CHANGE DETECTION IN URBAN AREAS USING VERY HIGH SPATIAL RESOLUTION SATELLITE IMAGES: CASE STUDY IN BRUSSELS

Frauman E.[1] *and Wolff E.*[2]

1. Université Libre de Bruxelles, Institut de Gestion de l'Environnement et d'Aménagement du Territoire, Av. Franklin Roosevelt, 50, CP 130/02 ; 1050 Brussels; Belgium ; +32/2/650.43.29 ; +32/2/650.43.24 ; evelyne.frauman@ulb.ac.be
2. Université Libre de Bruxelles, Institut de Gestion de l'Environnement et d'Aménagement du Territoire, Bd du Triomphe, CP 246 ; 1050 Brussels ; Belgium ; +32/2/650.50.76 ; +32/2/650.50.92 ; ewolff@ulb.ac.be

ABSTRACT

Attempts are done to find possibilities of updating the Urban Information System (UrbIS) topographic data base thanks to VHR satellite images (IKONOS and QuickBird); this 1: 500 database over Brussels, Belgium is currently established and updated by photo restitution of large scale aerial photos. Because of the difference of scales between the database and the satellite images, but also because of the continuous nature of the kind of update, the analysis focuses only on roads, buildings and vegetation changes, the purpose being to have an alarm signal for important changes to concentrate the field work in between two flight campaigns. The techniques implemented are multi-temporal supervised classification, multi-temporal non-supervised classification and post-classification change detection. These techniques are used as such and in GIS-based change detection. This latest is implemented with masks exported from information contained in the UrbIS database.

The Multi-temporal classification is used with two VHR satellite images. The first step is a multi-temporal coloured composition. This allows us to visually detect important changes. The selected scheme for the supervised classification is divided in two set of classes: changes versus non-changes. Different land cover classes are represented as the changes between all of them. Principal changes are well detected, e.g. new buildings where there was only vegetation or changes in buildings structures. To reduce the amount of “false changes” post-classification rules are tested.

In the case of the non-supervised classification 20 classes are differentiated from which 4 classes are kept for their interest in the study (unchanged vegetation, unchanged built-up, change to built-up and change to vegetation). Post classification rules are needed to correct the salt and pepper effect.

The post-classification change detection is tested for data from different sources and with different scales. The scheme used in this method is more complex. We detect as much classes as possible at a land-use level (26 classes). This was done to approach the legend used in the UrbIS database.

This GIS-based method is used for visualization and classification. This step allows to concentrate on classes of interest for the UrbIS database and to correct some false alarms. Three masks are used: built-up, vegetation and construction sites. The resulting change maps show all changes and do not contain many false changed areas. The masks also allow us to find changes and errors in the database where the classification techniques as such did not raise any alarm.

INTRODUCTION

Urban decision makers face complex and dynamic environments. They require up-to-date information supplied by efficient data extraction systems. Satellite images offer great potential, but up until now, their spatial resolution was too coarse for applications requiring high spatial resolution such as mapping of urban areas. The recently available Very High Resolution (VHR) satellite images hold a potentially rich source of useful information to support urban managers and planners. The two operational very high spatial resolution satellites currently in orbit (Ikonos and Quickbird) provide the opportunity to obtain information at urban scales for large areas. The potential applications that can be developed thanks to these images are numerous: mapping and assessing urban green areas, identifying urban morphological complexes, determining building density, etc. In urban areas however, this is especially challenging because of the complex morphology of cities and the varied materials used in structures. Although present-generation earth-observation satellites have sensors with high spatial resolution, their spectral resolution is limited and not well adapted to urban environments (i). A major drawback of these low Earth orbit satellite-based sensors is that they are limited to acquiring images at fixed times of the day. This implies that the presence of shadows is often unavoidable. Shadows cause a reduction or sometimes a complete loss of information in an image. In this case that area of the image cannot be interpreted (ii).

In the framework of the SPIDER project (www.vub.ac.be/spider), our research teams investigated through a survey, the potential of these new VHR images for supporting local and regional decision-making in urban applications in Belgium. Similar studies have been conducted in France (iii) and at the European level (iv). The survey's main purpose is to assess user needs and to find out how these needs can be potentially met by VHR data. It was launched in June 2003; 45 users were selected belonging to all administrative levels within the three Belgian regions. One of the things the survey demonstrated is that, at the present time, satellite data are hardly used by Belgian authorities. Much of the land use and land cover application needs are presently covered by aerial photography, mainly by ortho-photos. Nevertheless, approximately 40% of the organizations that took part in the survey seem to be interested in land use/land cover information at scale levels that correspond to the resolution of VHR data (1:5000 or less) (v). Within the project, the decision of developing applications meeting users' specifics needs has been taken. One of the users showed a particular interest in the possible use of the VHR data, and our team decided to enter in contact with them. It is the Regional Informatics Centre of Brussels (CIRB/CIBG). High levels of urbanization in the Brussels region, and the dynamic changes that take place in this area stressed the need for developing a large-scale reference database for the region. Thanks to the efforts of the Regional Informatics Centre of Brussels (CIRB/CIBG) and the relatively small size of the region (161 km²), a large-scale database, the Urban Information System (UrbIS), is now available and is extensively used by local and regional administrations (v, vi). This 1:1000 database is currently established and updated by photo restitution of large-scale aerial photos. We then decided to assess the eventual use of VHR data for updating the UrbIS database.

BACKGROUND

Updating digital databases is an important task. The procedure could be significantly reduced by the use of an automated change detection process, especially in urban and sub-urban areas (vii). Change detection is the process of identifying differences in the state of an area by observing it at different times (viii). The change detection process is only possible when changes in the phenomenon of interest imply detectable changes in radiance, emittance or backscatter value, which implicitly includes patterns. Particular attention must be given to the separation of those changes relevant to the phenomenon under study from other irrelevant changes. In addition, distortions and bias introduced by the registration of the different data sets have a relevant influence on the analysis (viii). Land cover changes result in alterations of remote sensing scene element over spatial and temporal scales. To measure these alterations two techniques can be used: post-classification comparison and pre-classification enhancement (ix). Post classification change detection examines changes over time between suites of independently characterized thematic categories. It is very advantageous when using data from different sensors, with different spatial and spectral resolutions. It also enables us to use data with inter-date phonological differences and provides information on the type of land cover transformations that have occurred (ix). Pre-classification enhancement techniques involve a combination of the images from different dates. This combination can be displayed as a composite image and changes are highlighted in distinctive colours (x). These techniques are often more accurate to identify areas of spectral change than post-classification techniques (xi). But they also require an accurate image normalization and co-registration. The quality of the change detection depends on the aspects related to the quality of image interpretation. It involves the objectives and requirements of the application, the methods used to evaluate the results and the change detection algorithms (viii). Accuracy assessment is an important aspect of land cover change mapping. According to Rogan et al. (ix) a standard overall accuracy for land cover mapping studies has been set between 85 percent and 90 percent. However no standard currently exists for change detection studies. The authors made a review of the change detection literature where map accuracy was reported. It revealed that the mean number of classes resolved in change-monitoring studies using high-resolution images is seven. The mean overall map accuracy of these studies with high-resolution satellite data is approximately 76 percent (ix). The most important thing to consider in change detection is actually the number of false alarms. These can be an especially problematic problem for areas with asphalt covered roofing felt roofs because then discerning roof and road is virtually impossible (vii). Pixel wise change detection methods often suffer from false alarm rates that may be prohibitive for certain applications (viii).

