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TREE SPECIES AND AGE CLASS MAPPING USING HYPERSPECTRAL DATA AND GEOSTATISTICS

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ABSTRACT

Geostatistics were used to improve tree species and age class classification of a forest in western Germany. The performances of different geostatistical techniques were compared using two HyMap images and a forest-GIS. Airborne hyperspectral data (HyMap) were acquired in the years 1999 and 2003. The 1999 HyMap image was spectrally degraded to Landsat-TM spectral resolution in order to compare the information content of hyper- and multispectral data. Four age classes of norway spruce and douglas fir stands were differentiated through image classification. One main objective was to improve the classification without using information from additional data. The improvement in classification accuracy was to be achieved by calculating image texture through geostatistical analysis from the existing bands. Geostatistical bands were calculated using moving window procedures. Different band combinations were used in spectral angle mapping (SAM) classifications to evaluate their value for discriminating tree species and age classes. Training and validation were performed using a Forest-GIS that contains stand information on species composition and tree age. The best results were achieved using maxima of pseudo-cross madograms derived from the first MNF channels of the hyperspectral data as geostatistical texture channels. Complete madograms as texture channels also led to good results. The gain in classification accuracy was comparable to the gain achieved by using a channel containing the stem density. Classification using the multispectral data could also be improved by adding geostatistical data.

Keywords: Geostatistics, Variogram, Madogram, hyperspectral, classification, forest.

1 INTRODUCTION

Information on tree species and age class composition in forests is critical to both forest resource management and scientific research. Forest inventories routinely collect species and age distribution, which is a very time-consuming task when done manually. Hyperspectral remote sensing data have the ability to differentiate between many classes of land cover (Lillesand & Kiefer, 2000; Koch et al., 1993), and two sets of HyMap data of the study area were available. They are better suited for a precise classification of forest stands than multispectral data (Lee et al., 2004; Ustin & Xiao, 2001; Köhl & Lautner, 2001). But to identify different kinds of coniferous tree stands is a difficult task as their spectral response pattern is very similar (Coleman et al., 1990; Niemann, 1995). The accuracy can be improved using additional data sources. Hildebrandt (1996) states three methodical ways to differentiate between classes that cannot be distinguished using classical remote sensing techniques:

- Using remote sensing data recorded at different dates (multitemporal approach)
- Using non-spectral additional information, and

- Using specific textural parameters.

Key et al. (2001) utilised multitemporal image data, but did not achieve better results compared to a single date classification. Franklin et al. (1994) improved classification by using topographic data additional to multispectral remote sensing data. Schlerf et al. (2003) employed stem density information derived from high resolution orthophotos to improve tree species and age class classification. The classification accuracy could be increased compared to a classification without using the stem density. However, high resolution orthophotos of the study area are not always available and the derivation of stem density from low- or medium resolution data is error-prone. So the intention of this work was to improve the classification accuracy without using additional data. Instead, image texture was derived from the image itself and used in the classification process.

The general objective of the study was to match the classification accuracies reached by adding information from high resolution remote sensing imagery without using additional data. Works by St-Onge and Cavayas (1995 & 1997), Hay et al. (1996) and Treitz and Howarth (2000) show the potential of texture aided classifications of remote sensing data. Different approaches of integrating geostatistic image texture data into the classification process were tested and compared.

2 STUDY AREA AND DATA

The area of study (49° 40' N, 7° 10' E) is located in the Idarwald forest in south-western Germany on the north-western slope of the Hunsrück mountain ridge. The dominant forest tree species are Norway spruce (*picea abies*), beech (*fagus sylvatica*), oak (*quercus petraea*) and Douglas fir (*pseudotsuga menziesii*). Active forestry practices in this area include selective cutting, plantation establishment and thinning.

