IMPROVING 2D CHANGE DETECTION BY USING AVAILABLE 3D DATA

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ABSTRACT:

Change detection with very high resolution imagery is difficult, because 3D objects as buildings appear differently in 2D imagery due to varying viewing angles and sun positions. This research proposes a method to improve change detection by using simple 3D models of buildings. Buildings have been modelled as flat roof or gable roof buildings. By knowing the position of the sun, the location of the shadow of a building is calculated. The location of the relief displacements is calculated using information on the position of the sensor. By introducing the projected shadow, relief displacement and roof in the automatic change detection process more reliable change signals are produced. An object-oriented approach for change detection is developed using segmentation techniques to create homogeneous segments from pixels. The method compares the object map t0 with the image t1. Information is gathered on how each object represents in the image t1 and at t0, by using the information of the image t0. In the case of shadow parts histogram stretched imagery are used. For the change detection on the roof, the roof segments are reprojected on top of each other to compare them. This method resulted in more reliable change detection results and increased the detection rate to 72% for changes to buildings.

1. INTRODUCTION

1.1 Change detection

Sustainability of geo-databases is a problem due to the enormous costs that are involved in keeping the databases up to date. If data are not regularly updated the results and decisions issued from spatial analysis become unreliable. Once a reliable database has been established, change information is what is required most. In order to keep geographic information up-to-date the following actions take place:

1. it is detected that a change has occurred;

2. the new situation is further investigated;

3. the new situation is recorded in the geo database.

Up to now cartographers detect changes by visual interpretation to update digital maps, which is both expensive and time consuming. As this procedure repeats regularly, automation would be the useful means to do such a task. Though manual work will always be necessary new technologies can reduce the work significantly and make the use of personnel more effective.

With the availability of new technologies as Very High Resolution (VHR) satellite imagery one has the possibility to capture a location every three days and since 2005 digital aerial imagery is available for the whole of the Netherlands yearly. These data are valuable to update existing geo-databases. However these images are so detailed in information that new algorithms need to be developed in order to recognise objects and determine the occurred changes. Pixel-based algorithms, are not suitable for the analysis of objects as individual houses, roads and waterways in VHR images, because important semantic information, necessary to interpret such an object, is not represented in single pixels, therefore, image analysis should be object based as well (Gorte,1998; Van der Sande et al., 2003; Walter, V. 2004). Image segmentation is the starting point to acquire, spectral, textural, spatial and contextual segment attributes that can contribute to the evidence of change of the database object under consideration.

1.2 3D objects in 2D imagery

This research is focussed on urban areas. To successfully apply change detection in this area, recognition of three dimensional objects as buildings and structures is crucial. Due to different viewing angles and sun positions between imagery, object recognition is difficult because of varying relief displacement and shadow of buildings. With 3D models of buildings and sun and sensor positions, the position of relief displacement and shadow can be calculated and used in the change detection process.

2. METHODOLOGY

2.1 3D knowledge

In the case of images taken with perspective geometery buildings will be causing relief displacements and shadow that disturb automatic change detection. If the heights of buildings and the shapes of their roofs were known exactly, this could be corrected for by true-orthorectification, but in a 2d database environment this is an unlikely scenario.

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It may be safely assumed, however, that each building has a height. From the type of building, a guess of this height may be obtained or calculated from the shadow length and the position of the sun. With use of the footprint of the building that is present in 2D databases a simple block 3D model for an apartment like building can be made. A typical house with two inclined roof parts needs a more advanced 3D model, but that can be predefined.

2.2 3D modelling

2.2.1 Building reconstruction

For each building a footprint needs to be available. By measuring the shadow length of a building in an image the height of the building is calculated by using the azimuth and elevation angles of the sun in simple trigonometric calculus, see formula 1.

$$Shadow\ length = \frac{building\ \ height}{\tan(sun\ elevation\ \ angle)} \qquad (1)$$

For the reconstruction of buildings in 3D a similar approach has been used as described by Suveg and Vosselman (2004) for flat roof and gable roof buildings.

