ON POTENTIAL OF SEVERAL METHODS FOR REVEALING TEMPORAL CHANGES IN SUBURBAN AREAS USING LANDSAT TM DATA

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SUMMARY

The paper deals with the methods of land cover change detection in suburban area of Brno (Czech Republic). As an input data two Landsat TM scenes acquired in May 1986 and August 1994 have been used. In the first part possible approaches to change detection using satellite data are summarized. The following methods are tested in the second part: (1) supervised classification comparison, (2) vegetation indices differencing and (3) change vector analysis. For simplification only temporal changes in build up areas were under investigation. From this point of view the first method gives the most promising results. Especially in highly urbanized areas automatic classification must be done as an iterative process and several classes of build up areas must be trained in classification. The use of "anniversary" images for classification comparison seems to be very important precondition. Based on three examples basic types of changes are described. The method based on simple differencing of vegetation indices images gives very similar results for various indices (RVI, PVI, NDVI, Greenness Index from Tasseled Cap transformation). The main problem is to find a proper threshold value which could separate real changes in land cover from the "false" changes caused by phenophases etc. The same is true on change vector analysis to some extent, even if there is some possibility to classify "the nature" of change objectively. In both methods the greatest changes are not connected with the real changes in land cover. These changes are "hidden" in histogram of resulting change image. Therefore methods based on diferencing of various vegetation indices are not very sensitive to reveal temporal changes in suburban areas.

KEY WORDS

Landsat TM – Change Detection – Classification – Vegetation Indices – Change Vector Analysis

INTRODUCTION

In the present paper the potential of three approaches to reveal temporal land cover changes in highly urbanized area is evaluated. The aim of the study is to compare temporal changes in areal extent of land cover classes represented especially by build up urban areas (concrete, pavements, communications, etc.) between 1986 and 1994.

REMOTE SENSING DATA CHARACTER

All data acquired in various Remote Sensing systems can be characterized with four types of resolution. The term resolution can be defined as the possibility of measuring system to distinguish between the signals which are close in spatial, radiometric, spectral or temporal sense. Thus we can define four types of remote sensing data resolution. They are spatial resolution, spectral resolution, radiometric resolution and temporal resolution.

Spatial resolution describes the size of the smallest objects yet identified on the image. In digital imagery the spatial resolution is roughly defined by the size of a pixel.

Spectral resolution gives the size and number of intervals of electromagnetic spectrum in which the sensor acquires radiance from objects.

Radiometric resolution is a measure of sensors sensitivity and defines the number of distinguished levels of signal. Thus e.g. 8 bits data record 256 levels of electromagnetic energy.

Temporal resolution defines the time interval between the two successive images of the same area and is a fundamental pre-condition for change detection studies using remote sensing data. According to Singh (1989) the change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times. It involves the ability to quantify temporal effects using multitemporal data sets.

As the temporal resolution of remote sensing data varies in a broad limits, also the processes (in the sense of their evolution) which can be detected with multitemporal data analysis can be of various dynamics - from very rapid catastrophic events to gradual evolution. For instance geostationary satellites creates the image of the Earth's disc each 30 minutes which is excellent material for the study of the large scale and rapid synoptic processes in the atmosphere. On the other hand sensors onboard sun-synchronous quasi polar satellites scan the same area with the time resolution of several days. With such data sets a lot of processes connected with plant phenological phases during the year can be studied. Moreover, some satellite systems operate for many years and there are large databases of images in which long term temporal changes are coded and can be studied. E.g. NOAA or Landsat satellites offer more than 20-year time series.

Even in each time scale applications of remote sensing multitemporal data can be of great number. They can include land use change analysis, changes in vegetation phenology, deforestation assessment, snow melt monitoring, day/night thermal or radiative characteristics, floods or forest fire monitoring, or time series analysis of snow cover in global scales.

The broad potential of remote sensing data for change detection study can also be found in other aspects. Even if satellite data are restricted by their lower spatial resolution when compare with aerial photography, they are characterized by a higher spectral resolution. Satellite images are not limited only to visible and near infrared part of electromagnetic spectrum. Images from other parts of spectrum can bring a new information to change detection studies.

DIGITAL CHANGE DETECTION METHODS OVERVIEW

With the progress in digital image processing several general algorithms for evaluating changes in the series of satellite images have been accepted. These methods have been used in a great number of applications.

It can be said, that all approaches first of all require precise geometric correction. Accurate spatial registration of the various dates of imagery is a requirement for effective change detection. Registration to within 0.25 or 0.50 pixel is generally accepted (Lillesand, Kiefer, 1985). When miss registration is greater than one pixel, numerous errors will result when comparing images.

In ideal case change detection procedures should involve data acquired by the same sensor, recorded using the same spatial resolution, viewing geometry, spectral bands and time of day. To minimize also seasonal changes often anniversary dates are used. Because the cloud cover in middle latitudes the use of anniversary images is sometimes rather problematic.

According to Feranec (1992) changes in land cover can be twofold. First they can be caused by the changes in spectral characteristics - it means for instance that one type of land cover has changed to another during the time. Second type of changes can be connected with the changes in spatial characteristics - e.g. one type of land cover became larger or smaller. In digital image processing both types of changes are studied through changes in spectral behavior of individual pixels.

