CHANGE DETECTION FOR UPDATE OF TOPOGRAPHIC DATABASES THROUGH MULTI-LEVEL REGION-BASED CLASSIFICATION OF VHR OPTICAL AND SAR DATA

E. Hanson [a, *], E. Wolff [a]

[a] Institut de Gestion de l'Environnement et d'Aménagement du Territoire, Université Libre de Bruxelles, Brussels, Belgium, (ehanson, ewolff) @ulb.ac.be

KEY WORDS: Change detection, updating, databases, classification, knowledge base, SAR, optical.

ABSTRACT:

The geographic database producers need improved and faster updating methods for their topographic databases to fulfil the user's demand. In this context, change detection methods using remotely sensed data are interesting tools applicable on wide areas and are less demanding for human work. Indeed, database update is currently mainly realized through a tedious and laborious photogrammetric restitution. The objective of this study is to compare built-up and roads extracted with a hierarchical region-based classification method (Definiens) from VHR optical and SAR data to the ones of an old geographic database in order to pinpoint changes. Simulation of PLEIADES data on Toulouse at a resolution of 0.7m in the panchromatic band and 2.8m in the multispectral one are used together with a DSM derived from SAR Cosmo-Skymet data. The NGI-France Topo-Pays database is generalised to map 5 classes: building, road, vegetation, water and other. Their outline is used as a first level during the segmentation process; the objects of the database are then subdivided according to their spectral homogeneity. This procedure allows the use of the database as prior knowledge and avoids objects matching between detected and database objects to map changes. Data are classified with a hierarchical scheme into 5 classes using spectral thresholds and the nearest neighbour algorithm. The results show that the use of the DSM in the classification process allows a better accuracy in the change detection process.

1. INTRODUCTION

1.1 Change detection in the scope of the map update

Keeping the topographic information up-to-date is essential for the National Mapping Agencies as well as for their user's applications (urban planning, network management, navigation…). Nevertheless most of those agencies carry out the update process through photogrammetric restitution and ground survey, collecting information about changes at best in a non-systematic way. The update work is time consuming, expensive, tedious and doesn't allow a sufficient update frequency regarding to the user's demand.

Therefore, the topographical data producers need an as operational as possible automatic method to detect the change areas where focus the update capacities and, if possible, to identify the change (Baltsavias, 2004; Bouziani et al., 2010).

Two principal objects of interest are identified by the data producers: roads and buildings which need the most frequent update. Those two types of object are focused by the geomatic community active in the change detection field (Knudsen et al., 2003; Baltsavias, 2004; Zhang et al., 2004; Unsalan et al., 2005; Bouziani et al., 2010).

Studies have been carried out to explore the possibilities offered by change detection in this map update field.

Bouziani et al. (2010) defines three main steps in the update process: (1) Detect change, (2) Identify the change and (3) Capture the change in the database. The authors, citing Walter (2004), pinpoint that the change detection step is the most difficult one.

More and more, new satellites (e.g. GeoEye, WorldView-2 and the future Pléiades constellation) provide image data with a very high resolution. Those images associate wide coverage, frequent temporal intervals and a resolution closer to the one of the aerial photography used by the database producers for the photogrammetric restitution. The possibilities offered by those products interest the data producers for mapping purpose including continuous update of the database (Cantou et al., 2006; Holland et al., 2006).

To achieve this update goal, different groups of change detection methods can be mobilized: the pixel-oriented methods, the object-oriented methods, and different strategies: image-image comparison and image-database comparison (Carleer et al., 2008; Bouziani et al., 2010). Change detection based on image-image approach consists on comparison pixel by pixel of images of two different dates while the image-database methods use an existing map to localise the change from a recent image.

In the image-database methods, Bouziani et al. (2010) differentiates post-extraction methods where objects extracted from the image are compared to those of the database (Knudsen et al., 2003) and map-guided methods which use the information extracted from maps to enhance the interpretation of the image (Walter, 2004; Carleer et al., 2008). Those last groups of methods use the a priori knowledge of the map.

1.2 Use of a priori knowledge

In the case of the update of topographic database, the existence of an a priori knowledge of the field is guaranteed. The outdated database can be used in the change detection to improve it (Bailloeul et al., 2003; Bouzinani et al., 2010).