Airborne hyperspectral data were acquired in July 1999 and in July 2003 using the HyMap sensor built by Integrated Spectronics, Australia. HyMap records data in 128 contiguous bands covering the spectral range of 0.4-2.5 μm with a spectral resolution of 10-20 nm. The spatial resolution was set to 5 m with a full scene covering about 2.5 km x 10 km. The 1999 data were geometrically and radiometrically corrected, the 2003 data were geometrically corrected. To correct the effect related to the change in sensor view angle an cross-track illumination correction was applied the each spectral band independently. For this purpose, a second-order polynomial was fitted to the data. Based on the fitted polynomials, a normalisation procedure was applied (cross-track illumination correction). Parametric geocoding was performed using the software PARGE (Schläpfer et al., 1998, 2002). Radiometric corrections of the HyMap data were performed at the Remote Sensing Department, University of Trier, following an approach by Hill et al. (1995, 2003) that uses a modified version of the 5S-Code by Tanré et al. (1991). The processing steps involved atmospheric correction and sensor calibration. The first step converted digital numbers to at-sensor-radiances. In the second step the effects of the atmosphere were removed including errors due to pixel orientation.

Data reduction and enhancement was performed using a Minimum Noise Fraction (MNF) transformation (Green et al., 1988). Only the first ten MNF channels were used in the further steps. The 1999 HyMap image was spectrally degraded to Landsat-TM spectral resolution (six channels in the visible, near-infrared and mid-infrared spectral regions) in order to compare the information content of hyper- and multispectral data for tree species classification. The HyMap data's spatial resolution of 5 m was kept. All together, three data sets were obtained: The MNF-transformed 1999 HyMap data, the simulated 1999 Landsat-TM data and the MNF-transformed 2003 HyMap data. The geostatistic calculations and the classifications were performed with each of these data sets.

The most recent forest inventory for the study area (October 1994) including stand information on species composition and age classes has been integrated into a Forest Geographical Information System (FoGIS) by Vohland (1997).

3 METHODS

3.1 GEOSTATISTICS

Several geostatistic measures were tested to quantify image texture. Geostatistics and the theory of regionalized variables have been introduced to remote sensing by Woodcock et al. (1988) and by Curran (1988). Geostatistics can be used to measure the spatial variability of a variable and so to quantify the image texture. Several geostatistic tools exist to measure the spatial variability. The best-known tool is the semivariogram, also called variogram or, to highlight that it is a monovariate measure, auto variogram. It gives the relationship between similarity and distance in a viewed surrounding. $Z(x)$ and $Z(x+h)$ are two realisations of the variable Z located at x and $x+h$. The two locations are separated by the vector h, which is called the lag. The variogram values ($\gamma(h)$) are calculated as the mean sum of squares of all differences between pairs of values with a given distance. The variogram is a discrete function of variogram values at all considered lags (e. g. Isaaks & Srivastava, 1989; Curran, 1988):

$$\gamma(h) = \frac{1}{2n}\sum_{i=1}^{n}\left(Z(x_i) - Z(x_i + h)\right)^2 \qquad (1)$$

Another measure of spatial variability is the madogram (or auto madogram). Instead of squaring the differences, the absolute differences are taken (e. g. Chica-Olmo & Abarca-Hernández, 2000; Deutsch & Journel, 1998):

$$\gamma(h) = \frac{1}{2n}\sum_{i=1}^{n}\left|Z(x_i) - Z(x_i + h)\right| \qquad (2)$$

Alternatively, the texture can be quantified by bivariate measures. The cross variogram measures the joint spatial variability (cross correlation) between two variables Y and Z at the locations x_i and x_i+h (Chica-Olmo & Abarca-Hernández 2000, Journel & Huijbregts 1978):

$$\gamma(h) = \frac{1}{2n}\sum_{i=1}^{n}\left(Y(x_i) - Y(x_i + h)\right)\left(Z(x_i) - Z(x_i + h)\right) \qquad (3)$$

The pseudo-cross variogram represents the semivariance of the cross increments instead of the covariance of the direct increments as above (Chica-Olmo & Abarca-Hernández, 2000):

$$\gamma(h) = \frac{1}{2n}\sum_{i=1}^{n}\left(Y(x_i) - Z(x_i + h)\right)^2 \qquad (4)$$

To combine the advantages of the before-mentioned texture measures, the pseudo-cross madogram is introduced. The pseudo-cross madogram is similar to the pseudo-cross variogram, but again instead of squaring the differences, the absolute values of the differences are taken which leads to a more generous behaviour towards outliers:

$$\gamma(h) = \frac{1}{2n}\sum_{i=1}^{n}\left|Y(x_i) - Z(x_i + h)\right| \tag{5}$$