In next paragraphs several basic change detection algorithms are briefly described. As mentioned by Jensen (1986), for selection of an appropriate change detection algorithm the analyst must know the cultural and biophysical characteristics of the study area.

Image differencing

Image differencing involves subtracting the pixel value of the imagery of one date from that of other. The difference in areas of no change will approach very small numbers (zero) and areas of change will have larger negative or positive values. The results are normally transformed into positive values by adding a constant for display purposes. Because pixel values of the output image have Gaussian distribution and the change pixels can be found at the edges of the distribution, a critical step of this method is to set up the threshold between the change and no-change pixels. Normally several attempts to find the threshold are necessary.

Image ratioing

Image ratioing involves computing the ratio from two dates of imaging. Output pixels of areas of no change tend toward 1 and areas of change will have higher or lower ratio values. For this method the problem to find the threshold between change and no-change pixels is the same as in the case of image differencing.

The advantage of image ratioing is, that changes in viewing conditions (e.g. seasonal reflectance differences due to sun angle), which can degrade the possibility to find real changes, are eliminated. This method was used e.g. Friedman and Angelici (1979) for mapping urban and suburban change. The rationed data are again normally scaled for display purposes.

Image regression

In this method one can assume that pixels values from the first time slice image should be a linear function of the pixel values from the second time slice image. Thus based on least square method from the regression function we can obtain "predicted value" for each pixel from the second time slice. After that the difference image can be defined as a difference between "predicted" image and the image of the first time slice.

Through thresholding technique areas of substantial change can be detected. According to Jensen (1983) effects caused by differences in Sun angle or by atmosphere are reduced in this method. In some cases image regression gives better results than image differencing (Singh, 1989).

Classification comparison

This approach is based on independent registration and classification of individual images according to the same classification scheme. Spectral pattern recognition is used in the process of classification and classified images are then compared. Comparison can rely on statistics or so called change maps can be created. With this maps the nature of all changes can be studied. The accuracy of this approach depends on the accuracy of each of the independent classification. As discussed in Singh (1989), when the accuracy of each independent classification is e.g. 80%, the accuracy of the result is only 64%. The problem in highly heterogeneous urban land cover areas is that there is a lot of "mixed" pixels and the accuracy of individual classification can be lower. Moreover according to Lillesand and Kiefer (1995) from various reasons it is difficult to generate comparable classifications from one date to another.

Similar method of change detection is classification of multitemporal (or multidate) data sets. It means that only single classification is performed on a combined data for two or more dates. The results of such approach depends upon the extent to which change and no-change classes are spectrally different. Because the dimensionality and complexity of this method is great, the necessary pre-classification step is to choose bands with substantial information content. Common approach how to reduce the dimensionality is to use e.g. principle component analysis. An important drawback of this approach is that the temporal and spectral features have equal status in the combined data set (Schowengerd, 1983). Thus spectral changes within one multispectral image cannot be easily separated from temporal changes between images in the classification. According to Jensen (1986) several pre-processing methods allow to improve change detection results. These methods involve various kinds of filtering or texture transformations.

A group of techniques called feature space transformation can be assumed as a substantial improvement in using classification comparison method for change detection. Normally original bands of satellite data are highly correlated. When using common "per-pixel" classifiers it is problem to classify classes, which are very close in multidimensional space. Feature space transformations are based on the calculation of new bands, which are mostly linear combination of two or more original bands. The result of such transformation enhances some feature in the scene in a sense that this feature is better separated in multidimensional space from the others. The use of transformed bands in classification leads in final effect to the improvement of classification results.

Change vector analysis

This method has the same background as image differencing. Two spectral variables (e.g. data from two bands or two spectral indices) are plotted in correlation field at both dates for a given pixel. The vector connecting these two data sets is called the change vector. At the end of this procedure two images are created. The first shows the Euclidean distance between pixels (the change vector), the other showing the angle of this change vector. So that the change vector describes both the magnitude of change and the direction of the spectral change between the dates. Critical point of this method is again the threshold definition on magnitude image for deriving substantial change classes. The direction image relates to the nature of change.

Visual interpretation of satellite images

All the above mentioned methods for change detection based on digital image processing have both drawbacks and advantages. The are usually faster than classical approaches but they often produce a lot of change classes and it is a problem to find real changes. There is no problem to quantify the changes found but classification methods usually use only the concept of spectral pattern recognition. Moreover today commonly used classifiers are based on "per-pixel" approach - it means they do not care on neighborhood of the classified pixel and they are not able to evaluate such type of signatures as context, pattern or structure. Because of that classical visual methods of both large scale aerial photograph and satellite imagery interpretation can also be used. For using in GIS it is necessary to digitize results of such methods. Large scale aerial photographs were used for urban growth monitoring by e.g. Bocco and Sanchez (1995). Land cover mapping based on visual interpretation of satellite images in European project CORINE was used (see e.g. Kolář, 1996).

Other digital change detection methods

Besides the above mentioned methods a lot of other approaches to change detection has been used. They are summarized in e.g. Singh (1989) or Piwowar and LeDrew (1995). Simple color mapping technique can be mentioned here, which is based on a color composite, where different time slice is mapped in a unique color. Transformation process from RGB system to other color system (IHS - intensity, hue, saturation) can also be used. According to Jensen (1986) promising results can be obtained from principal component analysis (PCA). This method uses linear transformation of multispectral data that results in a new set of mutually orthogonal variables (principal components - PCs). These variables are uncorrelated and the first three PC's generally contain 90-95 percent of the variance of original data set. With PCA number of input channels to change detection can be reduced without loosing important amount of information. Combination of spectral indices calculation and supervised classification method was used for urban change monitoring by Foster (1991).