The flat roof buildings is modeled as a primitive from three to an infinite number of sides, with all walls perpendicular to the terrain. The gable roof building is a primitive composed of a rectangular volume and triangular volume, the ridge of the gable roof has to be parallel to two other sides.

In case of complex building structures, e.g. connected buildings with different heights, the buildings are simplified by decomposing them to the two possible primitives.

The 3D models are stored in a database by storing for each vertex of the footprint x, y and z coordinates. The z coordinates on the ground are always zero, hence only the z coordinates of the roof are stored. For gable roof buildings the beginning and end of the ridge are also stored in x, y and z coordinates.

2.2.2 Shadow modelling

Crow’s (1977) shadow volume method has been to date the most practical method of rendering shadows. The basic idea is a source of light and a model to generate a projected shadow that has the silhouette edge of the model. The projection plane is always the ground level.

The implemented algorithm reads the 3D models of each building in a separate matrix. The algorithm reassigns the point closest to the sun as ID_new_min. This is done by calculating the centre of mass, **A**. Line, s_1, passes through **A** and the sun. Point **B** lies on line s_1, placed thousand meters away from **A** in the sun direction, so that **B** is external to the building, and is nearest to the sun respect to all the points of the footprint of the building itself. Another line, s_2, passes through **B** perpendicular to s_1. The distance between each point of the footprint and s_2 is evaluated. The other points of the footprint are then assigned clockwise, see figure 1.

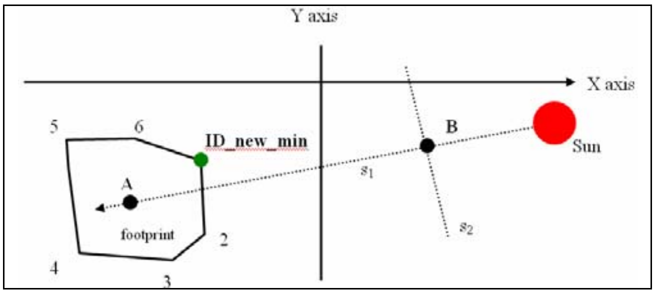


Figure 1. Determination of ID_new_min.

The shadow will be created by the most external visible points (3 and 5). In order to find these points (figure 2) a line p_1, has been drawn in a way that it has the same angular coefficient of the sun direction and that passes through the point with the id is ID_new_min.

Then n lines are drawn, one for each point of the footprint, that run through the n-th points and that have the same angular coefficient of p_1. For each point the distance line p_1, is calculated. The two greatest distances are associated with the two most external visible points and called clockwise ID_1 and ID_2, see figure 2.

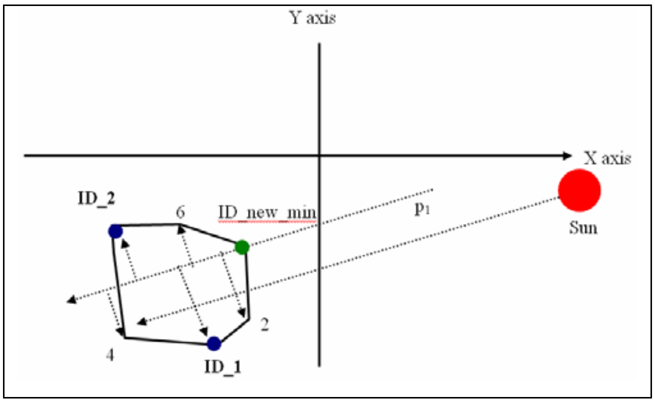


Figure 2. Determination of most external points

Since the height of each point and the position of the sun are known it is possible to calculate the length of the shadow with simple trigonometry

The shadow is determined by all the points that lie between or are equal to the external points ID_1 and ID_2 of the footprint and the projected shadow points, see figure 3.