Recent research has demonstrated the optimistic bias of pixel-level sampling approaches in change detection methods (ix). Traditional multi-spectral classification methods on pixel basis are no longer suited for the processing of very high-resolution and multi-source data from remote sensing (xii, xiii). In fact, a major drawback of pixel-based classification approaches is that when they are applied on VHR images (and moreover in urban areas) they often produce thematic maps that lack spatial coherence because of spectral heterogeneity and spatial variance in the image. To avoid this salt-and-pepper effect, Barr & Barnsley (xiv) proposed a reflexive mapping procedure that operates on individual regions, i.e. groups of adjacent pixels that are assigned to the same land cover class by the classifier.

OBJECTIVES

The SPIDER project aims mainly at using VHR satellite images in an urban and suburban context. Furthermore, in rural areas, the number of map objects is small and changes are rare and easy to spot manually, so automating the update process here is less important than in the urban/suburban case (vii). We focus the task on “building” and “transportation areas” object classes. Indeed, both classes are important mapping objects and very good indicators for urban development (vii). We try to map main changes implying these two classes of objects, as these are the most important phenomenon while updating the urban database. The result of the change detection procedure should be presented as a change map, also called an update report. It is a raster indicator map co-registered with the database where each pixel will be given a value of 0 or 1 indicating change or no-change respectively. At a higher level, further information about the nature of change will be available too, in the form of a legend. An image of the probability of changes will also be calculated.

METHODS

In the framework of this study we decided to work with per-region classifications. This procedure merges regions that fall below an a priori defined, class-specific area threshold with the smallest neighbouring region that exceeds the area threshold. After each re-labelling, the region-based topological structure of the image is rebuilt. These so-called image segments do not necessarily have any semantic meaning and can be considered as image primitives. Once they are created, they can be wholly labelled to a land cover class by any classifier. Image segmentation is one of the most critical tasks in automatic image analysis (xv). It consists of subdividing an image into its constituent parts and extracting these parts of interest (objects). A large variety of different segmentation algorithms have been developed (xvi). The segmentation procedure and the classification are implemented in the eCognition software (xvii). It uses a general segmentation algorithm based on homogeneity definitions in combination with local and global optimization techniques. A scale parameter is used to control the average image object size. Different homogeneity criteria for image object based on spectral and/or spatial information are developed. The resulting image objects are the raw material for further classification and refinement procedures. (xvii, xviii, xix). The classification of data with an enormous amount of characteristic features far beyond spectral analysis alone has become possible in object based image analysis: shape features (length, area, etc. of the image object), hierarchical features (relations to other levels of classification and relation to other objects), etc. The new problematic consequences are the overview of interaction of classification rules and the ability of the total complex project to be validated (xx). Classification as implemented in eCognition is based on a nearest neighbour algorithm.

Study area

The city of Brussels (50.50 N, 04.21 E) is the capital city of Belgium. It covers an area of 161 sqkm with a registered population of about 1 003 442 (2004). The city presents diverse land cover and land use types. From a previous study on the area of Ghent, Belgium (xxi, xxii) the fact that the size of the VHR satellite images could be a brake for the study was noted. Therefore we decided to work on four subsets or test-sites of about 4 sqkm. Each test-site was chosen to represent the different types of land use present in the scene: the zone of "Woluwé" and "Stalle" being in residential areas of the second crown of Brussels, the zone "Center" in the dense residential and commercial of the city centre, and the zone of "Meiser" located in an industrial area. The position of these test zones on the area of Brussels can be seen in figure 1.

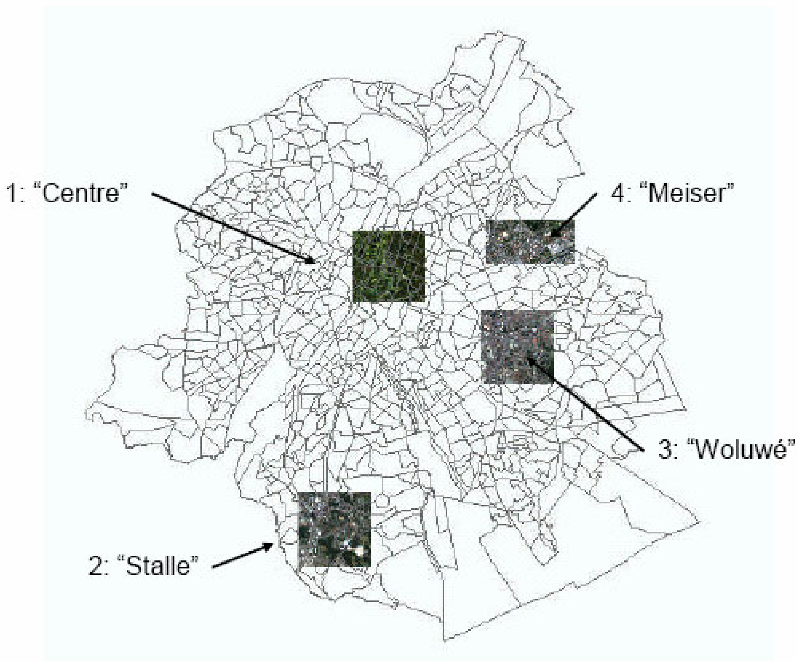


Figure 1: test zones showed on a map of Brussels

Data

Database

The Urban Information System (UrbIS-TOP database) last updated version (1999) was used in this study. It is a 1:1 000 database. It is built up by photo-restitution. Information is added through the digitalization of the cadastre files and completed by diverse administrative codifications. The aerial photographs of 1996 and 1999 helped during the initial photogrammetrical restitution phase (vi).

Aerial photographs

The CIRB kindly gave us access to the aerial photographs from the 1999 and 2004 flights.

The 1999 flight has taken place on the 1st and 2d of May. Each photograph covers an area of 800 m × 800 m. The resolution is about 0.1 m.

The 2004 photographs have been taken on the 31st of March. They have been taken during the spring period, when there is less vegetation cover. Each photograph covers a bigger area than the 1999 photographs: 840 m × 840 m, and the resolution is greater: more or less 0.84 m.

These aerial photographs are not geometrically corrected; therefore they don't have the precision of an "orthophotoplan".

Satellite images

We used a Quickbird bundled image product of July 13th 2003 fully ortho-rectified. The resolution is of 0.71 m for panchromatic and 2.84 m for the multi-spectral channels. Ground control points were measured using differential GPS in real-time mode. A reference digital terrain model (DTM) was created using the contour lines (with equidistance of 2 m and 10 m over the region of Brussels) from various topographical maps digitalized by the Brussels Institute for Environment Managing (IBGE/ BIM). An image fusion was made of the multi-spectral and panchromatic channels to support the visual sampling of training and validation data. The technique we used for the fusion is INRbpb (Intensity Normalized Ratio band per band) (xxiii). For the QuickBird images, the resolution ratio is 4 and the size of the moving windows for the computation of the local statistics was set to 11 by 11 pixels.

The second satellite image we used is an IKONOS image product of June 8th 2000 fully ortho-rectified. The resolution is of 1 m for the panchromatic channel and 4 m for the multi-spectral channels.

Training and validation data

To train the classifier and to evaluate the classifications, we gathered training and validation samples across the study areas. Training data were obtained by visual sampling using the satellite images and the aerial photographs as support. These sample zones were verified on the field where necessary.

For the validation data, we made random set of pixels. Attribution of these pixels within the different classes of the legend was done manually by visual sampling using the satellite images and the aerial photographs. Again, field visits were organised where necessary.

As we are using different kinds of data, we developed two methods. The first one, the change detection thanks to a multi-temporal classification, is used when comparing data coming from different sources and with very different scales. The second technique implemented in this study is post-classification change detection.

Coloured multi-temporal composition and unsupervised classification

The coloured multi-temporal composition (fig. 2) is the first change detection method tested. It is a method useful to visually detect most changes between the two VHR satellite images.