Vegetation component evaluation

When we try to find temporal changes with the help of classification comparison the main problem is to define a proper signatures for compared classes. According to Williams (1995) one of the necessary assumption of the commonly used "per-pixel" classification is that the pixel area is covered with a homogeneous type of cover. This assumption is not fulfilled especially in so complex covers like build up areas. On the other hand we can expect, that in build up areas artificial covers will prevail in their spectral response while in rural landscape reflectance from various types of vegetation will dominate.

Based on this assumption it would be valuable to convert raw pixel values (e.g. reflectance) to ordinal type of data. It means the data which can be ordered according to some measure of vegetation content. In digital image processing vegetation component is frequently evaluated using various vegetation indices.

Vegetation indices are computed as differences, ratios, or linear combinations of original data and they are based on the fact that strong absorbance in the visible red and strong reflectance in the near infra-red part of the spectrum are typical for vegetation. In Fig. 1 three spectral reflectance curves can be seen. Moreover vegetation indices are correlated with some quantitative biophysical parameters like amount of green leaf biomass or leaf area index (Danson, 1995).

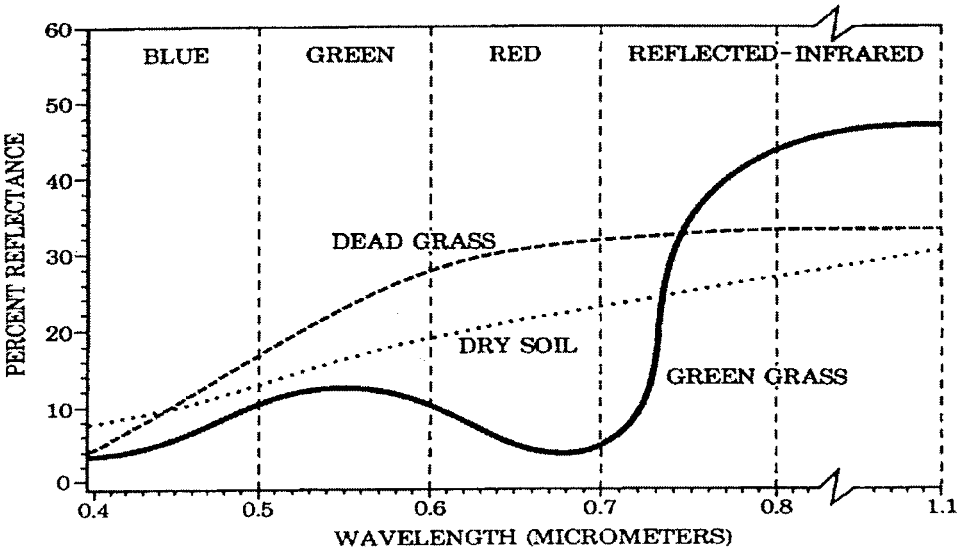

Fig. 1. Typical spectral signatures of green and dead grass and dry soil in visible and near infrared part of electromagnetic spectrum (adapted from Jensen, 1989)

All indices can be divided into two groups. First group can be denoted as ratio indices and the most common forms can be mentioned here:

Simple ratio vegetation index $$\mathrm{RVI} = \frac{TM4}{TM3}$$

Normalized difference vegetation index $$\mathrm{NDVI} = \frac{TM4 - TM3}{TM4 + TM3}$$

Transformed vegetation index $$\mathrm{TVI} = \mathrm{SQRT}\left[\ \frac{TM4 - TM3}{TM4 + TM3} + 0.5\ \right].$$

There are several important advantages of ratio vegetation indices connected with change detection problem. Ratio indices negate the effect of any extraneous factors in satellite data that act equally in all bands and that are multiplicative in nature. According to Singh (1989) strong differences in the intensities of the spectral response curves of different features can be emphasized through ratio indices and the last but not least all ratio images suppress the topographic effects and differences in irradiance when using multitemporal data. On the other hand random or coherent noise that is not correlated in different bands can be enhanced in ratio images.

The second form of vegetation indices are orthogonal indices. They are linear transformations of several original bands. In this group of indices the "Tasseled Cap" transformation can be mentioned which was extended to Landsat data by Crist and Cicone (1984) from the linear transformation produced by Kauth and Thomas (1976). The Tasseled Cap transformation defines three indices, which are weighted sums of all used bands and they are called Brightness (BR), Greenness (GR), and Wetness (WT). For Landsat TM data the tree indices are computed from the following equations:

$$BR = .2043TM1 + .4158TM2 + .5524TM3 + .5741TM4 + .3124TM5 + .2303TM7$$
$$GR = -.1603TM1 - .2819TM2 - .4934TM3 + .7940TM4 - .0002TM5 - .1446TM7$$
$$WT = .0315TM1 + .2021TM2 + .3102TM3 + .1594TM4 - .6806TM5 - .6109TM7.$$

Brightness is defined in the direction of the principal variation in soil reflectance. Greenness is approximately orthogonal to brightness and is strongly related to the amount of green vegetation present in the scene. The wetness index relates to canopy and soil moisture. According to Williams (1995) weights for individual indices can be regionally adjusted and more than three indices can be calculated, but the real meaning of further components is not clear sometimes.