Baltsavias (2004) reviews researches using a priori knowledge for object extraction by image analysis focusing on road and buildings. The author pinpoint that the a priori knowledge is

* Corresponding author.

often used through rules, models or use of the context (i.e. relations between neighbouring objects) but very few in the form of maps, GIS of other geodatabase.
Moreover, Bouziani et al. (2010) underline that, in most of the cases, the use of the geodatabase is limited to the geometric information of the object (Baltsavias, 2004). The geodatabase can also be used for the training of the classification (Petzold et al., 1999; Notarnicola et al., 2009).
The a priori knowledge can also cause problems in the object extraction (e.g. linked to the generalisation of the database) due to an insufficient accuracy or completeness (Baltsavias, 2004).
Another problem which occurs in the case of a post-extraction method is the matching between the object of the old database and the new ones detected by the image processing to identify the change. To solve object matching problems, Zhang et al. (2004) propose map conflation techniques to create a new database based on two databases covering the same area.
In the case of a map-guided method, this problem can be avoided. For example, the outdated database can be used to constraint the segmentation (Carleer et al., 2008).

1.3 Contribution of LIDAR data

The 3D information can also be useful as additional information in the change detection process. Indeed, a Digital Surface Model coming from a laser scanner, or derived data as laplacian filter and slope images, can be introduce as input in the segmentation process and in the classification with other features (e.g. form) in order to distinguish buildings from roads. A comparison between the outdated topographic map and the detected buildings can then isolate the new buildings. The extracted 3D information can also be extracted for each object and added as an attribute to the database (Hofman et al., 2002).
Hu et al. (2004) used the height data coming from LIDAR (subtracting the DTM from the DSM) together with LIDAR intensity and high resolution aerial imagery in both segmentation and classification to extract the road network from a dense urban area. A major advantage of LIDAR data is that, in dense urban areas where shadows or buildings occlude road segment, the height data can be used to detect the roads (Zhang et al., 2001). Hu et al. (2004) show that the use of both LIDAR data and very high resolution optical images greatly improves the road extraction in correctness and accuracy in dense urban area.
Poulain et al. (2009) proposed to use SAR images with optical data to extract features in a processing chain for cartography creation/update. First, the building objects of the database are verified by means of the features and then, the other areas are segmented and classified to obtain a probability score for each new building object.
Moreover, if 3D information exists for several period of time, these could be used for change detection (building construction or destruction).

1.4 Objectives

This paper focuses on the change detection process improvement allowing a facilitated update.
The presented method was carried out in the CHADE (Change detection for updates of vector databases through multi-level region-based classification of VHR data) project. It is based on the method proposed by Carleer et al. (2008) developed in the previous part of the project. This method is based on an image-database comparison using an object-based approach and was previously applied on two test areas in Belgium (a residential periurban area and an agricultural one). The first test concerns the change detection from the topographic database produced by the National Geographic Institute of Belgium and the second one from an agricultural parcel database.
One of the main goal of this article was to check if the method would be reproducible on another topographic database (Topo-Pays of NGI-France) and in another context (a periurban area in the South of France).
The contribution of the use of a Digital Surface Model (derived from SAR Cosmo-Skymet data) together with optical images to change detection and identification will be tested. Moreover, the a priori knowledge of the outdated topographic database will be used in the segmentation process especially to avoid object matching problems.

2. STUDY AREA AND DATA

2.1 Study area

The study area (about 1km^2) is situated in a periurban landscape at 6km of the Toulouse's center, France, and is characterized by large isolated buildings, small and large roads and parkings but contains also large vegetated open space, a canal, forest areas and large areas of bare soils.

2.2 Data

The image data is a Pléiades simulation acquired on the September 17, 2004 and has a resolution of 0.7m in the panchromatic band and 2.8m in the multispectral ones. The topographical coverage is extracted from the Topo-Pays database produced by the National Geographic Institute of France. The layers of the database used are: buildings, road axis, road surfaces (corresponding to parking areas), water surfaces and wooded surfaces. Those layers will be used as prior knowledge but will need first a generalization step described in the following methodology part.
Two reference maps are produced by comparison of the old database and the manually updated one: a nature of change map and a binary change map. The nature of change map does not include the occlusion classes introduced to handle shadows.
In order to test the radar data, a Digital Surface Model (DSM) derived by interferometry from a SAR COSMO-Skymed simulation of 2006 will be used in the classification process. Two DSM with pixel spacing of 1m and 5m were put at our disposal thanks to the collaboration with the EMSOR and GEMITOR projects (in the framework of the ORFEO program). Due to the noise and to the radar shadow effect, the 1m resolution DSM hasn't been used in the classification process.