The colours of the changed and unchanged areas depend on the coloured composition done. In our case we used the two NDVIs (one for each image) and the panchromatic layer of the QuickBird image as follow: the NDVI of the QuickBird image in the Blue channel; the NDVI of the IKONOS image in the Green channel and the panchromatic layer of the QuickBird image in the Red channel. In this case the colours of the composition can be interpreted:

Non changes: Vegetation: yellow
Built-up: dark blue
Shadows: black

Changes: Vegetation → built-up: turquoise
Built-up → vegetation: pink
Built-up → built-up: bright blue
Changes shadows: green

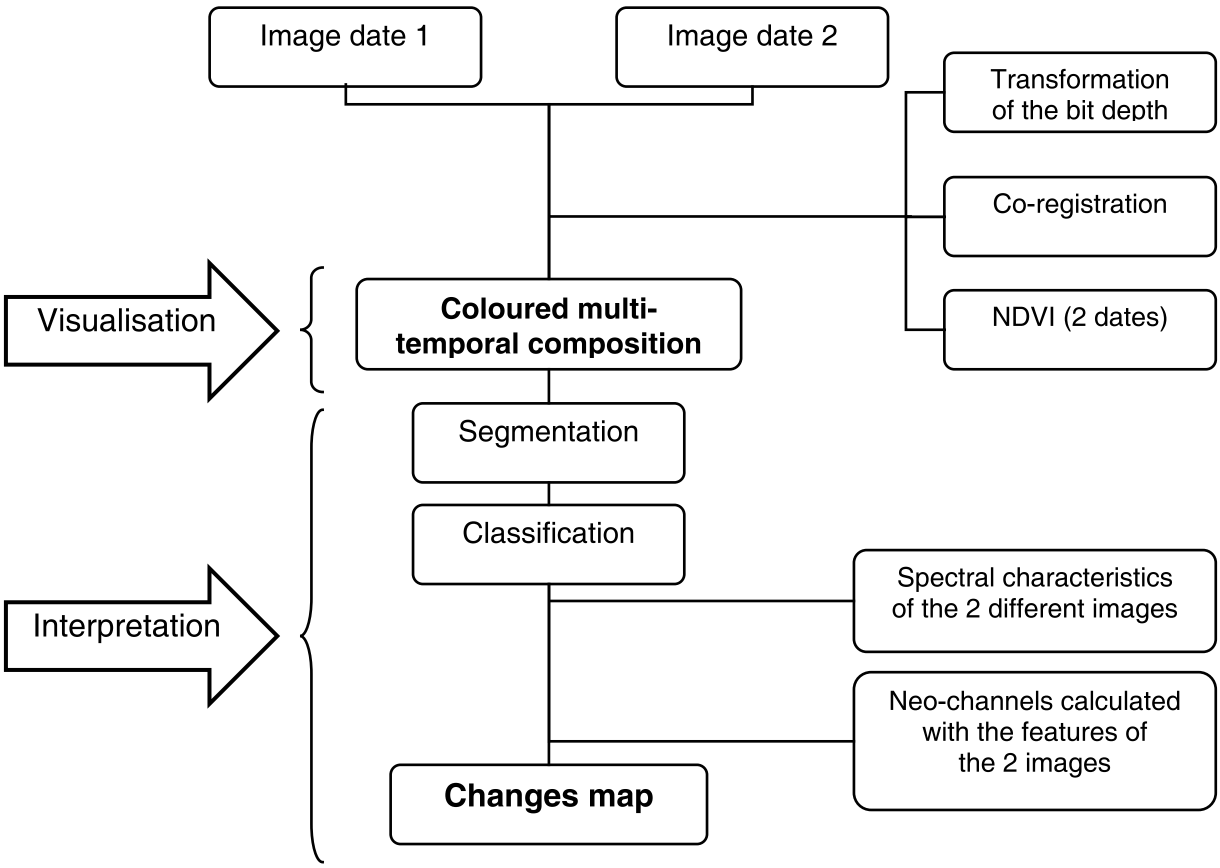


Figure 2: coloured multitemporal composition and classification: method

The unsupervised classification has been tested only for the test-zone of Woluwe. It has been performed by unsupervised clustering using the ISODATA method. This method iteratively determines sampled means for cluster centres. The user specifies the number of clusters desired. This specification only provides an estimate; the final number of clusters may vary. The user can define the maximum number of iterations allowed and the movement threshold. The result of the clustering is a theme map. It encodes each cluster with a unique grey level. Cluster number is represented by grey level. Therefore a pseudo-colour table should be loaded so that each cluster is represented by a different colour. It is possible too to generate signatures for each cluster. The user can then use the Maximum Likelihood Classifier to classify other images.

The classification has been implemented on the following layers of the two date's images: the panchromatic layers of the IKONOS image and of the QuickBird image; the NDVIs of both images; the Red layers of both images and the Near Infrared layers of both images. 21 clusters were asked to the clustering algorithm and the final result gave us a map with 19 clusters. These 19 clusters have been visually attributed to 4 classes of changed and unchanged areas:

built-up

vegetation

vegetation → built-up

built-up → vegetation

It would have been possible to obtain a more detailed final result, but this would have meant that more clusters should have been created and therefore the work of interpretation would have been heavier.

This step of unsupervised classification has been followed by the application of post-classification rules to smooth the final map. These rules concerned mainly the size of the polygons and the change class.

The change polygons that are smaller than 500 pixels are reclassified as the most probable non-changes class, taking the neighbourhood into account. For example, a polygon classified as "built-up → vegetation", surrounded by vegetation and smaller than 500 pixels will be reclassified as "vegetation".

The result is a change map that can be compared to the database to point changed areas and errors in the database.

Coloured multi-temporal composition and multi-temporal supervised classification

This method consists in classifying the multi-temporal composition with the per-region classifier using a manually implemented training set (fig. 3). The legend used contains 27 classes (table 1) of changed, unchanged and shadows classes. The use of the per-region classifier allows using factors as texture or shape of the objects to classify them.

Post classification rules allow reclassifying the shadows areas within the changed or unchanged areas. Another set of rules should also ameliorate the structure of the classification.

The shadows are reclassified in their second most probable class. Many of these post-classified shadow polygons belong to the "water" class. One possibility we envisaged to avoid this problem is to suppress this class that is not very represented in the region of Brussels and that is well recorded in the database. The database could then be used to discriminate the water areas.

The change polygons that are smaller than 500 pixels are reclassified as the most probable non-changes class, taking the neighbourhood into account.

Table 1: legend used for the multi-temporal classification.

Multi-temporal classification	
buildings	Unchanged
transportation areas	
vegetation	
water	
bare soil	
vegetation → buildings	Changed
vegetation → water	

vegetation → transportation areas	
vegetation → bare soil	
buildings → transportation areas	
buildings → vegetation	
buildings → buildings	
building → bare soil	
transportation areas → buildings	
transportation areas → vegetation	
bare soil → building	
bare soil → vegetation	
shadows	Shadows
shadows → vegetation	
shadows → water	
shadows → buildings	
shadows → shadows	
shadows → transportation areas	
transportation areas → shadows	
vegetation → shadows	
water → shadows	
buildings → shadows	

Post classification change detection

Post-classification change detection (fig.3) is one of the most common methods used for change detection. The scheme used (table 2) in this method is more complex than for the multi-temporal classification. We detect as much classes as possible. It is a hierarchical scheme composed of three levels. The first one concerns vegetation and non-vegetation. The shadow class is subdivided into two classes (shadow on vegetation and shadow on non-vegetation) as it has been showed that the “shadow on vegetation” class is closer to the “vegetation” class than to the “shadow on non-vegetation” class (xxv). The second one is based on the land cover scheme that had been established during the first part of the project on the Ghent area. The third level of the legend differentiates, for each built-up class of the second level, transportation areas from buildings. This was done to approach the legend used in the UrbIS database. By superposition of this classification with the second level of classification, information will be given about the land cover of the area and its use.