Another example of orthogonal index is Perpendicular Vegetation Index:

$$PVI = -0.43TM3 + 0.91TM4.$$

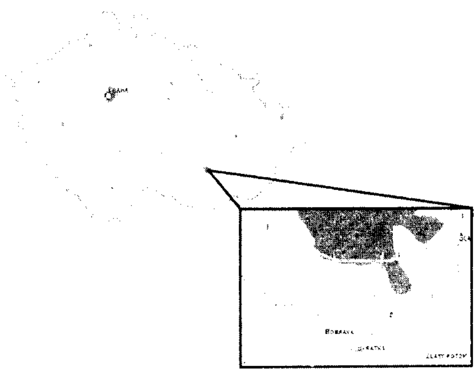

Fig. 2. Geographical location of the study area

STUDY AREA AND THE MATERIAL USED

Processed area (see Fig. 2) covers south fringe of Brno agglomeration and can be characterized by a strong change in land use and land cover, because it comprises both highly urbanized areas and rural landscape of Brno surroundings. For change detection study two LANDSAT Thematic Mapper scenes acquired in May 1986 and August 1994 were used. As mentioned above the precise geometric correction of used images is the first precondition for processing of multitemporal database. Both TM scenes were rectified to the same coordinate system according to the flowchart described in Fig. 3. The advantage of this approach is that the image-to-image registration is usually two to three times more accurate than the image-to-map registration (Lillesand, Kieffer, 1995). In the first step polynomial transformation was used, in the second step TM scenes were re-sampled to 25 m spatial resolution.

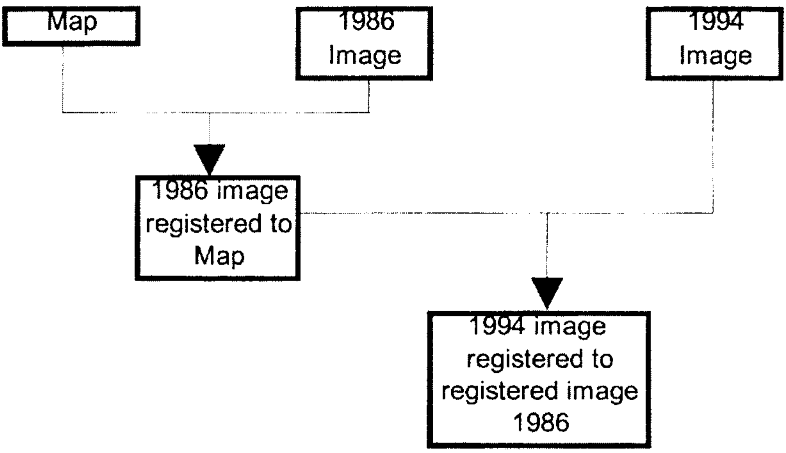

Fig. 3. Flowchart of geometric correction process of used images

Analysis of the main results of the tested methods

From the above mentioned methods three have been chosen for testing the possibilities to reveal changes in the highly urbanized area situated in the south fringe of Brno. The main results of analysis along with the advantages and drawbacks of each method are summarized in the following paragraphs.

Comparison of individual classification

As mentioned by several authors (e.g. Jensen, 1986; Singh, 1989; Lillesand, Kiefer, 1995), method of classification comparison gives usually the best results in the process of seeking for temporal changes even if algorithms of differencing or ratioing are more objective.

In the present paper individual supervised classification of both scenes was produced at first. For this classification simple scheme was adopted. Land cover which represents mostly rural landscape was described with 4 categories (forest, grassland and two classes of fields). For them training sites were created. Because of the course spatial resolution of TM images, pixels representing build up areas are mostly a mixture of several covers. So that 4 classes of build up areas were trained. These classes mostly reflect the different portion of such covers like concrete, barren ground, pavements, grassland, trees etc. For better discrimination of the above defined classes feature space of original TM bands was widen through principal component analysis (PCA).

Calculation of spectral signatures and selection of the best channels is normally an iterative process and the success in finding of the most informative channels is very important for the success of the whole classification. In this step algorithms for evaluation of signature separability and for channel selection were used. These algorithms are offered in EASI/PACE software, which was used also for supervised classification. Both signature separability and channel selection are measured through dissimilarity of classes called "transformed divergence" and full description of these algorithms can be found e.g. in Richards (1986). As the best channels for further classification bands TM3, TM4, TM7, and PC3 were determined. Signatures generated from the above mentioned channels were further edited and in the end all members of separability matrix generated from SIGSEP module were above 1.9, which means good spectral resolution for all possible combinations of classes. Generated signatures were used as an input to full maximum likelihood classification. For more simple comparison of tested approaches the result of each classification was presented in the form of bitmap - that is the first group of classes was aggregated to the "natural" (rural) covers and the second group of classified classes was aggregated to the "artificial" (urban) covers. This simplification of classification results was necessary for further comparison with other tested methods, because in the case of vegetation indices differencing and change vector analysis an arbitrary threshold based on statistics was taken into consideration. For revealing temporal changes in both types of covers cross classification of 1986 and 1994 bitmaps was generated and the results are summarized in Table 1 and Fig. 4.

