MULTITEMPORAL SPOT IMAGES FOR URBAN LAND-COVER CHANGE DETECTION OVER STOCKHOLM BETWEEN 1986 AND 2004

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KEY WORDS: Multitemporal, SPOT, Urban, Land-cover, Change Detection

ABSTRACT:

The overall objective of this research is to detect new urban areas over Stockholm Region between 1986 and 2004 using multitemporal remote sensing. Two SPOT images acquired on 13th of June 1986 and 29th of July 2004 were used for changed detection. Three change detection methods were tested for this purpose: image differencing, principal component analysis and change vector analysis using normalised difference vegetation index and brightness index. The results showed that image differencing using the red bands and second principle components performed better in detecting new urban features than change vector analysis (the overall accuracies: 89%, 87% and 83% respectively & kappa: 0.77, 0.74 and 0.67). Even though overall accuracies are all above 80%, the kappa coefficients were much lower indicating substantial amount of omission and commission errors presented in the change maps.

1. INTRODUCTION

Remote sensing applied to urban applications is of growing interest. Urbanisation is a fact and it can not be stopped, the question is how to manage it. The migration of people and jobs continues, attractive regions grow and the population increases. Nobody can predict with certainty that the development in a region like Stockholm will be sustainable, and will remain so in the future. Therefore new efficient systems are needed for monitoring the changes and to help to set up a strategy to handle the situation. Remote sensing and change detection can offer a tool for this process. Satellite images provide up-to-date information of earth's surface, thus can be used for analysing dynamics of the change and its effects. There are several approaches to perform change detection, including image algebra, transformations and classification of multitemporal images. The first method results in a binary change/non-change map, while with the classified images the information about the type of change can be identified.

Lu *et al.* (2004) compared several change detection methods and found that image differencing and principal component analysis were to recommend when performing direct change detection. Liu *et al.* (2004) examined the mathematical approaches for change detection and found that principal component analysis was one of the most accurate methods. Change vector analysis, on the other hand, operates on spatially contiguous groups of pixels rather than on individual pixel isolation. It has been found to be an effective multivariate technique, where the type of change, in some degree, can be classified (Malila 1980, Johnson and Kasischke 1998).

The increasing spatial resolution of satellite images provides opportunities to detect urban changes more accurately and SPOT images have shown their capability in this field (e.g., Martin and Howarth 1989). Today SPOT images are widely used in case studies (e.g. Zhang *et al*,. 2003; Weber and Puissant, 2003; Ferreira *et al.*, 2004).

The objective for this research is to detect new built-up areas, roads, and other new urban features over Stockholm Region during 1986 and 2004 using multi-date SPOT XS images.

2. STUDY AREA AND DATA DESCRIPTION

The study area is located in the county of Stockholm in Sweden, an area that covers approximately 2800 km^2 of highly fragmented landscape. The major land cover types are water bodies, forest, cultivated land, parks, roads, low and high density builtup areas. Stockholm region is constantly growing and between the mid-80ties and 2000 the population has grown with approximately 1 per cent each year (RUFS, 2001). The region has long traditions for planning towards an ecological sustainable society in several administrative levels. Two SPOT multispectral (XS) images acquired over the Stockholm on 13th of June 1986 and 29th of July 2004 were used in this study.

3. METHODOLOGY

1.1 Geometric and Radiometric Correction

Accurate geometric and radiometric correction of multitemporal images is an important component of change detection. In this research, the two SPOT images were geocoded to 1:50 000 digital topographic maps using a polynomial approach. For correction of the atmospheric attenuation, relative image normalization using regression, is applied on the 1986 SPOT images. Here radiometric ground control points, i.e, pseudo-invariant features (PIFs) were selected to establish the relation between the corresponding images from different dates.

2.2 Change Detection

In general, performing detailed classification in urban areas with a large number of land-cover classes is a huge challenge. Therefore, performing direct change detection on the remotely sensed images is a faster and easier approach to extract the changes than post-classification change detection. In this research, three direct change detection methods, namely, image differencing, principal component analysis and change vector analysis were selected to detect new built-up areas in Stockholm.

The main steps involved in the three direct change detection methods are shown in Figure 1.