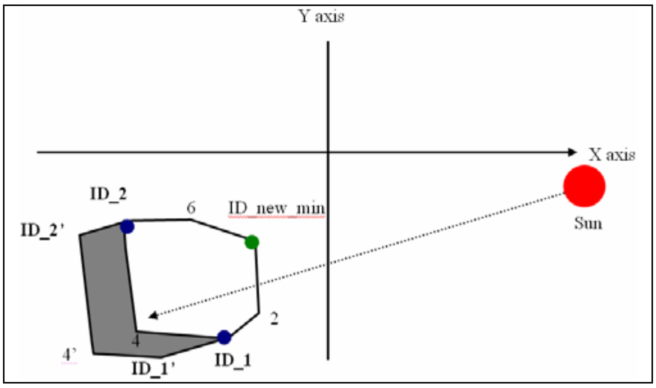


Figure 3. Location of shadow.

2.2.3 Relief displacement modelling

Relief displacement modelling is similar to the production of true orthophotos, because it uses height of buildings. The difference is that the relief displacement is not removed. To calculate the relief displacements and the new position of the roofs correctly a distinction is made between aerial and satellite imagery.

The satellite sensor (red) is placed 700 km from the earth surface and hence the projection of the new roof can be seen as parallel lines to the sensor. For aerial imagery with a sensor located e.g. 4 km to the earth surface the projection is relative to the aerial sensor position (red), see figure 4.

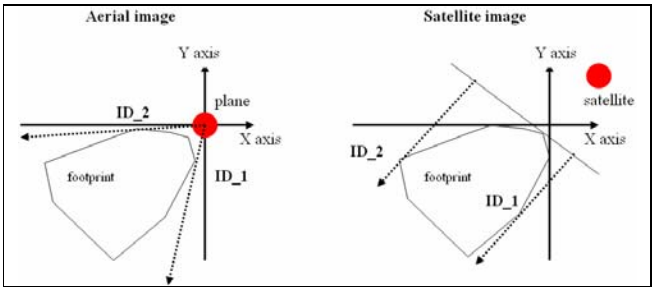


Figure 4. Difference in projection of relief displacement

In a similar way to the shadow calculation the position of the new roof is calculated. The determination of the most external visible points are necessary to know the sides that show the relief displacement, hence the ID_1 and ID_2. The new position of the roof is calculated using simple trigonometry, see figure 5.

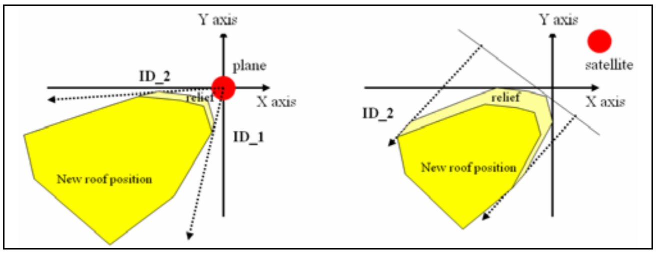


Figure 5. Location of the relief and roof.

2.3 Change detection process

Our approach to change detection is hypothesis-driven. We assume the union of objects in the database to be covering the entire area. Each object leads to a hypothesis (that an object of that class still exists at that place), and the imagery is supposed to provide the evidence for accepting the hypothesis – and in absence of sufficient evidence a change is detected.

An object-oriented approach for change detection is developed using Definiens Developer software. This software uses segmentation techniques to create homogeneous segments from pixels of VHR imagery.

In general the developed method compares the object map t0 with the image t1. Information is gathered on how each object represents in the image t1, and at t0. The information at t0 can be acquired of course best by using the information of the image t0.

To prove that 3D information in the change detection improves the reliability of the change signals, the object oriented approach is executed with and without 3D information. The change detection process with 3D information is divided in two parts: firstly changes on the ground level are detected, secondly changes on the roof level are detected.

As ground truth manually changes are detected to validate the automatic process.

2.3.1 2D change detection

The change detection process starts with the segmentation of all image layers t0 and t1 using the object map t0 as a thematic layer. These segments can be the evaluation unit for occurred changes, but since these are rather coarse (> 1 ha) it will not be successful to detect changes that are mostly smaller than 0.1 ha. Therefore, the segmentation continues on a finer scale using only layers from image t1. This is based on the assumption that ‘the world’ becomes more heterogeneous and to capture new objects one must segment on the most heterogenous image, thus image t1.