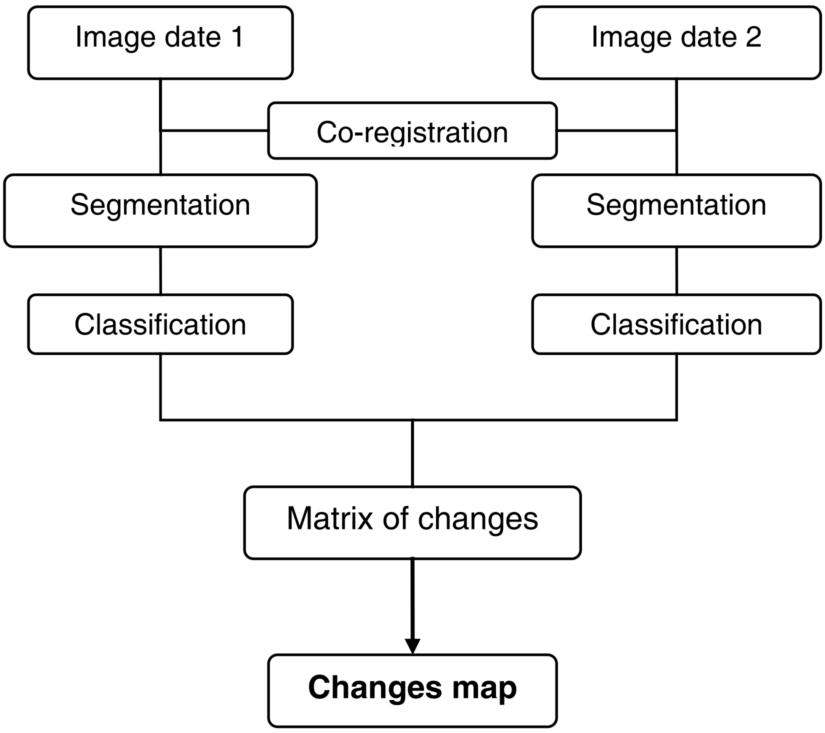


Figure 3: post-classification change detection method

For each image, post classification rules allow reclassifying the shadows areas within the changed or unchanged areas. Another set of rules should also ameliorate the structure of the classification.

The shadows are reclassified in their second most probable class.

The change polygons that are smaller than 500 pixels are reclassified as the most probable non-changes class, taking the neighbourhood into account.

Table 2: legend used for the classification of the IKONOS image and the QuickBird image

Level 1	Level 2	Level 3
shadow	on vegetation	
	on non-vegetation	
vegetation	trees	
	shrubs	
	grass	
	crops	
	non-vascular vegetation	
non vegetation	water	water bodies
		water course
		swimming pools
	red surfaces	
	bare soil	
	very reflective surfaces	buildings
	light grey	
	dark grey	transportation areas
	gravel	

Database masks

This third method implemented examines the use the database as a guiding tool for change detection. GIS change detection approaches are particularly useful in urban change detection (xxiv). They combine the use of different GIS data with satellite images. The binary masking technique is useful for quantitatively examining the changes dynamics by categories (xxiv). Then a classification of the image within the unmasked area defines the changes that have occurred within each of the object types. In order to achieve this, polygons and lines of interest are extracted from the database (table 3), and masks are created that are used in the classification process. The objects of interest we extracted are:

- buildings
- construction sites
- vegetation

We decided to focus on changes implying the buildings objects and the vegetation, as these are the most important changes. Changes in transportation areas do not happen often in dense urban areas like Brussels.

"Buildings" and "construction sites" masks were directly derived from the database.

The strategy used for creating the "vegetation" mask is different as vegetation objects are not extensively represented in the database. Only the road lined trees are represented in the UrbIS database. Therefore, we used a classification of the Ikonos image of 2000. The regions that are covered by both the vegetation classification (from the IKONOS image) and one of the two masks exported from the database (buildings or works) are reattributed to the mask from the database and erased from the vegetation mask.

The three raster files obtained are used as masks for classification: only the pixels not belonging to the mask are classified. This allows us to concentrate on possible changes within each class of objects of interest.

Table 3: objects extracted from the UrbIS-TOP database to map the two masks "buildings" and "construction sites". The layers Buildings, separation and transportation areas from the basic collection and the layers buildings from the complementary collection are used.

Layer	Object	Description
Buildings (Group BB)		
BB01	façade	Façade principale et latérale effective jusqu'à 5m ou jusqu'au premier point adéquat sur la façade latérale
BB01_ENT	façade comportant l'entrée	Indication sur la façade du bâtiment qui fait l'angle,
BB02	façade mitoyenne	Façade que 2 habitations contiguës ont en commun
BB05	Bord toiture	Bord visible de la toiture par photogrammétrie, là où il n'y a pas eu de reconnaissance de terrain
BB10	Contour habitation/façade arrière	Façades latérales et arrières et les façades des bâtiments situés en retrait.
Separation (Group BF)		
BF02	Mur	Axe du mur, mur de sécurité sur autoroute, etc

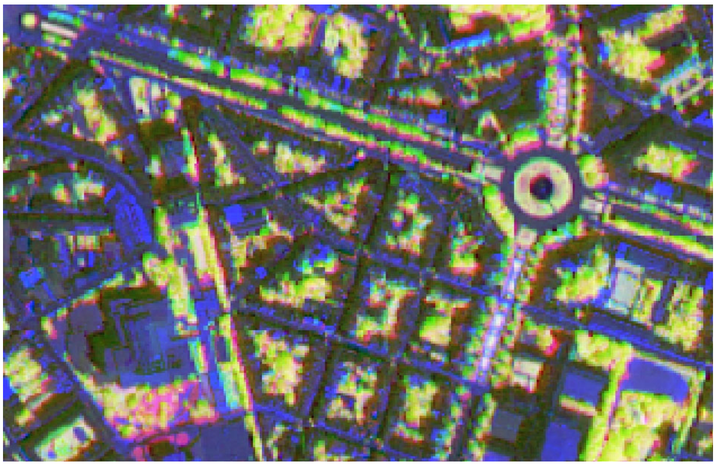
Buildings (Group CB)		
CB21	Délimitation des parties annexe d'un bâtiment principal (parties basses)	Limite entre les parties des bâtiments principaux les plus élevés à partir de la rue, et les annexes moins élevées contiguës à l'arrière ou sur le coté
CB23	Délimitation des tours	Ccontour des parties de bâtiments principaux pouvant être considérées comme des tours
CR42	Entrée carrossable	Indication de la largeur d'une entrée carrossable, le long de la limite entre le domaine public et le domaine privé
Transportation areas (Group BR)		
BR08	Travaux en cours	Délimitation du périmètre fermé d'un terrain qui est le cadre de travaux concernant des objets à porter sur la carte

RESULTS

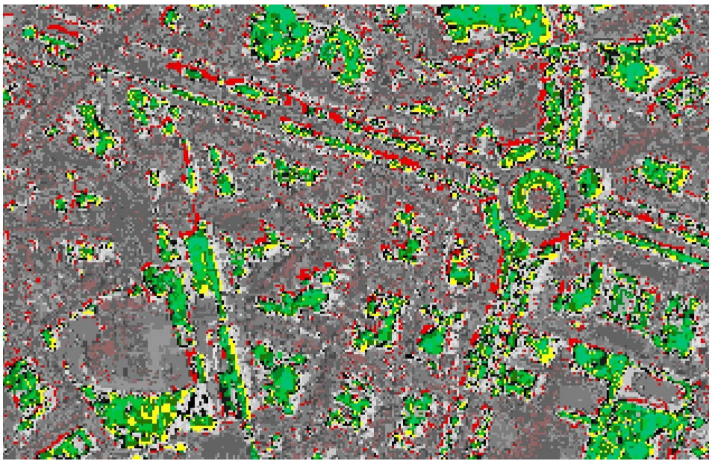
Coloured multi-temporal composition and unsupervised classification

The unsupervised classification has been tested only for the test-zone of Woluwe.