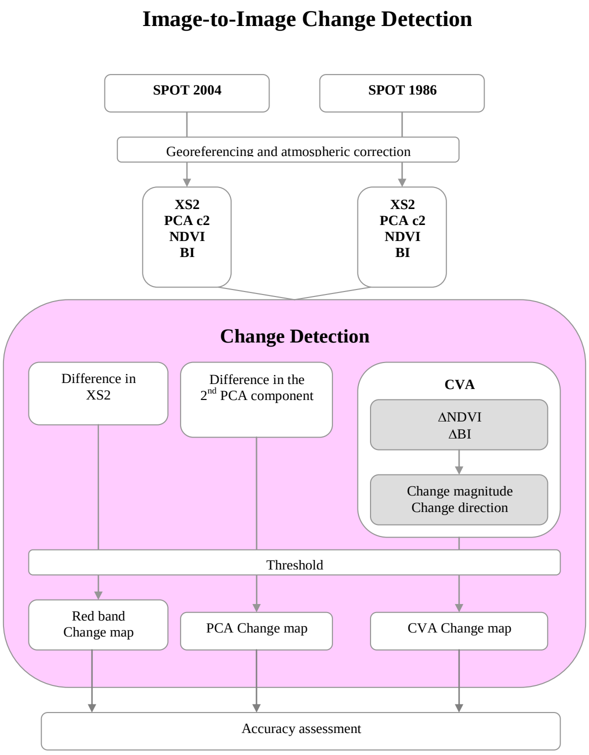


Figure 1. Change detection methodology

Image algebra and principal component analysis are frequently used in change detection. *Image differencing*, one of the most effective methods in image algebra, can result in a meaningful change/non-change map if suitable images are selected and appropriate threshold values are chosen. In this research, the red band (XS2) is selected for image differencing as builtup features usually have high reflectance in the red part of spectrum while that of vegetation is low due to absorption.

The second method chosen for the study is *principal component analysis*. The strength of principal component analysis is that it compresses the information from the different bands into principle components where some of them contain information of new urban features. Therefore by differencing this component a change image is created and major changes is highlighted by thresholding the change image. The first principal component contains majority of the variances from all the bands. The second principle component, on the other hand, is highly correlated to the visible part of the spectrum. Therefore, it captures the urban features better than the first component, since urban features have higher reflectance than vegetation in the visible spectrum.

The third method, *change vector analysis*, has also shown potential in image-to-image change detection. The spectral change is calculated for each pixel, both its magnitude and direction. The strength with change vector analysis is that it can, to some degree, identify the type of change. Classifying the type of changes, however, is highly dependent on the measures selected for quantification of the change. The red and near infrared bands are often used to create indices. This is based on that the all visible bands are highly correlated and the near infrared band is sensitive to vegetation. The change vector axes chosen for comparison in this study are: the difference in normalised difference vegetation index and the difference in the brightness index. A two-dimensional plot (Figure 1) is then constructed from these subtractions.

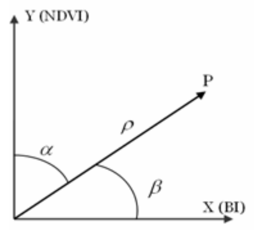


Figure 2. Change vector analysis in two dimensions

The magnitude and the direction of the change can be computed as follows:

$$\rho = \sqrt{\Delta NDVI^2 + \Delta BI^2} \qquad (1)$$

$$\alpha = \arccos\left(\frac{\Delta NDVI}{\rho}\right) \qquad (2)$$

$$\beta = \arccos\left(\frac{\Delta BI}{\rho}\right) \qquad (3)$$

where ρ = magnitude
α, β = directions
NDVI = normalised difference vegetation index
BI = brightness index

In image-to-image change detection, selecting a threshold is a trade-off between real changes and the noise level. There have been attempts to create statistical framework for the selection of the threshold (Rogerson, 2002; Liu *et al*., 2004), but usually the threshold has to be determined empirically. Values between one and two standard deviations from mean has shown to work well (Rogersson, 2002; Liu *et al.*, 2004, Jensen, 2005) and in this research the threshold values are tested and set for each change image separately.

3.3 Accuracy Assessment

The accuracy of the resulting change maps are evaluated using validation points, 440 in total, collected from areas where new urban features have appeared, and 310 points representing areas where there is no change. An error matrix is created to compute accuracies.

4. RESULTS AND DISCUSSION

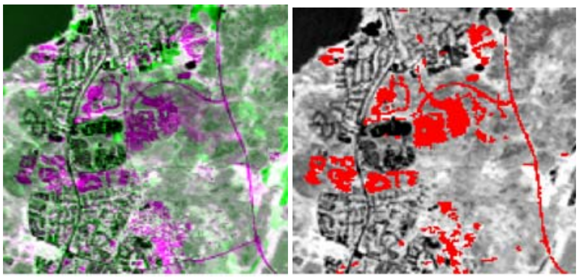
The images acquired on the 13th of June 1986 is referenced to the image from 2004 using 17 respectively 20 ground control points with a RMSs that are less than 0.18 pixels (or 3.2 meters). The SPOT image from 1986 was radiometric normalised to the 2004 images using pseudo-invariant features. The areas covered by clouds were masked out from both images. The overall accuracies of the change maps are summarized in Table 1.