Table 1 describes the segmentation parameters used in this process. Level 2 is the course segmentation based on the object map and level 1 is the segmentation based on the image layers t1.

Subsequently, each segment will have values on spectral, textural, shape and neighbour parameters for image t0 and t1. The change will be determined by defining thresholds for parameter differences , as e.g. mean value, standard deviation and textural homogeneity. Created image segments can be taught what they are by labelling them the class information of the object map. This contextual information is necessary to produce reliable change signals. A change classification has been executed using a classification tree for each object class in the object map.

Segmentation parameters	**Level 2**	**Level 1**
Scale	10000	20
Shape	0.0	0.5
Compactness	0.5	0.8
Image layer Weights		
Blue t1	0	0
Green t1	0	1
Red t1	0	1
Nir t1	0	1
Blue t0	0	0
Green t0	0	0
Red t0	0	0
Nir t0	0	0
Thematic layer weights		
Object map	1	0

Table 1. Segmentation paramers for the 2D change detection process

2.3.2 3D Ground level change detection

For the ground level change detection the 2D building maps are used to indicate where the projected positions of shadows, roofs and relief displacements are located for the images t0 and t1.

The buildings are left out of this change detection process, so that the area of roofs and relief displacements (at both t0 and t1) were set to no data. The shadow is used to indicate where changes are detected on the stretched image layers.

This leads to the creation of 4 levels of image segments. In level 4, only the thematic layers have been used to create segments, i.e. the object map t0 and the 2D building maps of t0 and t1. In level 3, the segments that do not have shadow parts created by buildings (in image t0 and t1) have been finer segmented based on non-stretched image layers t1. Again this is based on the assumption that the world becomes more heterogeneous. In level 2, finer segmentation has been applied to area were there is shadow located in the image t1. Finally, in level 1 the segmentation is applied to area that has shadow in t0.

Level 1 is the change classification level. In this level a classification tree is built for each object class in the object map. Changes then apply to the following 4 conditions:

- No shadow in 2003 and no shadow in 2007
- Shadow in 2003 and shadow in 2007
- No shadow in 2003 and shadow in 2007
- Shadow in 2003 and no shadow in 2007

For shadow areas the classification parameters are based on the stretched image layers.

Segmentation parameters	Level 4	Level 3	Level 2	Level 1
Scale	100000	20	20	20
Shape	0.0	0.5	0.5	0.5
Compactness	0.5	0.8	0.8	0.8
Image layer Weights				
Blue t1	0	0	0	0
Green t1	0	1	0	0
Red t1	0	1	0	0
Nir t1	0	1	0	0
Blue t0	0	0	0	0
Green t0	0	0	0	0
Red t0	0	0	0	0
Nir t0	0	0	0	0
Blue t1 Stretcheded	0	0	0	0
Green t1 Stretcheded	0	0	1	0
Red t1 Stretcheded	0	0	1	0
Nir t1 Stretcheded	0	0	1	0
Blue t0 Stretcheded	0	0	0	0
Green t0 Stretcheded	0	0	0	1
Red t0 Stretcheded	0	0	0	1
Nir t0 Stretcheded	0	0	0	1
Thematic layer weights				
Object map	1	0	0	0
2D_BuildingMap t0	1	0	0	0
2D_BuildingMap t1	1	0	0	0

Table 2. Segmentation paramers for the 3D ground level change detection process

2.3.3 3D Roof level change detection

The roof level change detection uses the projected position of the roofs. The segmentation starts at level 2 with the segmentation of the projected roofs at t1. A finer level 1 is created by segmenting image t1, see table 3.. These segments have been exported with the values of spectral and textural parameters.