All the above mentioned geostatistical tools were used separately in this work to obtain values for image texture. They were calculated from one (univariate case) or the two (bivariate case) MNF-channels using a 7 x 7 pixel moving window. Values were merged to form seven lags, so that seven geostatistic values were available at each pixel of each considered channel. To reduce the amount of data two general approaches were tested. In the first approach, variograms and madograms were calculated from only the first (monovariate case) or the first two (bivariate case) MNF channels resulting in seven additional channels per texture measure. In the second approach, auto madograms for the first ten MNF channels and pseudo-cross madograms of all combinations of the first five MNF channels were calculated. Accordingly, for the simulated Landsat TM data set, auto madograms of the 6 channels and pseudo-cross madograms of all combination of these channels were calculated. Of these madogram channels, the maxima were identified and taken as input channels for classifications. The results of the first approach are listed in table 1, the results of the second approach in table 2.

3.2 CLASSIFICATION

Two classification schemes were designed. The first scheme classified the 1999 HyMap data, the second scheme classified all three data sets. The primary aim of the first scheme was to compare different geostatistic texture measures, using complete vario- or madograms. The aim of the second scheme was to compare HyMap and TM spectral resolution and to compare the 1999 and 2003 images using madogram maxima.

All classifications were carried out in the same way to ensure comparability. Four age classes of Norway spruce (10-30 years, 30-50 years, 50-80 years, and above 80 years) and two age classes of Douglas fir (10-30 years and 30-50 years) were chosen to be differentiated as these were the most common types of coniferous stands. As a preliminary processing step, an unsupervised classification (Isodata algorithm) was applied on the HyMap data set to identify coniferous forest areas. The classification result was used to create a mask so that only the coniferous stands were considered in the following steps.

The supervised classification process can be divided into three stages: Training, classification and validation. The aim of the training stage is to collect a set of statistics that describe the spectral response pattern and/or the texture for each desired information class. The polygons in the FoGIS representing the forest stands were used to extract spectral signatures for each class (5-13 polygons per class, 100-1000 pixels per polygon). In total, 52 subclasses and 17 609 pixels were obtained.

The classification scenarios differ from each other in the input channels used. The first ten MNF channels (HyMap) or the six simulated TM channels were taken as input to the classification in each pass. Geostatistic or conventional texture channels were added to the input data sets. Before the main classifications, all input data channels were normalised to a mean value of zero and a standard deviation of one.

The classifications were performed using the Spectral Angle Mapper (SAM, Kruse et al., 1993). The SAM algorithm determines the spectral similarity between two spectra by calculating the angle between the spectra, treating them as vectors in a space with dimensionality equal to the number of bands (Kruse et al., 1993). SAM compares the angle between the spectrum vector of the known class and each pixel vector (unknown class) in n-dimensional space. In the classification stage, the class with the smallest angle is assigned to the corresponding image pixel.

The resulting 52 subclasses obtained from the classification were merged into the desired 6 main information classes. Then the post-classification algorithms sieve and clump were applied to the classification result to remove isolated pixels. For the validation stage 62 areas (6-15 polygons per class, 100-1000 pixels per polygon, 31 700 pixels in total) were selected as ground truth using the FoGIS. These areas did not overlap with the training polygons. A confusion matrix was generated from the validation pixels for each classification, both before and after the post-classification operations. The confusion matrices are not included in this article but can be obtained from the authors. Two measures of classification accuracy were reported. Overall accuracy (OAA) quantifies the percentage of pixels correctly classified:

$$OAA = \frac{1}{n}\sum_{1}^{q} n_{kk} \cdot 100 \tag{6}$$

where n_{kk} is the number of correctly classified validation pixels (confusion matrix diagonals), q is the number of classes, and n is the total number of validation pixels used.

The kappa coefficient compensates the effects of chance agreement:

$$KAPPA = \frac{n\sum_{k=1}^{q} n_{kk} - \sum_{k=1}^{q} n_{k+}n_{+k}}{n^2 - \sum_{k=1}^{q} n_{k+}n_{+k}} \tag{7}$$

where n_{k+} is the sum of the validation pixels in a class and n_{+k} is the sum of the classified pixels in that class (Foody, 2001).