It must be stressed that resulting image does not reflect only real changes connected with the change of land cover from or to build up areas, but other kinds of changes are also coded here and the result must be verified in field. At this moment the result of classification comparison can be tested for several cases marked with letters A,B,C in Fig. 4. Case "A" represents the area of change from "natural" to "artificial" covers. This is area of intensive construction of housing estate in the processed period and in the area under investigation it is the biggest example of real spreading of build up areas. Because the construction activity in the rest of processed area was not very intensive before 1994 other places of the same type of change are split mostly to the smaller units. Case "B" represents reverse change - from "artificial" to "natural". In this area sand pit is situated and the extent of the sand pit has changed during the time. Old excavated parts of this sand pit are filled with wasted material and re-cultivated. During the time this reclamation results in forming of grassland and shrub areas. Case "C" represents so called "false" changes. In both dates there are intensively cultivated fields in this area and the use of the images from different time of the year is the reason of this not real change in land cover.

Category No.	Geographical meaning	Per cent of image area
1	„urban" areas in both dates	11.6
2	„urban" areas only in 1994	7.4
3	„urban" areas only in 1986	5.6

Table 1. Results of supervised classification (in % of image area)

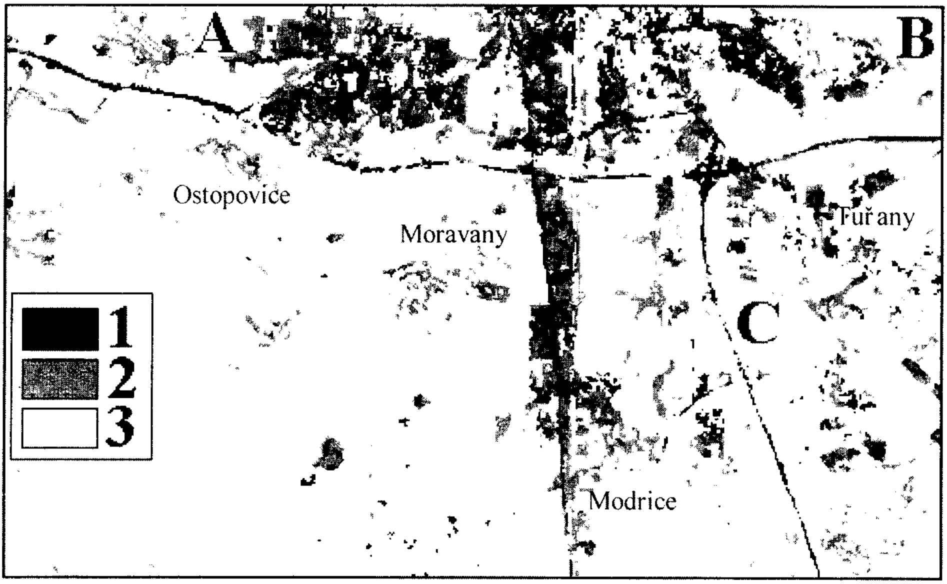

Fig. 4. Changes in areal extent of build up areas between 1986 and 1994 revealed through classification comparison. Legend: 1 - "urban" areas in both dates; 2 - "urban" areas only in 1994; 3 - "urban" areas only in 1986. Letters A,B,C see text

Vegetation indices differencing

From the spectral behavior theory mentioned above it follows that with the help of vegetation indices it is possible to order pixel values according to the amount of vegetation component.

There will be high pixel values for land cover classes with high vegetation content. On the other hand land cover classes like barren ground, concrete, pavements, communications etc. will be characterized with very low values. So that through vegetation indices spectral response of the "artificial areas" and "natural areas" could be enhanced. In the present paper four vegetation indices were tested:

- Simple ratio vegetation index
- Perpendicular vegetation index
- Normalized difference vegetation index
- Greenness index from Tasseled Cap transformation

At the first step these indices were calculated for both dates using equations mentioned above and then simple difference image was produced according to the formula:

$$\text{index}_{1994} - \text{index}_{1986}.$$

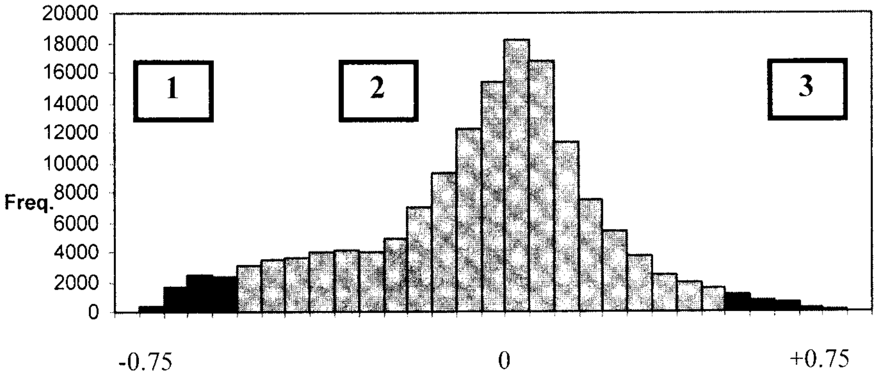

Fig. 5. Example of a histogram of the difference image ($NDVI_{94}$ - $NDVI_{86}$).