Segmentation parameters	Level 2	Level 1
Scale	10000	20
Shape	0.0	0.5
Compactness	0.5	0.8
Image layer Weights		
Blue2007	0	0
Green2007	0	1
Red2007	0	1
Nir2007	0	1
Thematic layer weights		
2D_BuildingMap t1	1	0

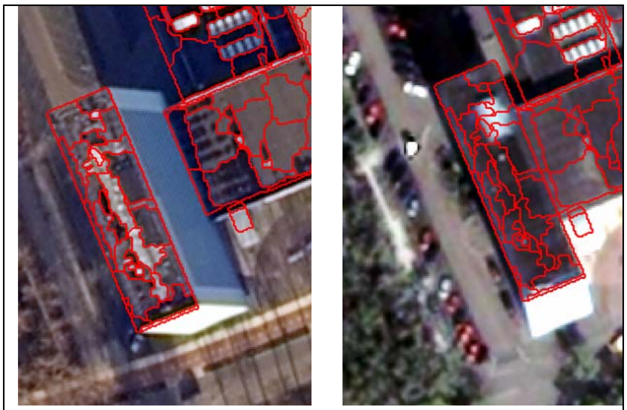
Table 3. Segmentation paramers for the 3D roof level change detection process t1

The exported roof segments of image t1 are projected to image t0 by using the sensor positions of both imagery and simple trigonometry. The segmentation of image t0 is based only on the segmented roof map t1, see table 4.

Figure 6. shows an example of roof segments of image t1 that have been projected on image t0. The roof segments have been classified for change by setting thresholds for several parameter differences.

Segmentation parameters	Level 1
Scale	10000
Shape	0.0
Compactness	0.5
Image layer Weights	
Blue2003	0
Green2003	0
Red2003	0
Nir2003	0
Thematic layer weights	
Segmented_roof t1	1

Table 4. Segmentation paramers for the 3D roof level change detection process t0



Roof segments image t1 — Roof segments t1 projected on the image t0

Figure 6. Roof segments image t1 projected on image t0.

3. STUDY AREA

For this study several types of data were available of the campus site of the TU Delft. Based on the Large Scale Base map a 2D object map was created in 16 classes. A Quickbird satellite image acquired on April 22, 2003 (figure 7) was used to properly create these classes. Thus, both the image and object map are at the t0 situation.

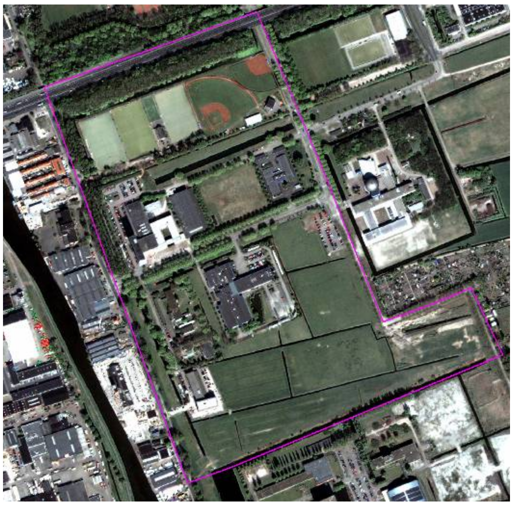


Figure 7. Quickbird satellite image acquired on April 22, 2003.

An aerial image acquired on January 14, 2007 was available as t1 image. Both imagery were georeferenced on the object map. The imagery were partially radiometrically corrected by manual histogram matching to allow differences due to seasonal effects. For the 3D change detection process the imagery were histogram stretched to analyse the shadows. All image and map layers have been converted to a raster with a resolution of 0.40 meter, see table 5 for the image characteristics.

Image characteristics	Quickbird	Vexcel UltraCam-D
Image t	t0	t1
Acquisition date	22-4-2003	1-14-2007
Image resolution (meter)	0.60	0.40
Spectral bands	Blue, green, red, near infrared	Blue, green, red, near infrared
Image depth	11bit (8bit after cubic resampling)	12bit (8bit after cubic resampling)
Sun elevation (degrees)	48.4	14.9
Sun azimuth (degrees)	156.5	162.2
sensor elevation (degrees)	79.9	Relative to building position and centre of image footprint
sensor azimuth (degrees)	173.2	Relative to building position and centre of image footprint
Image area extent (hectare)	36	36

