Assessment of some forest characteristics employing IKONOS satellite data

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ABSTRACT: In recent years, satellite remote sensing has become a new tool for estimation of forest condition. The paper deals with spruce timber growing stock and vegetation cover assessment employing IKONOS satellite data from a mountain forest area of Central Slovakia. Original digital data as well as enhanced digital images were used to estimate some forest variables. Image enhancement approaches employing topographic normalization, PCA analysis and different vegetation indices are a very important part of data processing. Apart from spectral characteristics, texture as an additional variable was utilized. In order to improve classification accuracy the knowledge of the vertical distribution of tree species also was incorporated into classifiers. Spectral signatures as auxiliary variables measured with the aid of training sets were utilized for the construction of spectral models for growing stock estimation. In spite of the fact that the standard error of these models is not very favourable as it varies about 30%, they offer initial information for application of different sampling designs for timber growing stock assessment, where the final precision is acceptable. Stepwise discriminant analysis was employed to choose appropriate sets for the classification of vegetation cover. Classification results show an assumed contribution of categorial knowledge for increasing the correctly classified pixel proportion and this improvement was on average about 10%. Likewise, the texture contributes to better resolution of some very near spectral classes.

Keywords: IKONOS; timber growing stock; texture; categorial knowledge; vegetation cover

A lot of applications have been developed recently for the forest inventory and monitoring employing LANDSAT TM and SPOT satellite data. The rapid quality development of a new satellite and radiometer generation with high spectral and ground resolution provides new application possibilities for this area mainly in combination with sampling methods. Space Imaging's IKONOS satellite belongs to this generation because in 1999 it made history with the world's first one-meter commercial remote sensing satellite. IKONOS produces 1-meter black-and-white (panchromatic) and 4-meter multispectral (red, blue, green, near infrared) imagery that can be combined in a variety of ways to accommodate a wide range of high-resolution imagery applications. Moving over the ground at approximately 7 km/sec, IKONOS collects black-and-white and multispectral data at a rate of over 2,000 km^2/min. To date, IKONOS has collected nearly 100 mill km^2 of imagery, through the nearly fifteen, 98-minute journeys it makes around the globe each day.

Different commercial and governmental organizations utilized IKONOS data to view, map, measure, monitor and manage different activities and applications. These range from disaster assessment to urban planning and agricultural and forestry assessment and monitoring. Due to the very high ground, spectral and temporal resolution of IKONOS data and imagery products, determined by the level of positional accuracy, the possibilities of forestry applications are endless.

This research, also with respect to recent experiences acquired from the application of Landsat TM and SPOT XS satellite data, is aimed at developing adequate methods for the assessment of spruce (*Picea abies* L.) timber growing stock as well as vegetation cover classification employing IKONOS satellite data.

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MATERIAL AND METHODS

Study area and image data

A forest section of the Management Plan Unit (MPU) in a mountain area of the High Tatras (Central Slovakia) was chosen as test area. The area of MPU is relatively multiple with the range of heights above sea level from 980 to 2,052 m. Different forest types occur there, mainly *Sombreto-Piceetum, Cembreto-Piceetum* with dominance of spruce (*Picea abies* L.), also *Cembreto-Mughetum* and *Mughetum acidofilum* with dominance of dwarf pine (*Pinus mugo* T.). Mountain crests of MPU are covered with the meadow community where *Calamagrostis villosa, Vaccinium myrtillus, Vaccinium vitis-idea* and *Juncus trifidus* are dominant.

The IKONOS Satellite image of the MPU was taken in August 2004 in panchromatic and multispectral modes. The satellite image was geometrically corrected using a digital terrain model with spatial resolution 1 m and 13 ground control points. The reached total RMS was 1.27 m and 0.73 m for coordinates *x* and *y* for panchromatic data and 1.32 m and 0.74 m, respectively, for multispectral data. Spectral digital values (DN) were converted from the range 11 bits to 8 bits (range of DN 0–255).

Stand mapping and enumeration of the forest compartments (compartments database) were performed using appropriate modules of INTERGRAPH software. Stand boundaries were digitized from a forest map at a scale 1:25,000. Auxiliary data (compartments variables) were gathered from the existing forest management plan.