Table 2 summarizes the basic statistics for the evaluated difference images. Histogram of such difference image has a normal distribution (Fig. 5). The greatest changes are presented by the tails of the histogram but the main problem of the change detection methods based on image differencing is the definition of the threshold between significant and non significant changes. We must take into account that the type of change - in our case from urban to rural or vice versa - does not correlate with the size of change.

Characteristic	NDVI	RVI	PVI	GR
μ	0.0	-0.2	-11.6	14.0
σ	0.25	1.4	29.0	29.1
min	-0.76	-7.8	-158	-156
max	0.79	5.4	90	179

Table 2. Statistical characteristics of the evaluated vegetation indices difference images. Difference image was calculated as a simple difference between the index value in 1994 and 1986 (μ - mean, σ - standard deviation)

There are several thresholding techniques which can be used. In the present paper method of reclassification was applied at first. Each difference image was classified to three categories using two standard deviations as indicated in Fig. 5.

Areas with pixel values in difference image in interval (m-2s;m+2s) indicate no significant change and create category No. 2. Areas with the pixel values lower than m-2s indicate those areas with high decrease of vegetation index value and create category No. 1. Areas with the pixel values higher than m+2s indicate areas with high increase of vegetation index value and create category No. 3. Even if this arbitrary threshold does not say anything about the type of change, it allows to compare results for individual vegetation indices using the method of cross classification. Cross classification generates from two input images one output image in which all possible combinations of classes are coded as a new classes. If the first input image of n classes and the second input image consists of m classes than resulting image would be composed of n x m individual classes if all possible combinations occur. As an input two difference images, each of them with three categories were taken and resulting image was formed according to the scheme in Table 3.

Class No. 1 in output image gives the percentage of corresponding areas for which both investigated indices indicate significant decrease in its values. Class No. 2 in output image gives the percentage of corresponding areas for which both investigated indices indicate non significant change in theirs values. Class No. 3 in output image gives the percentage of corresponding areas for which both investigated indices indicate significant increase in its values. Class No. 4 in output image gives the percentage of corresponding areas for which the first index indicates significant increase or decrease and the second index indicates no significant change for the same area and vice versa. In results of cross classification there was no one pixel which would indicate significant decrease (increase) for one index and increase (decrease) for the other. Results of cross classification of all difference images are summarized in Table 4.

Category from the first image	Category from the second image	Resulting class
1	1	1
2	1	4
1	2	4
2	2	2
3	2	4
2	3	4
3	3	3

Table 3. Cross classification scheme of difference images

Index	Class	NDVI	PVI	RVI
PVI	1	77.0		
	2	97.0		
	3	48.0		
RVI	1	91.0	84.0	
	2	98.0	99.0	
	3	49.0	68.0	
GR	1	90.0	93.0	83.0
	2	98.0	98.0	98.0
	3	84.0	74.0	68.0

Table 4. Results of cross classification comparison of difference vegetation indices images (in per cent of individual classes area, 100% = class area of the index in column). For explanation of individual classes see text

From Table 4 it follows, that investigated indices show mostly high percentage of agreement within each other. In some cases the percentage is lower, especially for those situations where class No. 3 is compared (i.e. for increase of index value between investigated dates). Amount of "miss classified" areas can be expressed in percent of image area and it varies from 3.0% (NDVI - GR) to 4.9% (NDVI - PVI)). Even if the investigated difference images have a normal distribution and the same threshold for positive and negative significant changes was taken into consideration, the percentage of coincidence for increase index value (that is change from "artificial" to "natural" cover is lower (from 48 to 84%) than in the case of reverse significant change - from "natural" to "artificial" cover (from 77 to 91%) for all investigated indices. The reason can be the fact that the causes of increase of vegetation index value can be of very diverse origin in the investigated area. As mentioned by Petrová (1996), who studied land cover and land use changes in much larger area with the help of supervised classification and visual interpretation of TM scenes, during the period of 1986-1994 there were significant land use changes connected especially with the process of re-privatization at the beginning of the 1990s. Substantial changes in agricultural land use categories (orchards, vineyards, gardens, cottages etc.) were reported for this area. Mentioned processes in the studied period of time are finally reflected not only in spectral domain as indicate the results of cross classification, but also in spatial distribution of land use categories (Dobrovolný, Petrová, 1996).

An example of NDVI difference image is shown in Fig. 6. The same figures were generated for other indices. When compare these images with the result of individual classification, only a small agreement can be seen. The reason is that the threshold for delineating substantial changes based on standard deviation does not describe the same type of changes. Difference images reclassified according to standard deviation characterize mostly changes in rural landscape i.e. for instance changes connected with the different phenophases. It means that the "real" changes - that is mutual changes in urban and rural land cover are smaller in their size when compare with the "false" changes and must be sought somewhere inside of the histogram.

Hence in the next step various parts of NDVI image difference histogram were tested against results of individual classification comparison. The histogram was divided into narrow intervals and percentage of agreement was computed between these intervals and the results of classification comparison (classes No. 2 and 3 in Fig. 4). In case of NDVI decrease (class No. 2) the highest agreement was found for the values (-0.15;-0.25) which is about 0.5-1.0 standard deviation but the agreement was only 12%. In the case of NDVI increase (class No. 3) the highest agreement was found for the values (+0.45;+0.60) which is about 1.8-2.3 standard deviation but this part of the histogram explains only 20% of changes which were founded using the first method.