This method is the easiest to implement as it requires no work of interpretation for the training and validation sets (fig.4). But the work of visual interpretation for grouping the clusters into useful classes within the change detection process is heavy and can become really long and complicated if the user wants to differentiates many classes of change (taking into account the colours of the different land cover classes possible).



(a)



(b)

Figure 4: (a) coloured multi-temporal coposition and (b) unsupervised classification (before application of post-classification rules). In green: unchanged vegetation area, in grey: unchanged building areas, in red: changed areas from vegetation to building areas, in yellow: changed areas from buildings to vegetation.

Coloured multi-temporal composition and multi-temporal supervised classification

Before application of the post-classification rules (fig. 5), areas that have changed are visually very well detected on the classification of the coloured composition, but many small areas of false changes are presents. These are principally due to the slant effects of the two images used, and also to the shadows present on both images. It is important to note that 38.7 % of the image is covered by shadows at one or both dates. The principal errors are due to the fact that we try to classify land use, for example confusion between transportation areas and buildings. A solution to that type of confusion is to add shape criteria to the classification. Unfortunately because of the large amount of occlusions due to shadows and trees along the streets on the transportation areas these criteria lose their interest in our case.

The results for the different test-zones are:

Woluwe test-zone:

> The result for the classification of the coloured composition is encouraging: the PCC of the classification of the type of changes is 67.1 % (Kappa = 59.0 %). This classification has been implemented using only the multi-spectral layers, the panchromatic layer and the NDVI calculated for both images. The segmentation was based on the multi-spectral layers and the NDVI.

Meiser test-zone:

> The PCC of the classification of the type of changes is 73.8 % (Kappa = 66.7 %).

Stalle test-zone:

> The PCC of the classification of the type of changes is 85.5 % (Kappa = 78.0 %).

Centre test-zone:

> The PCC and overall accuracies obtained for the Centre test-zones were too low to allow any use for change detection. Visually the results were not better. This is due to the fact that the central area of Brussels is covered by a very dense built cover. The thin roads are barely seen through the buildings. Therefore we decided to drop the Centre test-zone and to work on less dense areas, i.e. Woluwe, Meiser and Stalle test-zones.

A common problem of confusion for these three zones occurs when differentiating the “built-up” class from the “built-up → built-up class”.

For the Woluwe test-zone and the Meiser test-zone, other pairs of classes are confused. These problematic classes are: “shadows → vegetation” and “vegetation”; “vegetation” and “shadows → vegetation”; “built-up → vegetation” and “bare soil → vegetation”; “shadows” and “built-up”; “built-up → shadows” and “built-up”.

Many of these problems involve shadow classes. With the post-classification of the shadows, the impact of these problems on the change detection map is avoided (fig 6 and fig. 7).

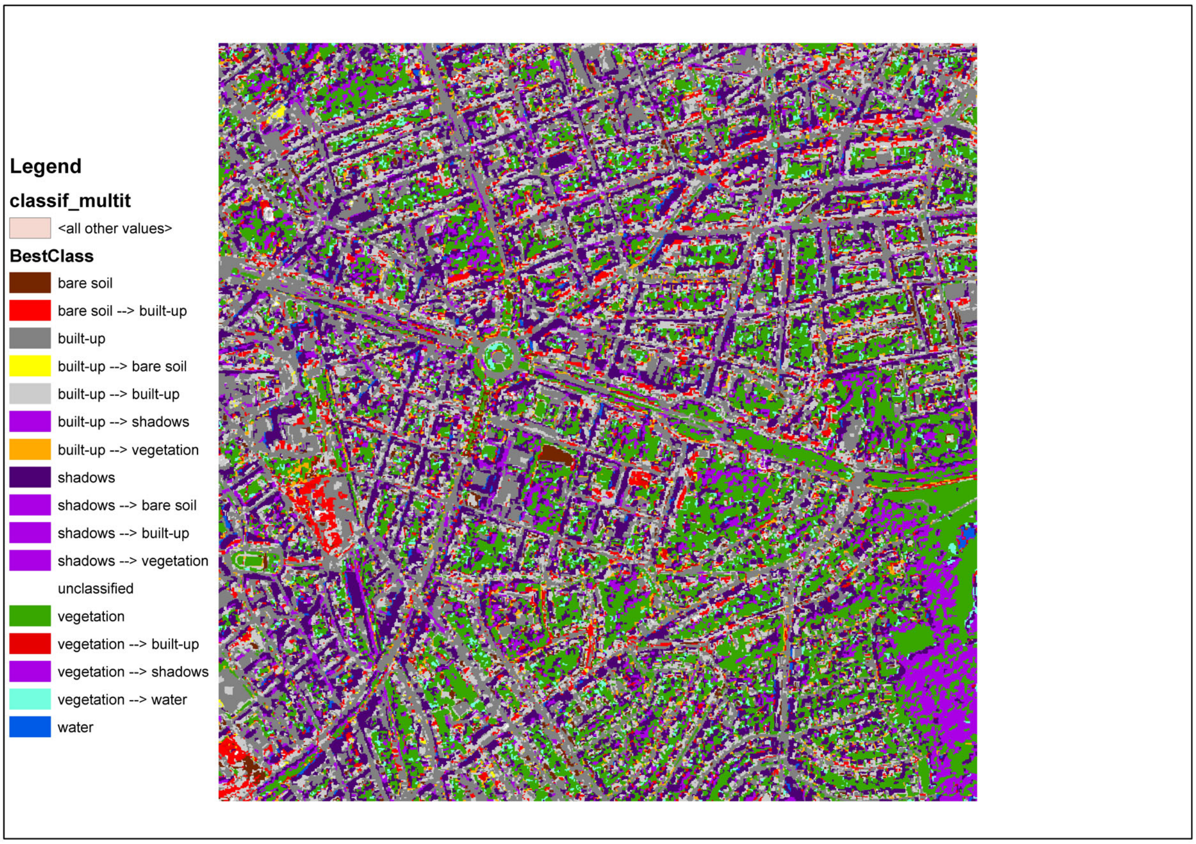


Figure 5: supervised multi-temporal classification before the application of the post-classification rules (the high amount of shadows (in purple) is visible)

