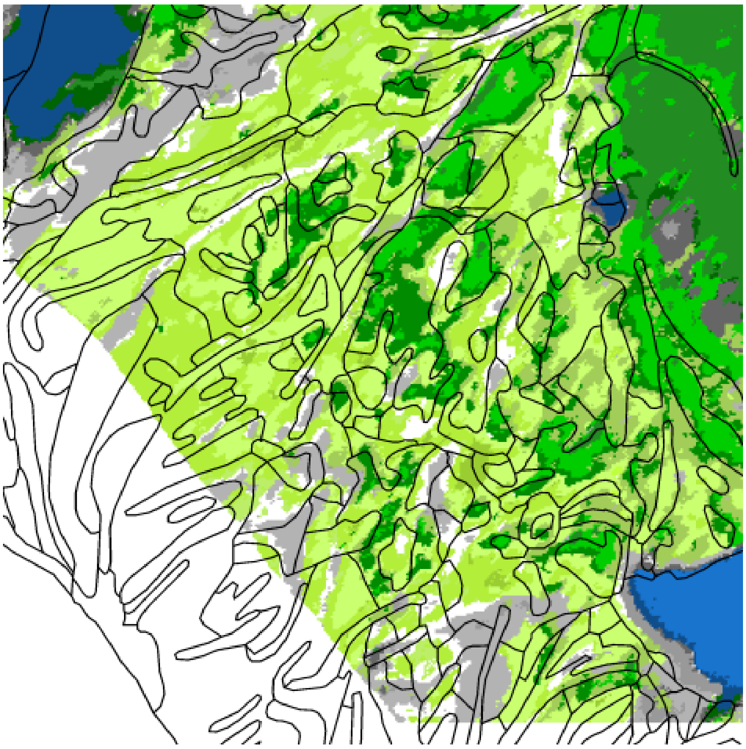

Figure 2: The results of the DAIS 7915 image classification using the maximum likelihood algorithm. The map is overlayed by the contours of the actual vegetation.

An attempt was also made to increase the number of class definitions by dividing the seven main land cover types into more detailed subclasses. Finally, 18 classes were created, and the classification process with the maximum likelihood algorithm was repeated. However, it gave much poorer results than in case of 7 classes - the specific subclasses were indistinguishable. More detailed division (into different soil moisture, aspect, altitude, etc.) requires further investigation.

Another attempt was made with data after PCA transformation. As mentioned above, 6 first principal components were used (from PC1 to PC6). The result of a supervised classification over PCA-derived image did not show good results. An overall accuracy of 71% was achieved, with the poorest results in case of forests and meadows (20-56%) and the best results in case of lakes and pine shrubs (83-100%). Errors were mainly connected with the incorrect classification of meadows pixels. They were assigned to mountain pine and rock classes, causing inaccuracies. Problems arose also in areas of shadow.

All the problems mentioned above were caused by high spectral diversity of different land cover types in the researched area. Moreover, the selection of data bands used for the classification process can probably be improved. High mountain vegetation identification and mapping require very specific spectral ranges. On the other hand, vegetation analysis should not be done as an automatic process for all of the plant communities, but rather for each of them independently. Also providing additional information, such as texture, would be a good idea.

Artificial Neural Network Classification

Traditional classification, that uses parametrical approaches (like maximum likelihood approach), does not show satisfying results. A method that uses artificial neural networks does not depend on statistical parameters of a particular class and hence makes it possible to include texture information as additional data. This method may be especially useful to separate and classify vegetation communities.

Texture is one of the main characteristics used in the visual interpretation of an image. Adding this information to automatic classification processes is possible both for the Artificial Neural Network (ANN) approach and for more traditional methods like the Maximum Likelihood (ML) classification. The main difference is the additional error, which is introduced due to the $\chi 2$ distribution characteristic of textural data in the case of the ML classification. To avoid this problem it is favourable to use non-parametric methods of classification, like ANN.