Change Detection Method	Overall Accuracy %	Overall Kappa Statistic
Red band diff	88.56	0.77
PCA	87.05	0.74
CVA	83.31	0.67

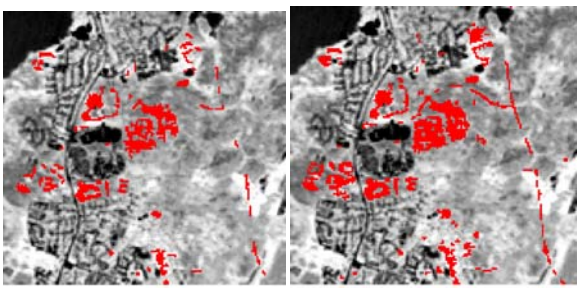
Table 1. The Overall Accuracy and Kappa Statistic

The red band differencing and principal component analysis yield high accuracy for detecting new urban areas than change vector analysis. Even though the overall accuracies for all three methods are above 80%, the kappa coefficients were much lower indicating substantial amount of omission and commission errors presented in the change maps. While the differences in overall accuracy are relatively small, the kappa from change vector analysis is much lower than that of the other two methods.

This is also visible in Figure 3 and Figure 4 where the resulting change maps are compared. In the top left corner the changes are visualised using three principal component images. The new urban features are in violet/lilac colour. The images that follows, in both Figures 3 and 4, show the resulting change maps in red colour from red band differencing (top right), principal component differencing (lower left) and change vector analysis (lower right).



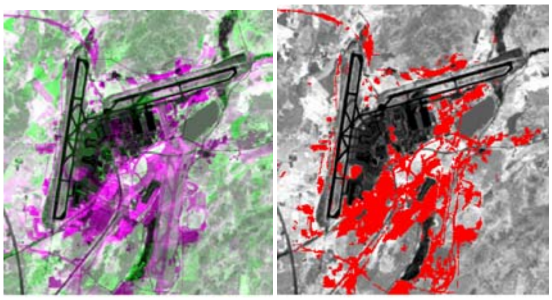
a. Visualization of changes b. Red band differencing



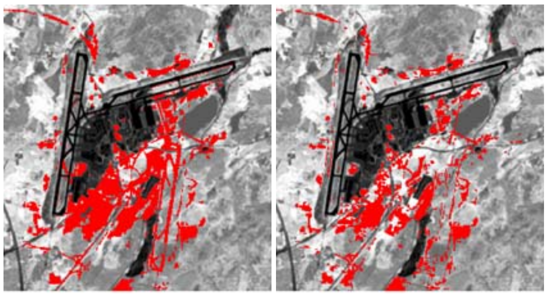
c. PCA d. CVA

Figure 3. Change maps, where the changes are highlighted using principal component bands (a). Then the three change detection methods are compared red differencing (b), 2nd principal component differencing (c) and change vector analysis (d)

Figures 3 and 4 show that the red-band differencing captures the changes well. In Figure 3 b, the major new road is detected, as well as the new residential areas. In Figure 4 b, the new road, in the upper left corner, and the new runway is detected. When the the results of PCA and CVA are compared, CVA shows better results in Figure 3 while the PCA marks the changes clearly in Figure 4, almost without any noise.



a. Visualization of changes b. Red band differencing



c. PCA d. CVA

Figure 4. Change maps over Arlanda airport, where the order of the change detection methods is the same as in Figure 3

The error matrices provide information on how well the new urban features are detected and how much over/under estimation the different methods have. When the change map is compared to the validation points, a measure of undetected points, i.e., omission errors and overestimation, i.e., commission errors can be computed. Table 2 shows the error matrices of the three change detection methods. Here it is also apparent that red band differencing and principal component analysis show much lower omission errors than that of change vector analysis. The commission error for CVA, however, is much lower than red band differencing and principal component differencing.

Change Detection Method	Urban change (%)		No change (%)	
	Detected	Not Detected	Detected	Not Detected
Red band diff	87.05	12.96	90.94	9.06
PCA	85.00	15.00	89.97	10.03
CVA	74.55	25.46	95.79	4.21

Table 2. The error matrices of the change detection methods

One possible reason for the poorer performance of the change vector analysis might be related to thresholding and further research is needed to develop a multiple thresholding system for CVA. Another possible cause is the use of two images that were not acquired on anniversary dates. On June 13, some of the agricultural crops are in earlier stage of vegetation development and vegetation covers on those agricultural fields are relatively lower, while in the end of July the fields have full vegetation cover. The seasonal differences in vegetation are more pronounced in the near infrared band. This difference is further enhanced by NDVI, thus affecting the change detection process using CVA.

5. CONCLUSIONS

This research demonstrated that the red band differencing and differencing the second principal component detected clearly the major changes and showed to be more accurate methods than change vector analysis, even though all the resulting change maps contained noise of unreal changes or omitted some real changes. It as found that the major challenge in direct change detection is to select appropriate threshold value that does not exclude real changes nor include unreal changes. The key for accurate results is to select suitable images or measures that reflect the change of interest. Further research will be conducted to improve the performance of change vector analysis, by using multiple thresholding and creating a change vector in three dimensions, instead of using only two measures.

ACKNOWLEDGEMENTS

This research was support a grant from the Swedish Research Council for Environment, Agricultural Sciences and Spatial Planning (FORMAS) awarded to Professor Ban. The authors thank the EU OASIS Program for providing the SPOT images. Karoliina Kolehmainen is grateful to the Swedish Cartographic Society for providing a travel grant to ISPRS 2008.

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