Ground survey and spectral signature collection

Location of training polygons was targeted by a ground survey employing GPS technology. The homogeneous groups of vegetation representing classification classes for training polygons were chosen.

Spectral signatures as auxiliary variables in order to derive spectral reflectance models for spruce growing stock estimation were collected in individual compartments employing training polygons. The size of these polygons for the calculation of mean spectral signature differed considering the knowledge that it is better to have a higher number of smaller polygons than a lower number of larger ones.

The ground data of the variable of interest (timber growing stock per ha) were measured in single compartments and in combination with the corresponding spectral signature they were used to derive spectral regression models for the estimation of timber growing stock from satellite data. In addition to spectral signatures, the age of the forest compartment was employed as an auxiliary variable because it could be easily determined from previous forest management plans and could be projected to the current data.

For the classification of vegetation cover the following classification classes were defined:

1 – dwarf pine	6 – *Calamagrostis villosa*
2 – cembra pine	7 – soil destruction
3 – spruce	8 – *Juncus trifidus*
4 – stony debris	9 – road
5 – rowan	10 – water

Spectral signatures for growing stock estimation as well as vegetation cover classification were obtained from different original and enhanced image data. Topographic normalization, PCA analysis, HIS transformation and different spectral indices were applied for original image data enhancement. Image texture was also employed in enhancement approaches for vegetation cover classification due to the latest knowledge that the object oriented approach could improve classification accuracy results (Ferro, Warner 2002; Franklin et al. 2001). It was analyzed by different algorithms which are based on the evaluation of image spectral variation in various

Table 1. Algorithms of texture image analysis

Relative richness	$R = n/n_{max} \times 100$
Diversity	$H = -sum\ (p \times \ln(p))$
Dominance	$D = H_{max} - H$
Fragmentation	$F = (n - 1)/(c - 1)$
NDC – number of different neighbours in the matrix	3 × 3, 5 × 5 or 7 × 7 (1–9, 1–25, 1–49)
CVN – pixel number different from pixel value in the matrix	3 × 3, 5 × 5 or 7 × 7 (0–8, 0–25, 0–48)
BCM – number of different pixels in the matrix	3 × 3, 5 × 5 or 7 × 7

n – number of different classes occurring in the matrix, H – diversity, n_{max} – maximum number of classes in input image, H_{max} – maximal diversity = ln(n), p – relative abundance of each class in the matrix, c – number of score cellules (9, 25 or 49), ln – logarithm selected matrices 3 × 3, 5 × 5 or 7 × 7 pixels. Some of them are listed in Table 1. Totally more than 80 image data sets were used for spectral signature collection. Stepwise discriminant analysis was employed to choose appropriate sets for the classification of vegetation cover. The most appropriate, with respect to visual interpretation as well as statistical evaluation, appear spectral vegetation indices for both applications. These are sensitive indicators of "on-the-scene" presence and condition of vegetation, mainly slope-based vegetation indices, which are combinations of the visible red and near infrared bands (Perry, Lautenschlager 1984). The values indicate both the status and abundance of green vegetation cover and biomass, e.g. the Corrected Transformed Vegetation Index (*CTVI*):

$$CTVI = \frac{(NDVI + 0.5)}{ABS\,(NDVI + 0.5)} \times \sqrt{ABS\,(NDVI + 0.5)} \quad (1)$$

where the values of Normalized Difference Vegetation Index (*NDVI*) are transformed to suppress the negative values. Also the distance based vegetation indices bring satisfactory results. They are based on the Perpendicular Vegetation Index (*PVI*) and the main objective is to cancel the effect of soil brightness to generate an image that only highlights the vegetation signal. This is important in areas where vegetation is sparse as well as in open forests. For example the Modified Soil-Adjusted Vegetation Index (*MSAVI*):

$$MSAVI = \frac{2pNIR + 1 - \sqrt{(2pNIR + 1)^2 - 8(pNIR - pRED)}}{2} \quad (2)$$

Vegetation indices also allow compensation for changing light conditions, surface slope, exposition and other external factors, but for the signature collection mostly topographically normalized data (TN data) employing radiometric statistic empirical correction were utilized.