3. METHODOLOGY

The method is presented in figure 1 and the principal steps are explained thereafter.

The outdated topographic database is used both in the segmentation process to reflect the geometry of objects (Carleer et al., 2008) and in the classification process using the previous type as feature in the landuse and the change classification tied with the spectral, textural and other context features.
The Digital Surface Model is used in the classification as well as two derived image: the slope image and a laplacian filter image (Hofman et al., 2002).

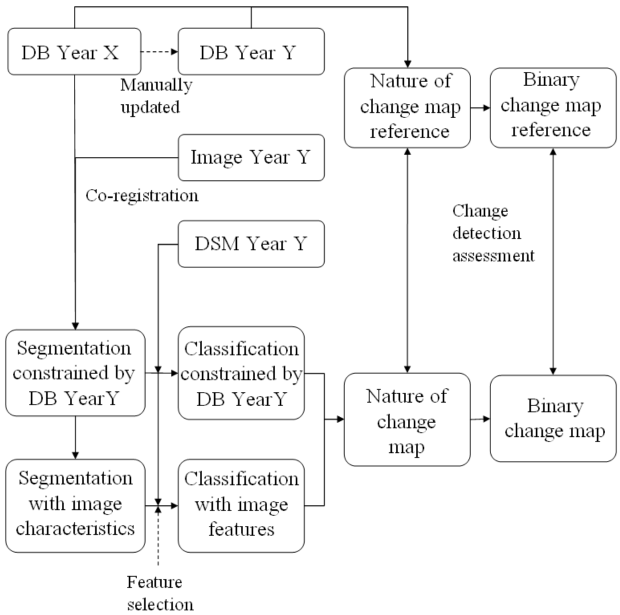

Figure 1: Proposed method

3.1 Co-registration

The first and maybe most important step of the change detection process is the correct co-registration between all data (Lu et al. 2003). Indeed, miss registration can lead to false change detection. The optical data and the DSM were co-registrate with the topographic database. The obtained Root Mean Square Error (RMS) for the Pléiades simulation is 0.65m in X and 0.79m in Y with 12GCPs. The co-registration of the DSM was more difficult because of its lower resolution: GCPs have to be chosen only where a great height difference occurs i.e. on the edge of tall buildings. 18 GCPs were found and the resulting RMS error for the Digital Surface Model is 3.4m.

3.2 Generalisation

In the case of the Toulouse study zone, the landuse database was derived from the different available layers: buildings, roads (linear data), surfaces of roads (parking), water and wooden surfaces. The road surfaces are derived from the linear data and the width is determined by the width category of the line. This leads to a cartographic generalization and decreased the spatial accuracy of the landuse data used in the experiment. No semantic generalization is needed.

3.3 Segmentation

The image was segmented in the Definiens Developer software.
In this software (Definiens, 2007; Benz et al. 2004), segmentation is achieved merging pixels or existing image objects by minimizing the average heterogeneity and maximizing their respective heterogeneity. Three parameters have to be fixed: the scale factor, (2) the shape factor (defining the relative importance of the colour to the shape) and (3) the compactness (the relative importance of the compactness to smoothness).
The hierarchical approach allows creating various level of generalisation. In this case, two different level of segmentation were created: the first level is constraint by the old database reflecting the geometric information of the objects. The second level is an over-segmentation of the first one and is created according to the spectral characteristics of the image.