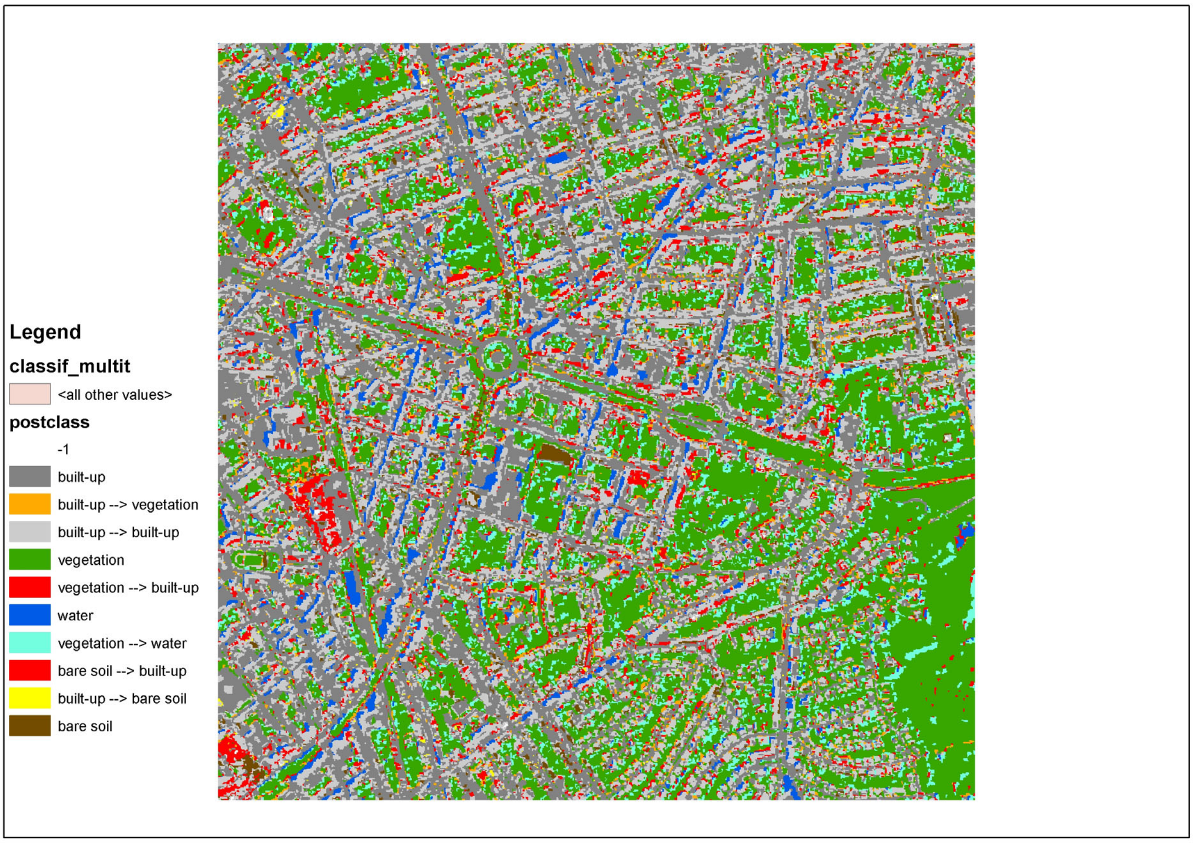


Figure 6: supervised multi-temporal classification after the application of the post-classification rules

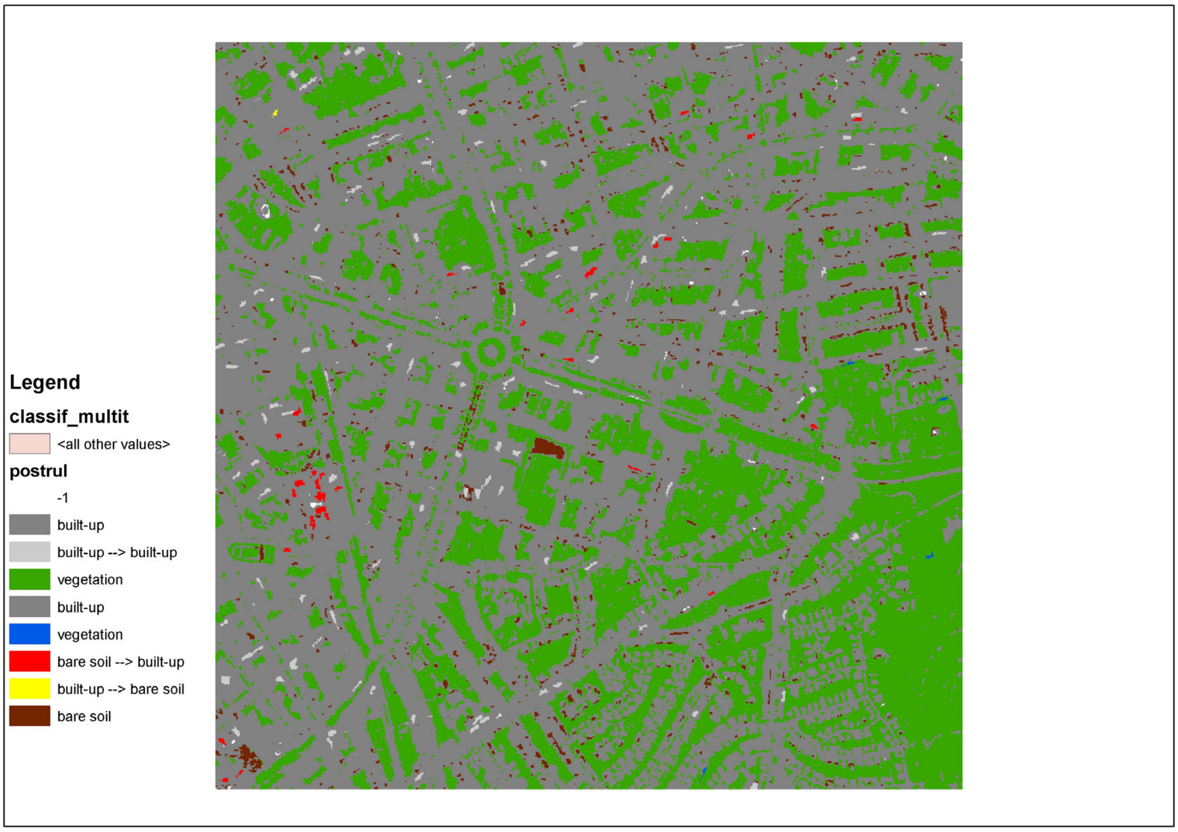


Figure 7: supervised multi-temporal classification after suppression of the "water" class

Post classification change detection

Classification of the QuickBird image

The results for the first level of the classification (two classes: vegetation versus non-vegetation) are obtained as follows: first segmentation is applied based on the multi-spectral channels, the panchromatic channel and the NDVI image. Then object-oriented classification is achieved using the following information: NDVI, PAN, Blue, ratio Red, ratio NIR. The ratios for a particular band are obtained by dividing the band value by the sum of the band values in all multi-spectral layers. For example the ratio Red for an image object is the mean value for the red channel divided by the sum of the mean values of all multi-spectral channels. The PCC-value obtained for the Woluwe test-zone level 1 is 97.3 % (Kappa = 94.4%). For the Meiser test-zone the PCC-value is 94.7 % (Kappa = 92.5 %). Finally for the Stalle test-zone the PCC-value is 95.6 % (Kappa = 89.7 %).

The second level of the classification is obtained by performing segmentation based on the panchromatic and the multi-spectral layers. The classification is done using information of the first level: non-vegetation classes must be classified as 'non-vegetation' at the first level, and the same is true for vegetation classes. The layers used to classify image objects at the second level are the panchromatic layer, the blue layer, the NDVI, the standard deviation of the red layer, the standard deviation of the NIR layer, the ratio Red and the ratio NIR.

The results of the second level of classification for the different test-zones are:

Woluwe test-zone:

PCC of 71.6 % (Kappa = 66.4 %).

Meiser test-zone:

The PCC of the classification is 69.3 % (Kappa = 63.6 %).

Stalle test-zone:

The PCC of the classification is 81.6 % (Kappa = 78.5 %).

The classes causing troubles for the classification of this second level are the "grass" class, which is confused with the other vegetation class: "trees and shrubs"; the "gravel surfaces" class, which is confused with the other built-up classes: "red surfaces", "light grey surfaces" and "dark grey surfaces"; the "bare soils" class which is also confused with the other built-up classes; there is a high level of confusion between the "shadows" and the "water" classes. As the water class is not very represented in the region of Brussels and as there exists a "water" class in the database, we decide to suppress this class from the classification procedure and to extract the water regions thanks to the information contained in the UrbIS-TOP database.