The maximum likelihood classification method was used for vegetation cover classification. This method enables to define also categorial knowledge for classified classes for the purpose of right classification improvement. Therefore the knowledge of the vertical distribution of single vegetation cover classes expressed by categorial likelihood images was applied in this research. These images from DTM data were created employing the sigmoidal membership function (Fig. 1). It enables to define the membership likelihood of single classes to fuzzy sets; value *a* represents full no membership, i.e. for heights above sea level lower or equal to this value the likelihood of assigned class is equal to 0. Value *b* represents full membership, i.e. likelihood 1,

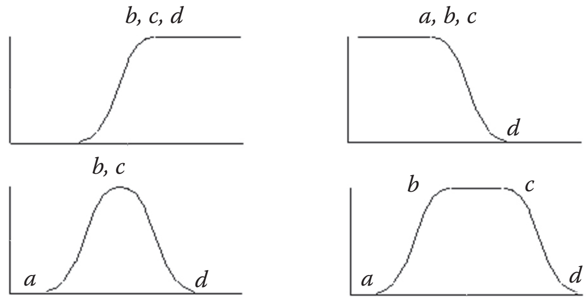

Fig. 1. The sigmoidal membership function

in *c* the function starts to drop below 1 and in *d* it gains likelihood 0 again. Likelihood between *a, b, c, d* fluently changes from 0 to 1 or 1 to 0 with respect to the type of selected function. The *S* curve was selected for our application. Fault values of the used function are shown in Table 2. For the evaluation of texture and categorical knowledge contribution to classification accuracy the following classification approaches were applied:

A. Classification without utilization of categorial likelihood images;
B. Classification with utilization of categorial likelihood and texture;
C. Classification with utilization of categorial likelihood and with the exclusion texture image analyses.

RESULTS AND DISCUSSION

Growing stock estimation

The parameters of the best spectral reflectance models for growing stock estimation (timber growing stock per hectare) are shown in Table 3. The independent variables that best suited to multiple regressions were chosen by stepwise variable selection.

The spectral reflectance models are linear and exponential, simple or multiple stochastic models, where dependent forest variable is the function of its mean spectral signature in single vegetation indices (models 1, 2, 3, 4) or transformed variable employing the ratio between the square of spectral value and the age of compartment (models 5, 6). Multiple linear models are a combination of both approaches. In contrast to simple regression, multiple regressions do not provide better results if only spectral signatures are used; however, if we introduce additional variables to multiple regression (transformed variable), the results are better. All models are significant; correlation coefficients vary from 0.63 to 0.80. In spite of the fact that the accuracy of these models is not very favourable, they offer initial information for the application of different sampling designs for

Table 2. Values of categorial knowledge of the likelihood of single class occurrence

Class	Membership to fuzzy set			
	a (0)	*b* (1)	*c* (1)	*d* (0)
Dwarf pine	1,300	1,450	1,780	1,970
Cembra pine	1,500	1,600	1,650	1,800
Spruce		1,360	1,360	1,800
Stony debris	For the whole image likelihood is 0.1			
Rowan		1,300	1,300	1,800
Calamagrostis villosa	1,100	1,400	1,400	
Soil destruction	For the whole image likelihood is 0.7			
Juncus trifidus	1,300	1,600	1,600	
Road	polygon			
Water	polygon			

timber growing stock assessment. The application of two-phased sampling design utilizing derived spectral reflectance models was investigated in previous research employing different remote sensing data (Scheer et al. 1997; Scheer, Akça 2001). Mainly two-phased sampling with regression or stratification is frequently applied in conjunction with aerial or satellite images. The results show that this approach is precise enough mainly for large-scale application and very effective in comparison with ground survey.

Vegetation cover classification

With respect to the results of stepwise discriminant analysis the following image data with spectral as well as textural information were chosen for vegetation cover classification:

- *NRVI*: normalized ratio vegetation index *R/NIR*,
- *V2*: texture defined by diversity H analyzed on *NIR* image enhanced by topographic normalization,
- *RATIO*: ratio vegetation index *NIR/R*,
- *MSAVI*: modified soil-adjusted vegetation index,
- *RAT V5*: ratio of *RATIO* and texture image *NDC*,
- *VIR*: texture characterized as relative richness employing *R* channel of the image,
- *PCA2ST V*: ratio of PCA 2nd component and texture *R* analyzed on *RATIO*.