4 RESULTS

The results of the first set of classifications are listed in table 1. These all refer to classifications of the 1999 HyMap data set. Classifications were performed using the SAM algorithm. The performances of the classifications are presented in terms of two accuracy measures, kappa coefficient and overall accuracy. Both, results before and after the application of post-classification procedures (sieve and clump) are shown as considerable differences are present. The first two lines of results in the table show the results of two classifications using no texture channels. Classification A uses only the spectral information of the HyMap data (MNF bands). Additionally to the first 10 MNF bands, the standwise means and standard deviations of stem density, derived from high spatial resolution orthophotos (Atzberger & Schlerf, 2002) were used in classification B. This led to slightly higher accuracies, and set a benchmark for the following classifications. The kappa coefficient before post-classification was increased from 0.53 to 0.61, after post-classification from 0.66 to 0.74.

The accuracy assessments' results of the classifications using each of the geostatistic measures of spatial variability mentioned above are presented in table 1 as classifications C to G. The madograms lead to higher accuracies than the variograms, a difference between mono- and bivariate measures is hardly discernable. After post-classification, the madogram classifications reach a kappa coefficient of 0.74 like the benchmark classification B, before post-classification the results are slightly lower than those of classification B.

Table 1: Overall accuracies and kappa coefficients of SAM classification using different input data sets

		No post-class.		Sieve & clump	
	Input data (all HyMap 1999)	Kappa	OAA	Kappa	OAA
	Spectral data				
A.	MNF	0.53	59.9	0.66	70.0
	Spectral data and stem density from high spatial resolution data				
B.	MNF, stem density (mean & variance)	0.61	66.6	0.74	77.2
	Spectral and geostatistic texture data				
C.	MNF, variogram	0.54	59.9	0.68	72.7
D.	MNF, madogram	0.58	63.7	0.74	77.3
E.	MNF, cross variogram	0.52	58.6	0.69	73.7
F.	MNF, pseudo-cross variogram	0.53	59.8	0.67	71.6
G.	MNF, pseudo-cross madogram	0.59	64.8	0.74	77.8
	Spectral and conventional texture data				
H.	MNF, 8 co-occurrence channels from MNF 1	0.55	61.4	0.68	72.7
I.	MNF, 16 co-occurrence channels from MNF 1 & 2	0.53	59.3	0.64	69.0
J.	MNF, 10 co-occurrence channels from MNF 1-5 (mean & variance)	0.59	64.5	0.73	76.2
	Combination of all data types				
K.	MNF, 10 co-occurrence channels from MNF 1-5 (mean & variance), pseudo-cross madogram channels, stem density (mean & variance)	0.66	71.1	0.74	77.8

The co-occurrence matrix based channels (classifications H to J) only partially increase the classification accuracies. The kappa coefficient of classification H, which uses co-occurrence matrix based bands from MNF channel 1, is increased by 0.02 compared to classification A. Classification I, which adds co-occurrence matrix based bands from MNF channel 2, performs even worse than classification A. Classification J, using the mean and variance texture measures from the first five MNF bands, has high kappa coefficients comparable to the madogram-based classifications (D and G).

A combined input data set consisting of the first ten MNF channels, ten co-occurrence matrix based channels from the MNF bands 1 to 5 (mean & variance), pseudo-cross madogram channels and the stem density channels, resulted in the highest classification accuracy (classification K). Obviously, the information contained in these different bands is not completely redundant.

Table 2 shows the classification accuracies of the second approach. The first ten MNF channels (classifications L, O, and R) and the maxima of monovariate auto madograms of the first five MNF channels (classifications M, P, and S) and bivariate pseudo-cross madograms of all combinations of the first five MNF channels (classifications N, Q, and T) were taken as input data.

Table 2: Overall accuracies and kappa coefficients of SAM classifications using input data sets of two different spectral resolutions and two dates. For each data set classification results with and without maximum-of-pseudo-cross madogram channels are presented.