To classify land cover types for the ROSIS scanner image, we applied a multilayer, one-directional network, trained using a supervised method of back-propagation. The Stuttgart Neural Network Simulator (SNNS) was used for that purpose. This software was developed at the University of Stuttgart and is available for free on the internet (14).

To assess the usefulness of the artificial neural network classification approach, many tests were performed for the cover type of mountain pine. In the first stage, training was limited only to this single class due to the great deal of time that was needed to accomplish this task. Mountain pine was used because it is very common in the study area. It was assumed that the ANN structure that showed the highest classification accuracy for the mountain pine class, should also provide good results for the other cover types (Figures 3, 4) (15).

Table 1: Mountain pine classification errors.

Threshold	0.3	0.4	0.5	0.6	0.7	0.8
Hidden layer 3x3	15.35%	15.13%	14.55%	14.85%	16.95%	17.18%
Hidden layer 5x5	15.97%	15.08%	14.89%	15,65%	17.82%	17.85%

The evaluations of the results were conducted using a point-to-point comparison with an actual vegetation map of the High Tatras. Table 1 presents the results obtained from the comparison of different maps generated by neural network classification with different hidden layers and threshold values. The error varies between 15 and 18% and is below 15% for the best combination.

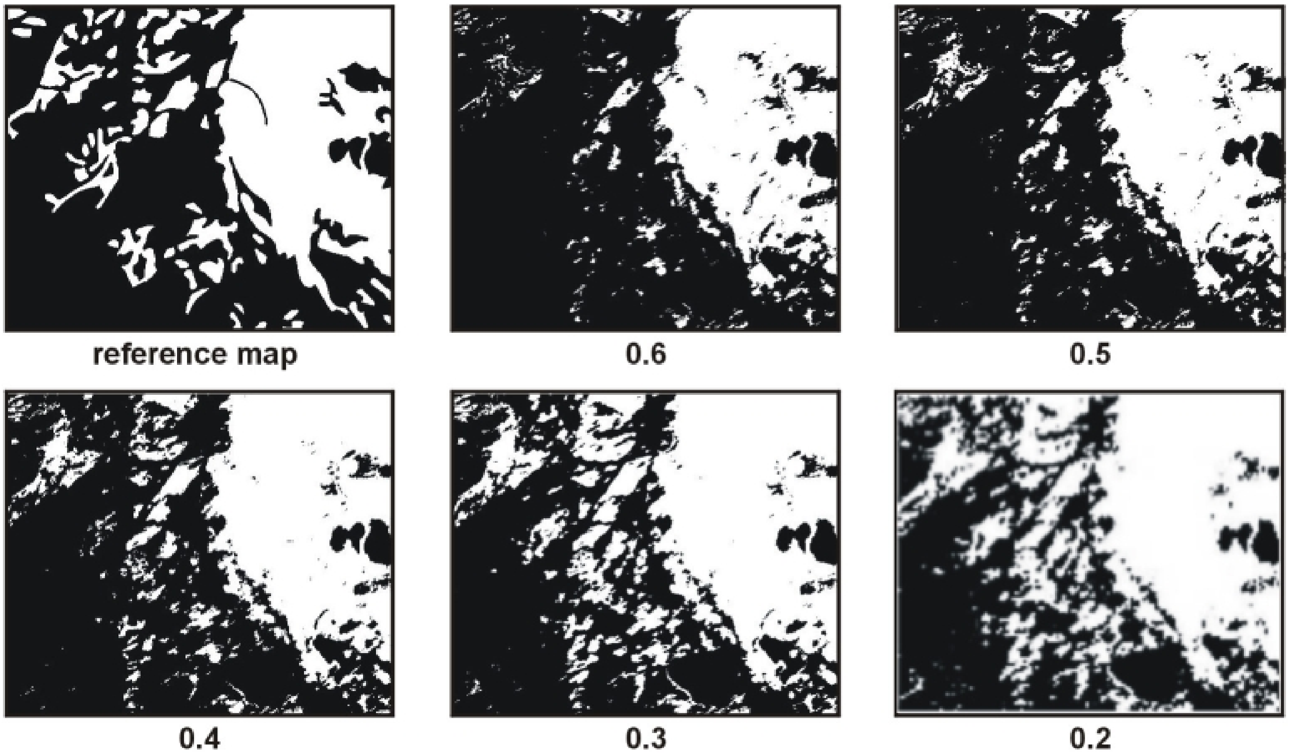