Classification of these image data sets is marked as *B* in classification results. Totally 8,380 pixels were used for the evaluation of classification results, when 23% of them were used purely for control and 77% of training polygons from the ground survey were also applied for the training polygon creation.

The results of classification precision and accuracy evaluated on the basis of ground true data are shown in Table 4. The most exact is classification *C* with categorial likelihood utilization without texture images ($\Delta w = \pm 0.68$, $P = 0.95$). The accuracy of classification by two characteristics was evaluated; as the ratio of right classified pixels (p) and by *kappa* or *KHAT*

Table 3. Parameters of spectral reflectance models from IKONOS satellite data

Dependent variable	Independent variable	Model	*SE* (%)	Variance explained (%)	F
Timber growing stock per ha (V/ha)	*RVI*	1	± 31.61	41.1	33.7***
	CTVI	2	± 31.65	40.9	37.3***
	MSAVI	3	± 31.51	41.6	35.7***
	TTVI	4	± 31.72	41.0	34.8***
	$MSAVI^2$/age	5	± 29.83	47.5	21.6***
	NIR^2/age	6	± 28.75	51.2	16.5***

Multiple regression (Model 7)

$$V/ha = 1{,}533.65 - 1{,}522 \times 55\ NRVI - 1{,}580 \times 22\ TVI - 177.89 \times RATIO - 403.47 \times \frac{NDVI^2}{AGE} + 103.58 \times \frac{RATIO^2}{AGE}$$

SE (%) = ± 24.26%, variance explained: 65.3%

RVI = *RED*/*NIR*, *RATIO* = *NIR*/*RED*, *SE* (%) = standard error in percentage, *CTVI* = corrected transformed vegetation index, variance explained = r^2, *MSAVI* = modified soil-adjusted vegetation index, *F* = *F* value (***highest significance), *TTVI* = thiam's transformed vegetation index, *NDVI* = normalized difference vegetation index

Table 4. Comparison of classification precision and accuracy

Classification approach	p (%)	Δw (%) $P = 0.95$	$KHAT$ (%)
Classification A	80	± 0.86	69
Classification B	86	± 0.74	78
Classification C	89	± 0.68	82

Table 5. Classification contingency table employing categorial likelihood images of spectral characteristics as well as texture characteristics

Class	Reference data										Total	e_2	$KHAT$
	1	2	3	4	5	6	7	8	9	10			
1	**4,200**	0	10	0	0	24	0	23	0	0	4,257	0.01	0.97
2	9	**102**	0	0	0	0	0	0	0	0	111	0.08	0.92
3	8	45	**1,441**	0	9	0	0	0	1	0	1,504	0.04	0.95
4	0	1	2	**232**	0	0	36	0	1	0	272	0.15	0.85
5	1	22	108	0	**73**	0	0	0	0	0	204	0.64	0.35
6	293	7	9	0	12	**476**	0	76	0	0	873	0.45	0.52
7	0	1	8	27	0	0	**39**	2	0	0	77	0.49	0.50
8	429	4	3	1	0	7	0	**593**	0	0	1,037	0.43	0.53
9	0	0	0	0	0	0	1	0	**21**	0	22	0.05	0.95
10	0	0	0	0	0	0	0	0	0	**23**	23	0.00	1.00
Total	4,940	182	1,581	260	94	507	76	694	23	23	8,380		
e_1	0.15	0.44	0.09	0.11	0.22	0.06	0.49	0.15	0.09	0.00		0.14	
$KHAT$	0.70	0.55	0.89	0.89	0.77	0.93	0.51	0.83	0.91	1.00			0.78

statistic, which ranges between 0 and 1 and expresses a proportional reduction in the error achieved by a classifier as compared with the error of a completely random classifier. Thus, the value 0.80 would indicate that the classifier was avoiding 80% of the errors that a totally random process would have produced. With respect to a comparison of both characteristics the expected share of categorial knowledge for classification was unambiguously confirmed, higher $KHAT$ statistic was achieved for classification B and C as compared with classification A, by about 9% and 13%, respectively. Quite surprising is lower $KHAT$ statistic for classification B in comparison with classification C in spite of the fact that with respect to the results of discriminant analysis images with texture characteristics were also chosen for classification B.