The third level was the most problematic. The classification is done only for regions (segments) that have been classified as non-vegetation. By superposition of the two classifications, information will be given about the type of cover of the area and its use (transportation area or building). In the classification procedure, a third class is added: unbuilt-up areas. This should help us in the detection of the works areas.

But in general the results for level 3 did not produce encouraging results. The PCC and Kappa values are contained between 77% and 43% but the quality of the classification is not useable for further processing. The problems causing these bad results are the large amount of occlusions caused by the presence of vegetation (the image has been taken during the vegetative season) and the dense built-up cover.

Classification of the IKONOS image

The results for the first level (two classes: vegetation versus non-vegetation) are obtained with the same steps than for the QuickBird image (the segmentation phase is conducted on the multi-spectral channels, the panchromatic channel and the NDVI image. The classification is conducted using the following information: NDVI, PAN, Blue, ratio Red, ratio

NIR). The PCC for level 1 for the Woluwe test-zone is 94.1 % (Kappa = 87.5%). The PCC-value for the Meiser test-zone is 87.9 % (Kappa = 85.2 %). The PCC-value for the Stalle test-zone is 90.4 % (Kappa = 87.6 %).

The results of the second level are obtained by segmenting on the panchromatic and multi-spectral layers. The classification is done using information of the first level: non-vegetation classes must be classified as 'non-vegetation' in the first level, and the same is true for vegetation classes. The layers used to classify this second level are the panchromatic layer, blue layer, the NDVI, the standard deviation of the red layer, the standard deviation of the near-infrared layer, the ratio red and ration near-infrared.

The results of the second level of classification for the different test-zones are:

Woluwe test-zone:

PCC of 75.8 % (Kappa = 71.4 %).

Meiser test-zone:

The PCC of the classification is 63.3 % (Kappa =55.6 %).

Stalle test-zone:

The PCC of the classification is 67.9 % (Kappa = 62.6 %).

The problems encountered for this second level of classification are similar to those encountered for the classification of the second level of the QuickBird image: "dark grey surfaces" is confused with "shadows"; "dark grey surfaces" is confused with other built-up classes ("light grey surfaces" and "red surfaces").

The classification for the third level is done only for regions (segments) that have been classified as non-vegetation. Again, the results are unsatisfactory and will not be used for the following stages of the post-classification change detection. The problems causing these bad results are the large amount of occlusions caused by the presence of vegetation (the image has been taken during the vegetative season) and the dense built-up cover.

Overlay of the two classifications

As the third levels of both classifications are unusable, we chose to complete the post-classification change detection process using only the second level of classification.

Prior to the superposition of the two classifications, post-classification rules are applied. It is important to reclassify the shadow classes as about one third of the images are covered by shadows and therefore unusable in the change detection.

This first post-classification step is followed by the application of other rules concerning the size of the polygons and their neighbourhoods to smoothen the result of the classification.

Once these post-classification steps are applied, the two resulting maps can be superposed and change polygons detected with information concerning the land cover (fig. 8). The two legends are crossed. A second round of post-classification rules are applied to suppress the improbable change classes and to smoothen the resulting map by reclassifying the "border polygons" (caused by an imperfect superposition of the polygons of both dates).

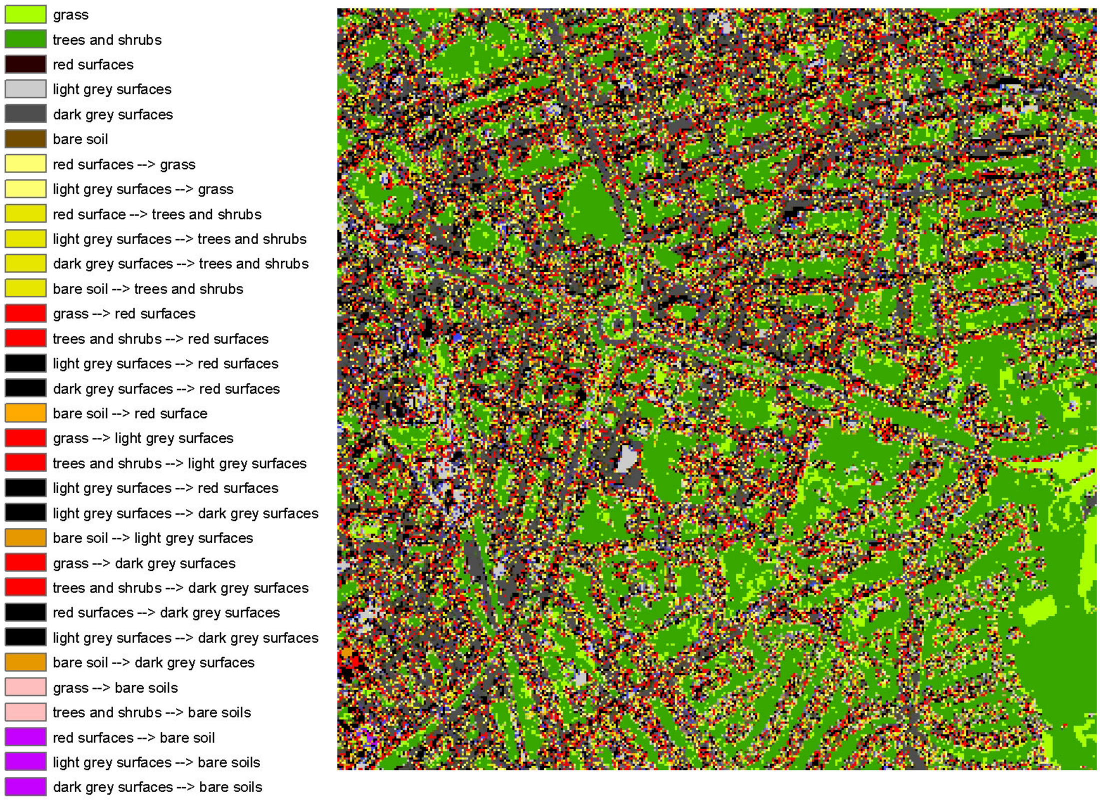


Figure 8: post-classification change detection after application of post-classification rules to smooth the result and suppress the shadows.

Database masks

The superposition of these masks over a coloured composition of the QuickBird image or over the multi-temporal coloured composition could probably be used without further treatments as they allow to visually finding most of the changed areas. However, further processing allows a better understanding of the changes and requires less work of interpretation from the interested user.

The superposition of the masks that have been produced to the classifications, which is the basis of the GIS-based procedure of change detection, allow us to concentrate the work on objects of interest (fig. 9).

An interesting step is the post-classification of all the polygons belonging to the “construction sites” of the UrbIS database into changed classes. In fact, because they belong to the “construction sites” objects, these polygons should be checked for the updating of the database.

The use of the masks also allows us to get round some problems encountered in the classification process. In fact, changed areas that are wrongly classified as unchanged areas can be spotted in the mask. For example an area that has changed from vegetation to built-up and that is wrongly classified in the “built-up” class will appear as “built-up” but in the “vegetation” mask and will therefore draw attention.

Another interest of the masks use is that errors in the database can be detected. These errors are unchanged areas that had been wrongly attributed in the database. For example a vegetation area that has been attributed to “buildings” objects and that has not changed will not appear as a changed polygon on the classifications but will appear as “vegetation” within the “buildings” mask, which will dram attention.

Figure 9: overlay of the masks with the unsupervised classification of the multi-temporal composition. In green: unchanged vegetation area, in grey: unchanged building areas, in red: changed areas from vegetation to building areas, in orange: changed areas from buildings to vegetation.