Figure 3: DAIS 7915 image classification using ANN algorithm. Upper left image presents the reference map of the mountain pine shrubs (white areas). Rest of the images present the comparison of the classifications with different threshold values (0.2-0.6).

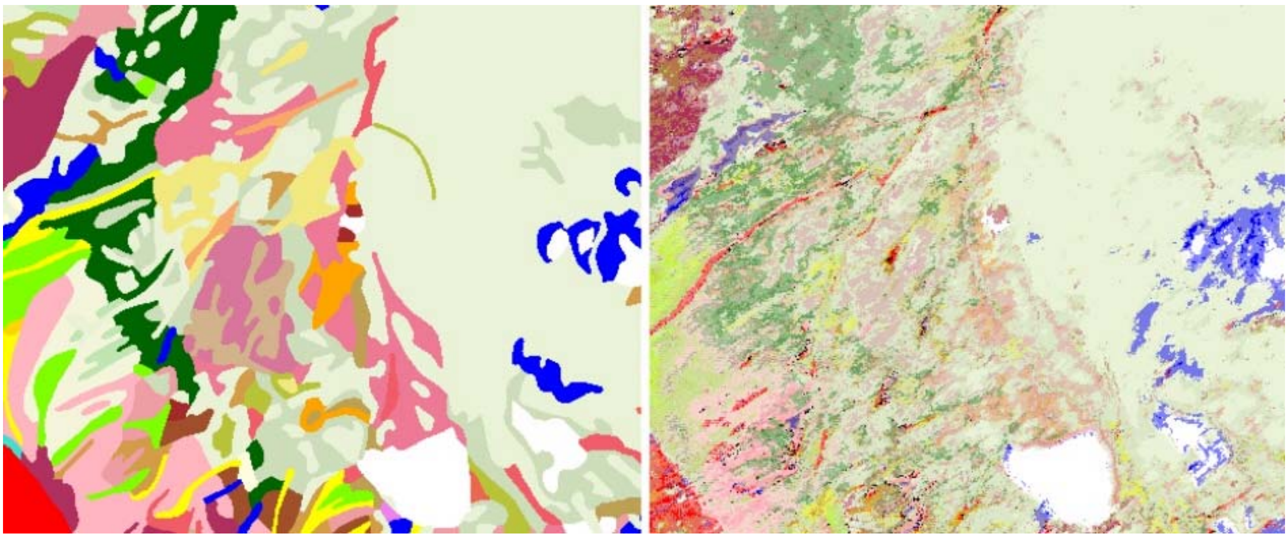

Figure 4: Comparison of the terrain mapping (right) and the DAIS 7915 image classification (left) using the ANN algorithm. Colours represent different land cover

CONCLUSIONS

Hyperspectral remote sensing techniques show a potential for vegetation mapping in mountainous areas and mapping at large scales. Combination of field remote sensing techniques and hyperspectral DAIS 7915 and Rosis imagery allow plant habitats and most of the investigated vegetation units to be recognized (research and mapping). However, the different classifications approaches themselves, without using additional data, do not give satisfactory results yet. The methods described above need to be modified and adjusted in a way that will allow more precise and accurate vegetation mapping. Such a way could be an approach that takes into account only one cover type at a time. Another could be adding auxiliary data, such as texture, to the classification process.

More attention should also be given to the other classification methods, specifically to the hyper-spectral data, like Spectral Angle Mapping, Linear Spectral Unmixing, etc. This kind of image classification allows fuzzy borders between different land cover types, which corresponds to reality. These methods should also be tested in detail.

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