Table 5. Image characteristics

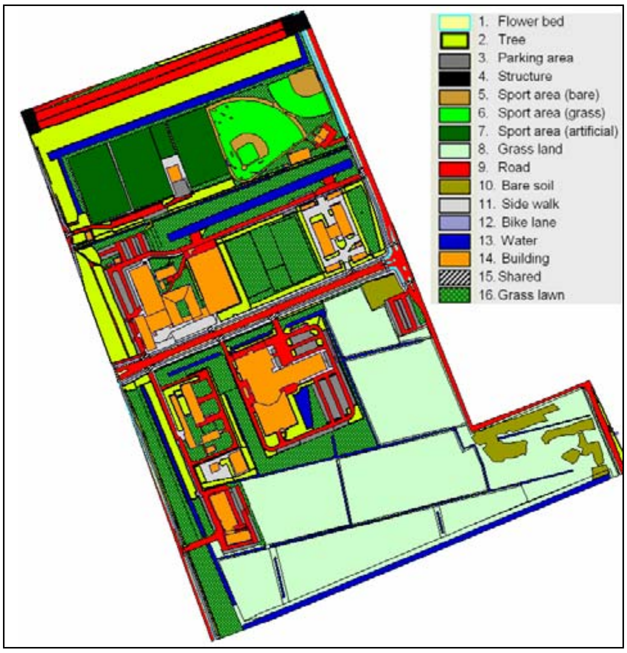
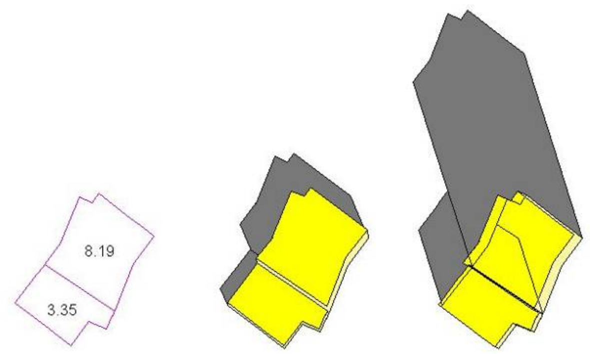


Figure 8. Object map.

4. RESULTS AND DISCUSSION

4.1 3D building representation in a 2D map

For both images a 2D building map were created indicating the projected position of the roof, the relief displacement and the shadow. This was done based on the footprints of the buildings and the in section 2 described algorithms. Figure 9 shows part of the footprint map and the building representation in a 2D map for the images of 2003 and 2007.



Footprint and building heights (meter) from object map t0	Shadow, relief displacement and roof position in image t0 (2003)	Shadow, relief displacement and roof position in image (2007)

Figure 9. 3D building representation in a 2D map.

4.2 Change detection results

4.2.1 2D change detection

The 2D change detection process resulted in classification tree for which of each class parameters were determined that indicated the change best. A threshold value classified the segments in that class as 'changed' or 'not changed'. Table shows the parameters that have been used. The change was determined by a parameter in the two years that were compared as either (absolute) difference, a ratio or an if then else statement. Combinations of parameters were also used.

	Class	Parameters
1	Flower bed	NDVI
2	Tree	NDVI
3	Parking area	GLCM homogeneity NIR for all directions
4	Structure	Sum of Blue, Green, Red, NIR
5	Sport area (bare)	Sum of Blue, Green, Red, NIR
6	Sport area (grass)	NDVI
7	Sport area (artificial)	Ratio Green (Green/(Blue+Green+Red+NIR)
8	Grass land	NDVI
9	Road	NDVI
10	Bare soil	GLCM homogeneity NIR for all directions Sum of Blue, Green, Red, NIR
11	Side walk	NDVI
12	Bike lane	NDVI
13	Water	Sum of Blue, Green, Red, NIR NDVI
14	Building	Sum of Blue, Green, Red, NIR Ratio red (Red/(Blue+Green+Red+NIR) GLCM homogeneity NIR for all directions
15	Shared	Sum of Blue, Green, Red, NIR
16	Grass lawn	NDVI

Table 6. Classification parameters

4.2.2 3D change detection

The 3D change detection was divided in ground level and roof level change detection. The 2D building map was created and used to indicate the roof, the relief displacement and the shadow. The histogram stretched imagery was used to evaluate changes in shadow areas. The same parameters were used as for the 2D change detection process, see table 6.