CONCLUSIONS

In general it has been seen that the classification results obtained for the QuickBird data were usually better than those obtained for IKONOS data. This is probably due to the difference of resolution between these two images. Therefore it would be better to use QuickBird images when possible.

The different methods give different results and can find their applicability in different conditions. In a general way the use of the database adds very important information. It should be noted that the objects extracted can vary depending on the application.

The fastest method to visualize changes is the multi-temporal coloured composition. The major drawback of this method is that it needs a long work of interpretation and the results are visual: no map of changes linked to a table of changes is obtained.

The unsupervised classification gives these maps and tables and is quickly implemented but there are not many classes differentiated and once again the work of interpretation is important.

The multi-temporal supervised classification is a good intermediary between the unsupervised classification and the post-classification change detection: it is less heavy to implement than the latest but it gives more information on the direction of the changes than the unsupervised multi-temporal classification.

Finally the post-classification change detection is the longest and heaviest method, but also the most precise method concerning the information about types of changes that have occurred. Visually, the thematic map obtained has a better precision. But it is important to note that this method depends on the results of the classification of both images. The classification of the QuickBird and the Ikonos images shows that interesting results can be obtained from the second level. The third level of the legends does not reach usable results. This is caused by problems inherent to the very nature of urban areas: slant effect, occlusions, shadows… make transportation areas almost impossible to detect.

In all cases, the classification images need to be smoothed by the application of post-classification rules.

The GIS-based technique holds great potential. It allows focusing the change detection on areas of interest, and it avoids us to use the third level of the classification which was problematic.

Most of the problems encountered can be classified as follow:

- high amount of shadows present on the areas
- large amount of occlusions (vegetation and buildings) preventing us from using shape factors to differentiate transportation areas from buildings
- in the Centre area, where the streets are narrow and the built-up is high, the change detection methods using VHR images are not performing well and the results are unusable.

To avoid these problems it is important to work with images acquired during the winter, at hours when the shadows are the shortest possible and taken as vertically as possible.

These change detection results could be used to focus the field work for the updating of the database. Except for the multi-temporal composition visualisation, the results are presented as a change map or tables giving the coordinates of the change polygons and their area. This should allow planning the field visits to areas where important changes have been recorded.

REFERENCES

i. Herold, M., Gardner, M. & Roberts, D. A. 2003. Spectral Resolution Requirements for Mapping Urban Areas, IEEE Transactions on Geoscience and Remote Sensing, 41, 9, pp. 1907-1919.

ii. Dare P. M. 2005. Shadow analysis in High-Resolution satellite imagery of urban areas. Photogrammetrc Engineering & remote sensing 71, no. 2, pp. 169-177.

iii. Puissant, A. and Weber C. 2001. “The use of image in Geographical Information Market : results of an inquiry on the needs of end-users in urban studies”, Proceedings of the 7th EC-GI & GIS WORKSHOP, EGII – Managing the Mosaic, 13-15 June 2001, Potsdam, Germany

iv. SCOT-Conseil. 1997. “User workshops to define the requirements of town/city local government departments” Ispra, Space Applications Institute – Joint Research Center: 48.

v. Stephenne N. Canters F. and Wolff E. 2004. Geographic information needs of local and regional authorities in Belgium: Potential of VHR image data for local and regional decision makers. Survey report.

vi. Van Acker M. 2000. UrbIS version 2: la Région Bruxelloise à grande échelle. Gis News - AM/FM-GIS BeLux 18.

vii. Knudsen Thomas and Olsen Brian P. 2003. Automated Change Detection for Updates of Digital Map Databases. Photogrammetric Engineering & Remote Sensing 69, 11, pp. 1289-1296.

viii. Smits P. C., Annoni A. 2000. Towards Specification-Driven Change Detection. IEEE Transactions on Geoscience and remote sensing 38, No. 3, pp. 1484-1488.

ix. Rogan J., Miller J., Stow D., Franklin J., Levien L., Fischer C. 2003. Land cover Change Monitoring with Classification Trees Using Landsat TM and Ancillary Data. Photogrammetric Engineering & Remote Sensing 69, 7, pp. 793-804.

x. Pilon, P. G., Howath P. J., and Bullock R. A. 1988. An Enhanced Classification Approach to Change Detection in Semi-Arid Environments. Photogrammetric Engineering & Remote Sensing 54, pp. 1709-1716.

xi. Singh, A. 1989. Digital Change Detection Techniques Using Remotely Sensed Data. International Journal of Remote Sensing 10, pp. 989-1003.

xii. Schiewe J. 2002. Segmentation of high-resolution remotely sensed data – concepts, applications and problems. Proceedings of the Symposium on Geospatial Theory, Processing and Applications, Ottawa, Canada.

xiii. Zhang Y. J. 1995. Influence of segmentation over feature measurement. Pattern Recognition Letters, vol. 16, pp. 201 – 206.

xiv. Barr, S.L. and Barnsley, M.J. 2000. Reducing structural clutter in land cover classifications of high spatial resolution remotely-sensed images for urban land use mapping. Computers and Geosciences, 26, pp. 433-449.

xv. Zhang Y.J. 1996. A survey on evaluation methods for image segmentation. Pattern Recognition 29, no. 8, pp. 1335 – 1346

xvi. Zhang Y.J. 1997. Evaluation and comparison of different segmentation algorithms. Pattern Recognition Letters 18, pp. 963 – 974.

xvii. Definiens Imaging, eCogintion Professional user guide, URL: http://www.definiens-imaging.com/, last consultation: March 2005.

xviii. Baatz M. and Shäpe A. 2000. Multiresolution Segmentation: an optimization approach for high quality multi-scale image segmentation. In Strobl, Blaschke & Greisebener (eds), Angewandte Geographische Informationsverarbeitung XI. Beiträge zum AGIT-Symposium, Salzburg

xix. Burnett, C., Blaschke T. 2003. A multi-scale segmentation/object relationship modelling methodology for landscape analysis. Ecological Modelling. 168, no. 3, pp. 233-249.

xx. De Kok R., Buck A., Schneider T., Ammer U. 2001. Modular project design in object oriented analysis. Proceedings of the Joint ISPRS Workshop “High Resolution Mapping from Space 2001”, Hannover, Germany

xxi. Van De Voorde T., De Genst W., Canters F., Stephenne N, Wolff E. and Binard M. 2004. Extraction of landuse / landcover related information from very high resolution data in urban and suburban areas, proceedings of the 23rd symposium of the EARSeL, Ghent, Belgium, 2-5 June 2003, Remote Sensing in Transition, Goossens (ed.), pp. 237-244, Millpress, Rotterdam, Netherlands.

xxii. Binard M., Frauman E., Van De Voorde T., Stephenne N., De Genst W., Cornet Y., Wolff E., Canters F. 2004. "Classification of VHR satellite images in urban and suburban areas" poster présenté lors de la troisième journée de rencontre du Programme de recherche en observation de la terre "STEREO" et "VEGETATION", Bruxelles, Belgique, 6 mai 2004.

xxiii. Cornet, Y., Schenke C., de Bethune S., Binard M. & Muller F. 2003. Stratégies de fusion d'images P/XS basées sur les principes colorimétriques et l'Égalisation de Statistiques Locales. Bulletin SFPT n° 169 (2003-1), Saint-Mandé Cedex, pp. 35-45.

xxiv. Lu D., Mausel P., Brondizio E. And Moran E. 2003. Change detection techniques, International Journal of Remote sensing, vol. 25, no. 12, pp. 2365-2407.

xxv. Carleer A.P., Wolff E. 2004, Use of spatial information after segmentation for very high spatial resolution satellite data classification, Proceedings of SPIE Image and Signal Processing for Remote Sensing X, Vol. 5573, ed. Lorenzo Bruzzone, 150-160.