3.4 Classification and change detection

The first level of the segmentation is classified with rules according to the old database classes: building, road, water, vegetation (wooden areas) and other.
The second segmentation level is then classified according to same legend. However, the low vegetation and bare soil, aggregated in the old database in the “other” class, are too different spectrally to be aggregate in this classification. The low vegetation has been grouped with the wooden surface to form the vegetation class and a new class has been created for bare soil. A first step in this classification is carried out by rules (for vegetation and shadows) and secondly, the unclassified segments are classified with the Nearest Neighbor classification method in the Definiens software. This Nearest Neighbor classification uses spectral, textural and contextual features of the segments including features from both optical and DSM data. It also uses the nature of the object in the old database.
Thirdly, the change detection map was done according to the class in first and the second classification, identifying the nature of change: construction of buildings, construction of roads, destruction of buildings, destruction of roads, occlusion of roads, occlusion of buildings, destruction of vegetation and no change.
Special classes have been introduced in the classification to group the probable occlusion areas: the “road occlusion” class which groups the former roads identified in the classification as vegetation and the “building occlusion” class grouping segments from former buildings which are classified as vegetation and which are not a destruction (this difference is done according to the form of the segment and the importance of the vegetation in the former building).
Finally, a binary change map (change/no change) was created grouping all the change classes and considering road and building occlusion as No-change.

3.5 Assessment

A validation set using a total amount of 886 points randomly chosen is extracted from the reference maps and used to create the error matrix.
The accuracy of the results is then estimated by the comparison of the well-classified point (on the diagonal in the error matrix) in regards to the whole validation set.

4. RESULTS

The results of the classification of the nature of change are presented in the Figure 2. Visually, the results of the change classification are good: the major changes occurring (construction of road -in dark blue- and construction of buildings –in red-) are well identified as well as the building destruction –in orange.
However, over-estimation occurs for building and road construction. The building over-estimation problem is mostly linked with the forest edges where bare soils are associated to shadows. Indeed the proximity to shadow was used as a feature identifying the buildings. This feature works well for new building but causes over-detection. Another cause of building construction over-estimation is large areas of shadows surrounding the tall buildings.

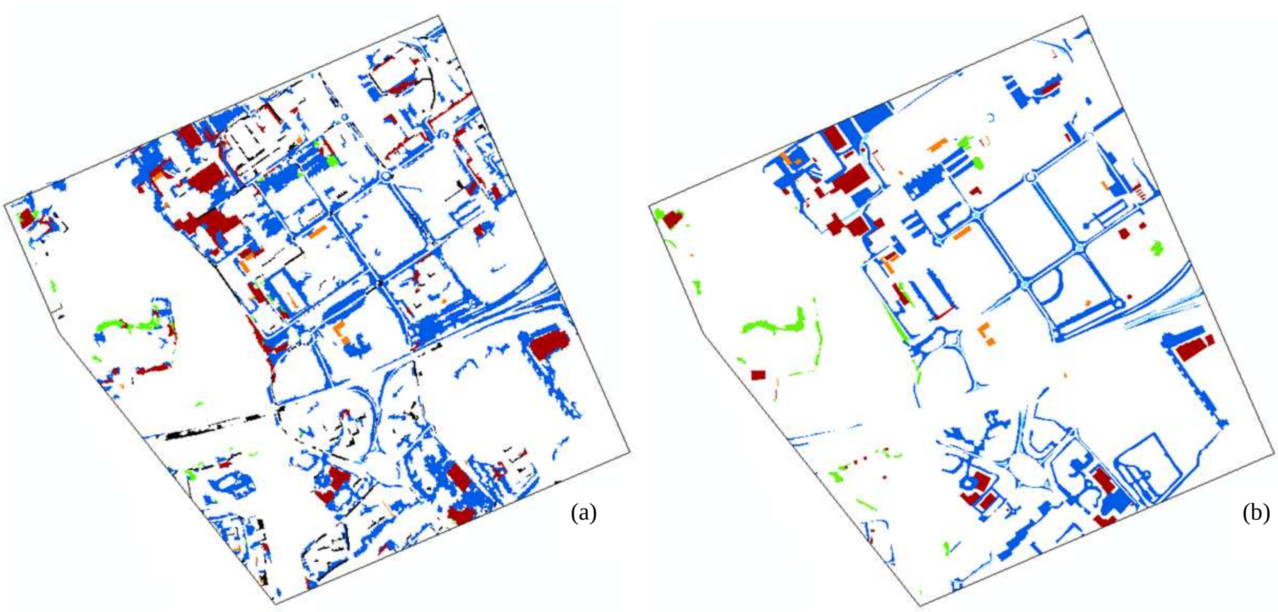

Figure 2.(a) Classification of the nature of change; (b) Reference map;

Legend: white: no change; red: construction of building; dark blue: construction of road; orange: destruction of building; light blue: destruction of road; light green: destruction of vegetation; black: occlusion.