This means that in both cases changes in the extent of build up areas found with the help of individual classification comparison are split in the histogram of difference vegetation index image almost equally and it is hard to define interval in difference image which corresponds to individual classification comparison results.

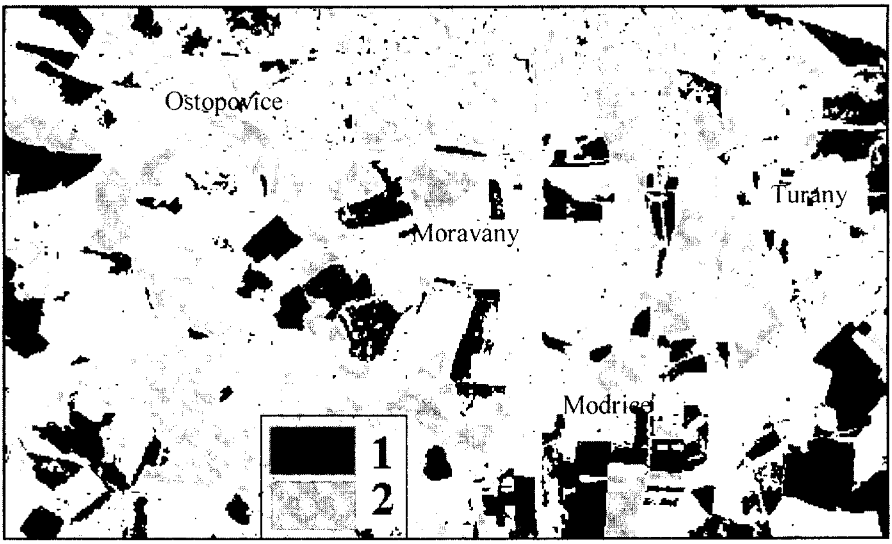

Fig. 6. Reclassified difference image $NDVI_{94}$ - $NDVI_{86}$. Legend: 1 - areas of decreasing NDVI values; 2 - areas of increasing NDVI values

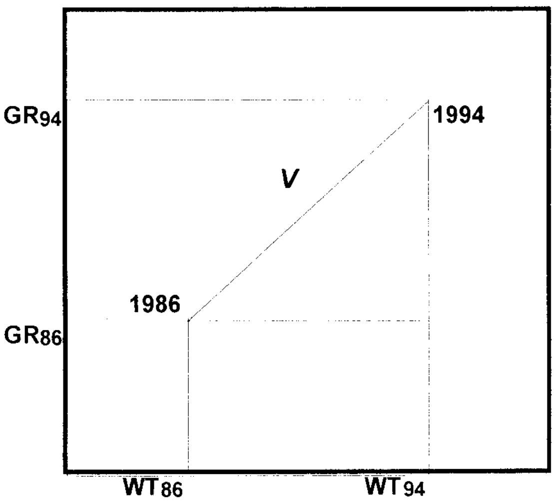

Fig. 7. Principle of change vector analysis

Change vector analysis

The third approach which was tested for revealing changes in processed area was based on the concept of the change vector mentioned previously. As an input to the analysis two indices computed from the Tasseled cap transformation have been used - Greenness (GR) and Wetness (WT) - both for 1986 and for 1994. As in the case of previous approach we can expect that the change of land cover from "artificial" to "natural" or vice versa will be manifested in the values of both indices.

Values of GR and WT for 1986 and 1994 years were taken as a co-ordinates of two points in correlation field. These two points define the vector, whose size (V) was calculated using Pythagorean theorem:

$$V = \sqrt{(GR_{94} - GR_{86})^2 + (WT_{94} - WT_{86})^2} \, .$$

Fig. 8. Change vector image showing the magnitude of change in land cover between 1986 and 1994

The size of a vector calculated for each pixel generates a new image whose pixel values "measure" the amount of change (Fig. 8). The histogram of the change vector image is skewed and the pixel values directly correlate with the amount of change for each pixel. The brighter the pixel value the greater the change in spectral domain. From the change vector image we can see that the problem to find the threshold value for substantial changes in this method is even more complex than in vegetation index differencing. This is caused by the fact that the sought changes are cumulated only on the right tail of a histogram. As mentioned by Singh (1989) the type of a change can be calculated as a direction of the change vector.

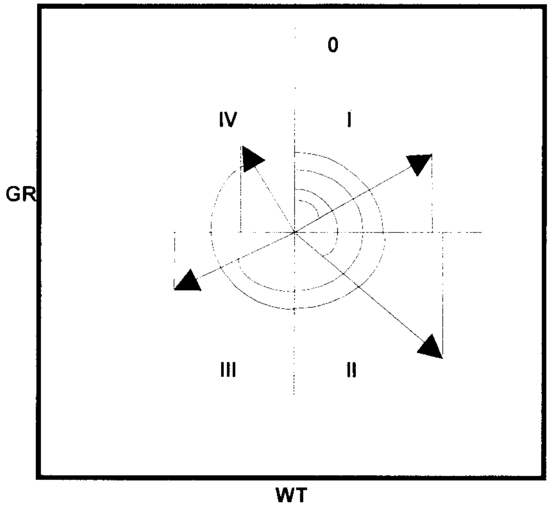

Fig. 9. Principle of deriving the direction of the change vector

In this paper the "type" of change was computed as an angle from vertical axis in two-dimensional space (Fig. 9). Depending on the value of both indices, the change vector can be situated in one of the four quadrants and the equations for the direction of spectral change vector are following:

I. quadrant: $$S_I = 1 - tg\frac{|GR_{94} - GR_{86}|}{|WT_{94} - WT_{86}|}$$

II. quadrant: $$S_{II} = 90 + tg\frac{|GR_{94} - GR_{86}|}{|WT_{94} - WT_{86}|}$$

III. quadrant: $$S_{III} = 270 - tg\frac{|GR_{94} - GR_{86}|}{|WT_{94} - WT_{86}|}$$

IV. quadrant: $$S_{IV} = 270 + tg\frac{|GR_{94} - GR_{86}|}{|WT_{94} - WT_{86}|}$$

As in the case of previous method substantial changes must be defined using thresholding or reclassification methods because they are not cumulated in the tail of the histogram. As can be seen from Fig. 8 the greatest changes revealed using the change vector are again connected mostly with the different phenological phases of rural areas. For comparison with the classification results from the change image were separated those areas that indicated decrease both for Greenness index and for Wetness index (i. e. the third quadrant) from 1986 to 1994. Using map algebra only those changes within interval (μ+1σ;μ+2σ) were taken to the resulting image which is shown on Fig. 10. This image then shows areas in which change from natural to artificial land cover during the period 1986-1994 was detected. Finally it is possible to compare this image with the category No. 2 in Fig. 4 which map the same type of change. From this comparison it follows that the change vector method gives more areas with this type of change and corresponds with the classification comparison method only for 34% of areas.

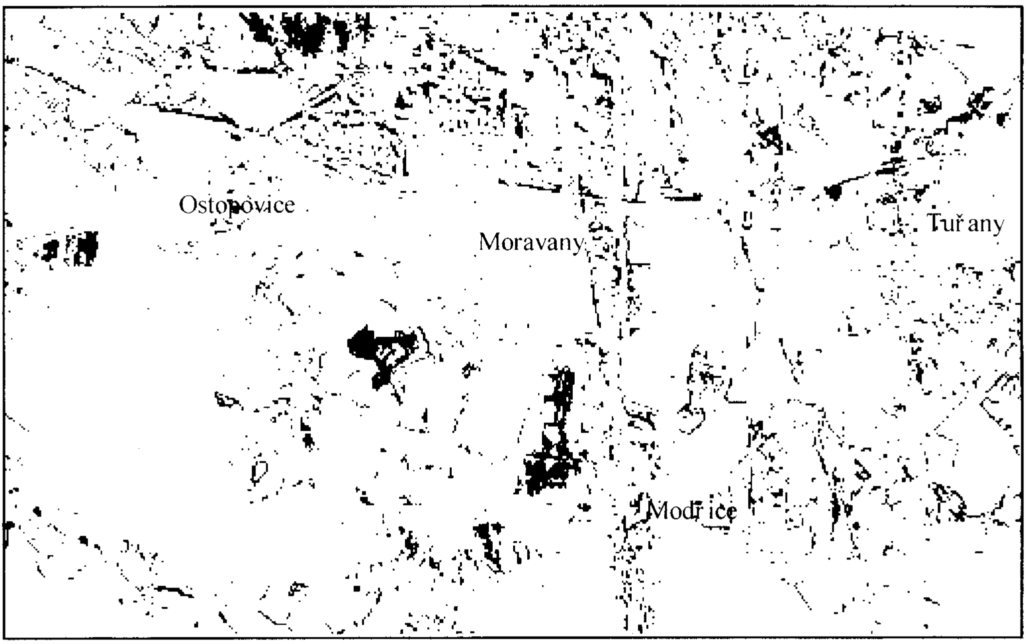

Fig. 10. Areas of changes from natural to artificial land cover according to change vector analysis in the period 1986-1994

CONCLUSIONS

Comparing the spatial distribution of revealed changes in land cover of the processed area we can conclude that the most promising results can be obtained using comparison of individual supervised classifications. With careful defining of training sites and using some additional transformed channels very fine classes can be recognized even in areas which nature is "mixed" from spectral domain point of view. The success of classification comparison is influenced in great extent by the fact whether "anniversary" images are compared. In case of different dates of compared images there is a lot of false changes in natural land cover due to the different phenophases. Through e.g. histogram matching this drawback can be minimized to some extent.

Using of various vegetation indices transformation gives very similar results and the indices are interchangeable in this sense. The main problem of differncing methods is to find a proper limit for detection of real changes. Vegetation indices are able to enhance differences in spectral behavior between "artificial" (lack of biomass) and "natural" (higher content of biomass) covers only to some extent and in some cases many "false" changes can be produced. Because the method of change vector is based on the same principle as image differencing also the drawbacks of this method are very similar. Possibility to generate "type of change" image gives some chance to distinguish the nature of land cover changes but it is strongly dependent on selection of input variables. In both methods real changes connected with the shift from rural areas to urban areas or vice versa are "hidden" in the histogram of the change image.

When consider the results of the first method (classification) as the most correct, better coincidence with this method shows the method of the change vector then the differencing of vegetation indices. Results of each tested method must be checked in field survey.

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