Table 6. Classification contingency table employing categorial likelihood excluding texture images

Class	Reference data										Total	e_2	$KHAT$
	1	2	3	4	5	6	7	8	9	10			
1	**4,523**	71	136	0	7	4	0	2	0	0	4,743	0.05	0.89
2	174	**32**	0	0	0	2	0	0	0	0	208	0.85	0.14
3	170	41	**1,365**	0	5	0	0	0	0	0	1,581	0.14	0.83
4	0	0	1	**229**	0	0	16	0	0	0	246	0.07	0.93
5	34	16	48	0	**74**	9	0	0	0	0	181	0.59	0.40
6	25	15	7	0	8	**487**	0	59	0	0	601	0.19	0.80
7	0	2	13	30	0	0	**56**	5	0	0	106	0.47	0.52
8	14	5	11	1	0	5	0	**628**	0	0	664	0.05	0.94
9	0	0	0	0	0	0	4	0	**23**	0	27	0.15	0.85
10	0	0	0	0	0	0	0	0	0	**23**	23	0.00	1.00
Total	4,940	182	1,581	260	94	507	76	694	23	23	8,380		
e_1	0.08	0.82	0.14	0.12	0.21	0.04	0.26	0.10	0.00	0.00		0.11	
$KHAT$	0.81	0.15	0.83	0.88	0.78	0.96	0.73	0.90	1.00	1.00			0.82

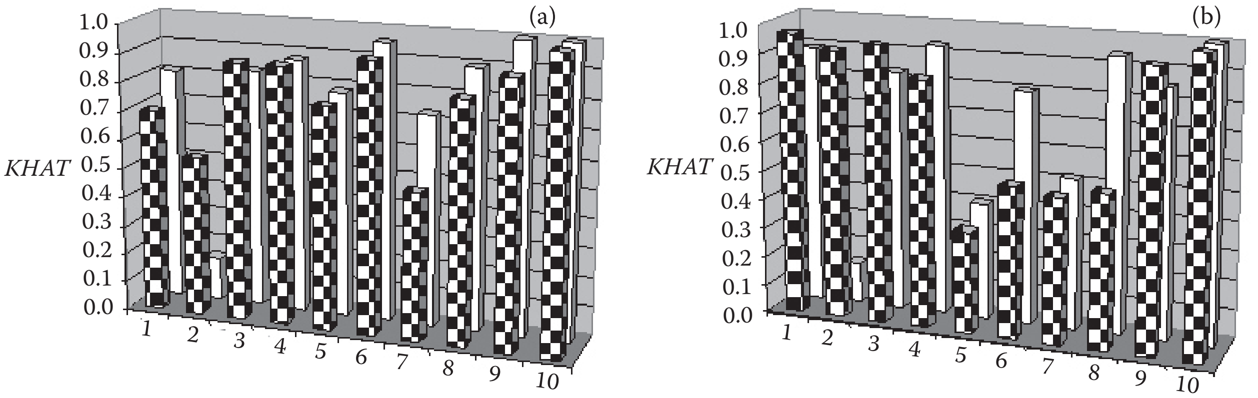

Fig. 2. Comparison of KHAT omission (a) and commission (b) statistics employing texture or spectral characteristics (▪ texture, □ spectral)

It points out that training polygons used for classification better represent the whole image spectral variation than texture characteristics.

A more detailed analysis of classification results in single classes for classification *B* is shown in Table 5. This contingency table or so-called confusion matrix is prepared by classifying the training set of pixels, where the known class types of pixels used for training are listed versus the classes chosen by the classifier. In an ideal case, no diagonal of the confusion matrix would be zero, indicating no misclassification. From the matrix also classification errors of omission and commission as well as *KHAT* statistic for single classes can be studied. Commission errors (e_2) are represented by no diagonal elements of the matrix where pixels are classified into a class to which they do not actually belong; omission errors (e_1) represent the reverse type of situation.