		Reference					
		No change	Road construction	Building construction	vegetation destruction	Building destruction	Road destruction
Classification	No change	509	44	14	16	2	19
	Road construction	86	90	7	1	4	1
	Building construction	11	12	24	5	0	0
	vegetation destruction	1	1	1	7	0	0
	Building destruction	2	0	0	0	7	0
	Road destruction	0	0	0	0	0	0

Table 1. Nature of change error matrix

About the road construction over-estimation, it seems to be partially linked with problems of generalization: a part of the non-detected segments consist of long and narrow segments along the roads. An erroneous width category in the outdated database leads to a false detection of change in the road edges.
It is here an example of the limitation of the use of an outdated database as defined in Baltsavias (2004).
The error matrix of table 1 allows calculating the change detection accuracy for the nature of change classification. With the use of the DSM, the change detection accuracy reaches 74%. However, too many changes remain classified as No change. The non-detected construction of building mainly concerns modifications of the shape of a pre-existent building. The three destruction classes are less frequent in the study area and the areas of those segments are smaller than the one of the other classes. It partially explains the difficulty in their detection.

The accuracy of the change detection classification (discerning change from no change) benefits from the broader classes and reaches 78% (table 2). This accuracy is comparable to the one described by Carleer et al. (2008).

		Reference	
		No change	Change
Classification	No change	520	100
	Change	99	167

Table 2. Change error matrix

To test the real contribution of the DSM information in the change detection process, those results have to be compared to the results of the classification which don't use DSM information. The table 3 presents the change detection error matrix for the binary change/no change detection without DSM information. The detection accuracy reaches 75% i.e. lower than the 78% of the previous classification. The DSM information seems then to allow better accuracy in the change detection classification.

Classification	Reference	
	No change	Change
No change	499	102
Change	120	165

Table 3. Change detection without DSM error matrix

Classification	Reference					
	No change	Road construction	Building construction	vegetation destruction	Building destruction	Road destruction
No change	491	46	11	17	3	19
Road construction	95	90	3	1	3	1
Building construction	21	9	31	3	0	0
vegetation destruction	2	2	1	8	0	0
Building destruction	0	0	0	0	7	0
Road destruction	0	0	0	0	0	0

Table 4. Nature of change without radar data error matrix

The table 4 shows the accuracy of the classification of the nature of change without using the DSM information. Here also the accuracy (73%) is lower than using DSM (74%).

The classification benefits from the DSM information except for the identification of the object (especially road) in the sun shadow of tall buildings (counter to Zhang et al. 2001) probably due to the low resolution of the used DSM.

5. CONCLUSIONS

Change detection for map update remains a challenging topic in order to produces operational Image-based system to fulfil the data producers' needs.

In this paper, the reproducibility of the change detection method developed by Carleer et al. (2008) has been proved: the accuracy reaches 78% for the change detection and 74% for the identification of changes. Aside from the generalisation difficulties, the general method has been successfully applied on another database (the IGN-France topographic database) and in another context (a periurban landscape in the South of France).

The benefit of the DSM information in the change detection process using the old database as constraint has been discussed, showing a small improvement of the classification accuracy (3% for the change detection and 1% for the identification of the nature of change) but also limits due to the DSM resolution. Due to this low resolution of the DSM, the problem of identifying objects in the shadow has not been handled in this case.

Further works could assess the benefit of the integration of other SAR-derived data as coherence image (Chi et al., 2009).

This method and its results could allow map updaters in cartography Agencies e.g. to identify the change areas and the most interesting types of change for them (involving road or buildings) and to focus the resources on those areas.

REFERENCES

Bailloeul T;, Duan J., Prinet V., Serra B., 2003. Urban digital map updating from satellite high resolution images using GIS data as a priori knowledge. *Proceedings of the 2nd GRSS/ISPRS Joint workshop on Remote Sensing and Data Fusion over Urban Areas*, Berlin, Germany, pp.283-287.

Baltsavias, E.O., 2004. Object extraction and revision by image analysis using existing geodata and knowledge: current status and steps towards operational systems. *ISPRS Journal of Photogrammetry & Remote Sensing,* 58, pp.129-151.