4.3 Overall results

The result of both processes were validation with ground truth data. Table 7 shows the change detection results per class in detection rate, false positives and false negatives. The detection rate is higher for the 3D change detection process, especially for the building class, but also classes effected by the shadows of building, e.g. sport grass and parking.

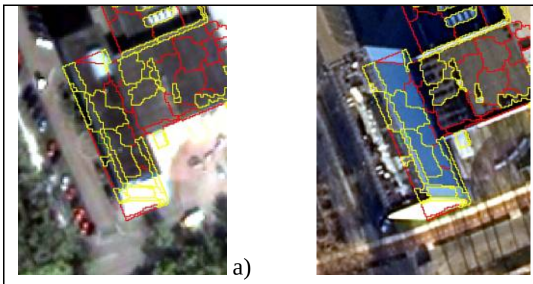
	2D			**3D**			
Classes	**detection rate (%)**	**false positives (%)**	**false negatives (%)**	**detection rate(%)**	**false positives(%)**	**false negatives(%)**	**total changes (ha)**
1	95	5	310	95	5	310	0,039
2	18	82	253	62	38	265	0,038
3	89	11	83	91	9	86	0,383
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0
7	89	11	33	89	11	17	0,559
8	76	24	1012	76	24	1012	0,076
9	4	96	1061	0	100	973	0,023
10	36	64	564	15	85	105	0,056
11	0	0	0	0	0	0	0
12	0	100	13400	0	100	12800	0,001
13	43	57	380	53	47	376	0,074
14	**48**	**52**	**148**	**72**	**28**	**234**	0,464
15	0	0	0	0	0	0	0
16	43	57	146762	42	58	137431	0,911
							2,624

Table 7. Change detection results.

4.4 Discussion

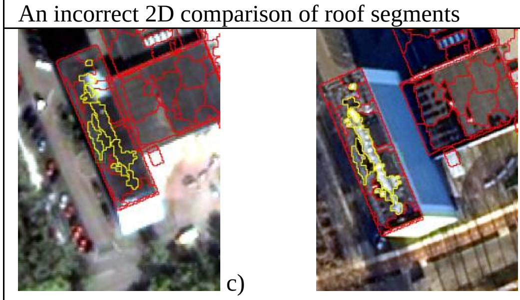
In the 3D change detection process, more reliable change signals are produced. This is in fact obvious because the object recognition process is improved, by using the 2D building map that indicates correctly the projected roof, relief and shadow, see figure 10. For several classes the amount of false negatives is high due to shadows from trees not taken into account in this research as a 3D object. Next to it, the difference in both images in phenological state of the vegetation (no leafs in trees in the image of 2007) introduced false negatives. Also, the different illumination by the sun of the study area made the objects represent differently and difficult to classify for change.

With the two 3D building primitives it is possible to create correctly 90% of the types of buildings. Complex buildings can be decomposed to these two primitives. Correct building heights are needed to create a reliable 3D model and its 2D projection. It is possible to refine an approximate building 3D model by including different heights or shapes in alternative hypotheses, and accept the one with the maximum evidence. Projection errors occur when a building throws its shadow on another building, this is not modelled.



a) b)

An incorrect 2D comparison of roof segments



c) d)

A correct comparison of roof segments using 3D information

Figure 10. Changed roof segments with yellow outline

5. CONCLUSIONS

By introducing 3D building models, and their projection in 2D of shadow, relief displacement and roof, the automatic change detection process is improved and more reliable change signals are produced.

The projection of 3D buildings can be refined by modelling as well the shadow thrown by a building on another building.

Not only buildings should be taken into account as 3D objects in the change detection process also trees introduce shadow and relief displacement.

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