As we can see, the most omitted classes are cembra pine and soil destruction. Value e_1 = 0.44 for cembra pine denotes that 44% of reference pixels are misclassified, 45 as spruce and 22 as rowan. For the class soil destruction (e_1 = 0.49) 49% pixels was misclassified as stony debris. The most committed classes were rowan (e_2 = 0.64), soil destruction (e_2 = 0.49), *Calamagrostis villosa* (e_2 = 0.45) and *Juncus trifidus* (e_2 = 0.43).

For a better explanation of texture contribution to classification accuracy classification results of classification *C* (classification without texture utilization) are also summarized in Table 6. The meaning of classification omission and commission in class cembra pine is evident again. *KHAT* statistics indicate that only 15% and 14% of pixels, respectively, in this class were classified correctly. In comparison with *B* classification, where these values were 55% and 92% respectively, it indicates a positive contribution of texture images, mainly to the elimination of this class spectral likeness with classes dwarf pine and spruce. These comparisons also for other classes are allowed by graphs in Fig. 2. It is evident that in class dwarf pine texture helps to decrease the commission error in favour of spruce, which contributes to accuracy classification improvement in both classes. At the same time texture markedly suppressed spectral differentiation from similar textural classes of meadow communities. The last dominant wood species class rowan does not register with typical texture in spite of the prediction from the ground survey. Generally we can state for this class a very high proportion of incorrectly classified pixels, mainly in favour of spruce and partially dwarf pine as well. The overall classification accuracy of vegetation cover employing texture images was improved by about 16%.

CONCLUSION

Forestry is a very important area for remote sensing applications where it is possible to estimate different forestry variables employing different methods of image analysis.

Spectral signatures as auxiliary variables measured with the aid of training sets are a good and acceptable basis for the construction of spectral models for growing stock estimation. In spite of the fact that the standard error of these models is not very favourable, it varies about 30%, they offer initial information for the application of different sampling designs for timber growing stock assessment, where the final precision and effectiveness are acceptable.

On the basis of vegetation cover classification it is possible to draw the following conclusion and recommendations:

– in spite of broken topography topographic normalization does not contribute meaningfully to classification accuracy, for visual interpretation its addition was significant, but for classification topographic normalization was sufficiently substituted by vegetation indices,

– the assumed contribution of categorial knowledge for result improvement employing maximum likelihood classification was achieved,
– texture is an additional variable whose precise classification and utilization can be recommended mainly in applications where there exists a strong conjunction between spectral characteristics, e.g. for tree species classification.

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Určovanie niektorých charakteristík stavu lesa pomocou kozmických snímok IKONOS

ABSTRAKT: V poslednom období sa kozmický diaľkový prieskum stáva dôležitým nástrojom pre účely zisťovania stavu lesa. Práca je zameraná na odhad porastovej zásoby smreka a klasifikáciu vegetačného krytu pomocou kozmických snímok IKONOS. Pôvodné a vylepšené digitálne kozmické údaje boli použité k odhadu niektorých charakteristík. Topografická normalizácia, analýza hlavných komponentov a rôzne vegetačné indexy, ktoré radíme medzi metódy vylepšovania obrazu, sú dôležitou súčasťou jeho spracovania. Ako pomocná premenná bola okrem spektrálnych charakteristík použitá textúra. Za účelom zlepšenia správnosti klasifikácie boli do klasifikátorov zahrnuté aj kategoriálne poznatky o vertikálnom rozmiestnení jednotlivých druhov drevín. Spektrálne signatúry k odhadu porastovej zásoby pomocou spektrálnych modelov odraznosti boli určené pomocou trénovacích polygónov. Napriek tomu, že presnosť týchto modelov nie je veľmi priaznivá (stredné chyby kolíšu okolo 30 %), poskytujú počiatočné informácie pre aplikáciu rôznych výberových postupov k odhadu zásoby porastov s akceptovateľnou presnosťou. Kroková diskriminačná analýza bola použitá k výberu vhodných obrazových súborov pre klasifikáciu vegetačného krytu. Výsledky klasifikácie potvrdzujú predpokladaný prínos kategoriálnych poznatkov na zlepšenie správnosti klasifikácie; toto zlepšenie bolo v priemere o 10 %. Rovnako textúra prispela k lepšiemu rozlíšeniu niektorých spektrálne blízkych tried.

Kľúčové slová: IKONOS; porastová zásoba; textúra; kategoriálne poznatky; vegetačný kryt

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