		No post-class.		Sieve & clump	
	Input data	Kappa	OAA	Kappa	OAA
	HyMap 1999				
L.	MNF	0.53	59.9	0.66	70.0
M.	MNF, Madogram maximum channels	0.56	62.2	0.72	75.6
N.	MNF, Pseudo-cross madogram maximum channels	0.60	65.7	0.70	74.2
	TM 1999				
O.	TM	0.39	47.2	0.51	56.6
P.	TM, Madogram maximum channels	0.34	42.1	0.39	44.8
Q.	TM, Pseudo-cross madogram maximum channels	0.50	55.7	0.52	57.3
	HyMap 2003				
R.	MNF	0.47	53.2	0.56	61.9
S.	MNF, Madogram maximum channels	0.51	56.5	0.62	66.8
T.	MNF, Pseudo-cross madogram maximum channels	0.61	66.1	0.69	72.5

The 1999 HyMap data's classification results were improved by adding geostatistical channels. The kappa coefficients of the classifications before post-classification rose from 0.53 using only MNF channels to 0.56 using auto madogram maxima to 0.60 using pseudo-cross madogram maxima. After application of the post-classification measures, the auto-madogram lead to better results than the pseudo-cross madogram. The pseudo-cross madogram still performed best. After post-classification, the differences between the input data sets became low; the auto madogram input data set (classification M) performing worse than the basic ML classification (L).

The simulated TM data yielded lower classification accuracies. The classification of auto madogram data (classification P) performed worse than that using no texture data (classification O). The pseudo-cross madogram (classification Q) data increased the accuracy from 0.39 (Kappa before post-classification) to 0.50.

The 2003 HyMap data shows the same pattern as the before mentioned data sets. The classification using the pseudo-cross madograms (classification T) reached higher accuracies than one using the auto madogram (classification S), which reached higher values than those using only the reflectance data (classification R).

5 DISCUSSION

Most of the texture channels used improved the classification accuracy. Among the geostatistic measures (classifications C-G, table 1), the madograms performed better than the variograms. The madogram's better performance is probably due to the fact that outliers are less emphasized than in the variogram where differences between pixel values are squared. The pseudo-cross madogram (data set G) yields the best results both before and after post-classification. The classification accuracy increases from 70.0% OAA after post-classification using dataset A (only MNF channels) to 77.8% using data set G (MNF- and pseudo-cross madogram channels). After post-classification, data set G even exceeds the performance of data set B (77.2% OAA) where very high spatial resolution data was included into the classification procedure. Because of this, pseudo-cross madograms were the basis for the second set of classifications, where the stability of the classification in terms of the classifier, the spectral resolution of the input data and the temporal aspects was inspected.

The co-occurrence channels perform comparably well. The best result is achieved by taking the first five channels but only two texture measures into account (classification J). The reduction of classification accuracy between classifications H and I is a hint towards the effect of the Hughes phenomenon. The number of input channels is increased but the classification accuracy decreases. Presumably, the information in the additional channels seems to be redundant. The combination of geostatistic, co-occurrence, and stem density channels increased the accuracy further than any of the other input channel combinations, at least before the post-classification measures. So there is little redundancy in these channels.

The ability of geostatistic texture measures to improve classification accuracies is also observable in the second approach. Each of the three remote sensing data sets could be classified better by adding pseudo-cross madogram maxima. This improvement takes place at all classification scenarios (HyMap data from 1999 and 2003 and artificial TM data from 1999). The improvement can most clearly be seen before the post-classification procedures which dampen the effect a little. The concept seems to be transferable to different data as the positive effect exists on all three tested data sets, two of which are hyperspectral data and the third is multispectral data. The highest raise in classification accuracy could be observed at the classifications of 2003 HyMap data where the kappa coefficient before post-classification rose from 0.47 to 0.61. The raise in accuracy for the TM data from 0.39 to 0.50 (without post-classification), though on a low level, is also impressive. The lack of detailed spectral information could obviously be compensated by the use of textural information. Most of the classifications were also improved by adding maxima of auto madograms, but the pseudo-cross madogram is clearly superior.

6 CONCLUSIONS AND FUTURE PERSPECTIVES

A problem in this approach to textural classification is the emphasis of stand borders. In some of the resulting geostatistic channels, the surroundings of such borders stand out because of the great variance of these borders. One way to cope with this issue would be to combine object-based and textural classification procedures, which was not tested in this study. Therefore, in a further research it is aimed to compute geostatistical texture measures on objects rather than using a moving window of fixed size. But still the positive effects outweigh the negative ones so that this approach of a classification using geostatistic channels to include textural information can be deemed a success.

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