Benz, U., Hofman P., Willhauck G., Lingenfelder I., Heynen M., 2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry and Remote Sensing*, 58, pp.212-223.

Bouziani M., Goïta K., He D-C., 2010. Automatic change detection of buildings in urban environment from very high spatial resolution images using existing geodatabase and prior knowledge. *ISPRS Journal of Photogrammetry and Remote Sensing*, 65, pp.143-153.

Cantou J.Ph., Maillet G., Flamanc D., Buissart H., 2006. Preparing the use of Pleiades images for mapping purposes : preliminary assessments at IGN-France. *International Archives of Photogrammetry & Remote Sensing* .Vol. 36.

Carleer A., Wolff E., 2008. Change detection for updates of vector database through region-based classification of VHR satellite data. *Procedings of the Conference: Pixel, Object, Intelligence: Geographic Object Based Image Analysis for the 21st century*, University of Calgary, Alberta, Canada.

Chi H., Sun G., Ling F., 2009. Urban dynamic change detection in southeastern China based on interferometric SAR. *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium*, Cape Town, South Africa, III, 432-435.

Definiens Developer, 2007. User Guide 2007, Software: http://www.definiens.com

Hofman, A.D., Maas H-G, Streilein A., 2002. Knowledge-based building detection based on laser scanner data and topographic map information. *International Archives of Photogrammetry and Remote Sensing*, 34, part. 3A, 169-174.

Holland D.A., Boyd D.S., Marshall P., 2006. Updating topographic mapping in Great Britain using imagery from high-resolution satellite sensors. *ISPRS Journal of Photogrammetry and Remote Sensing*, 60, pp.212-223.

Hu, X., Tao, C.V., Hu, Y., 2004. Automatic road extraction from dense urban area by integrated processing of high resolution imagery and LIDAR data. Proceedings ISPRS XXth Congress Istanbul, Turkey.

Knudsen T., Olsen B., 2003. Automated change detection for updates of digital map databases. *Photogrammetric engineering and remote sensing*, 69(11), 1289-1296.

Lu D., Mausel P., Brondizio E., Moran E., 2003. Change detection techniques. *International Journal of Remote Sensing*, 25, pp. 2365-2407.

Notarnicola C;, Frick A., Kass S;, Rastner P;, Pulighe G., Zebisch M., 2009. Semiautomatic classification procedure for updating landuse maps with high resolution optical images. *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium*, Cape Town, South Africa, IV, pp.975-978.

Petzold B. & Walter V., 1999. Revision of topographic databases by satellite images. In Schroeder M;, Jacobsen K., Konecny G., Heipke C. eds., Sensors and Mapping from Space 1999. Institute for Photogrammetry and Engineering Surveys, University of Hannover, Hannover, Germany, unpaginated CD ROM.

Poulain V., Inglada J., Spigai M., Tourneret J_Y., Marthon P., 2009. Fusion of high resolution optical SAR imagees with vector data bases for change detection. *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium*, Cape Town, South Africa, IV, 956-959.

Unsalan C; Boyer K.L., 2005. A system to detect houses and residential street networks in multispectral satellite images. *Computer Vision and Image Understanding*, 98, pp.423-461.

Walter V., 2004. Object-based classification of remote sensing data for change detection. *ISPRS Journal of Photogrammetry & Remote Sensing*, 58, pp.225-238.

Zhang C., Baltsavias E., Gruen A., 2001. Knowledge-based image analysis for 3D road reconstruction. *Asian Journal of Geoinformatics*, Vol.1, n°4, 3-14.

Zhang Q., Couloigner I., 2004. A framework for road change detection and map updating. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Vol.34, Part 35, pp.720-734

ACKNOWLEGEMENTS

The experiences have been carried out during the CHADE (Change detection for updates of vector databases through multi-level region-based classification of VHR data) project financed by the Belgian Science Policy in the framework of the Optical Radar Federated Earth Observation (ORFEO) program.
The optical and the radar interferometric data were put at our disposal by the CNES in the framework of the ORFEO accompaniment program.
The DSM data were furnished thanks to cooperation with the EMSOR and GEMITOR projects (Signal & Image Centre/ Royal Military Academy/ and Centre Spatial de Liège/ Université de Liège).