A method for monitoring building construction in urban sprawl areas using object-based analysis of Spot 5 images and existing GIS data

Nasser Najibi[1], Sepideh Rahbar[2]

1, 2- Department Of Surveying and Geomatics Engineering
Faculty Of Engineering
University Of Tehran
AmirAbad, Tehran, Iran
P.O. Box 11155-4563
E-mail: nsr.najibi@gmail.com

Abstract

We know that Urban sprawl has been identified as one of the most negative effects of global population growth on the environment and biodiversity. Frequent monitoring of urban sprawl is needed to limit the impact of this ongoing phenomenon. This paper proposes precise monitoring of building construction using an object-based classification methodology applied to Spot 5 images with a 2.5 m resolution. An application at a regional scale on Reunion Island in the Indian Ocean shows that this building extraction methodology has limitations in the production of reference urban maps because of difficulties in defining the shape and the number of buildings compared to classical photo-interpretation of aerial photography. However, these results are of great value for planning in urban sprawl areas where up-to-date information is lacking because of the rapid pace of house construction and residential development.

Keywords: Spot 5, Reunion Island, ISPRS, Integrated urban sprawl, Object - based image analysis

Introduction

Global population trends suggest a massive increase of the world population in the next 50 years. In their most recent projection, the United Nations Population Division projects a global population of 8.04 billion for the year 2025 and 9.1 billion for 2050 with a major increase in urban population (United Nations, 2005). The main negative environmental implication of urbanization is linked to the patterns of land use, specifically unwieldy urban expansion and low-density housing, typically castigated as "urban sprawl". Urban sprawl is directly related to the ongoing decline of average urban densities (-1.7% in developingcountry cities and -2.2% in industrialized countries during the last decade). By 2030, if average densities continue to decline at those rates, the builtup area will increase to more than 600,000 square kilometers in developing-country cities and to some 500,000 square kilometers in industrialized-country cities (Shlomo et al., 2005). To implement policies adapted to this inevitable urban growth, up-to-date spatial information on urban sprawl is needed at local and regional scales. The changes resulting from this fast urbanization are ideally monitored and detected from remotely sensed images as demonstrated by numerous studies applied to core urban areas and the urban–rural fringe (Civco et al., 2002; Masek et al., 2000; Ridd and Liu, 1998; Thomas et al., 2003; Yang, 2002; Yeh and Li, 2001).
The remote sensing techniques used are generally based on a combination of change detection algorithms using

[1] UnderGraduate
[2] UnderGraduate

multi-temporal imagery to delineate new urban areas. The change detection algorithms are divided into two categories: image-to-image comparison or map-to-map comparison. While the first is generally accurate, but lacking detailed information on how various land-use/land-cover categories change, the second is generally preferred as it can detect a full matrix of landuse/landcover changes (Yang and Lo, 2002). However, classifiers advocated by this second method are still very sensitive to radiometric normalization between images since they generally do not use the image spatial contents. A general drawback of all the previous pixelbased change detection approaches is that when they are applied on high spatial resolution (HR) images of urban areas, they often produce change maps that lack spatial coherence because of spectral heterogeneity and spatial variance that lead to the well-known salt and pepper effect. Blaschke et al. (2000) showed that with per-pixel classification, single pixels are classified differently from the surrounding area and homogeneous regions cannot be generated. The only way to smooth the image is to use filters, which, however, work without considering the original information. Blaschke et al. (2000) proposed as an efficient solution the use of object-based image analysis (OBIA) where homogeneous regions are first built up through a segmentation process (segments also called image objects) and in a second step, a classification process is applied to these image objects. We propose here an alternative methodology for urban sprawl monitoring based on an image-to-map comparison using an object-based image analysis of Spot 5 HR images. Recent developments in OBIA based on a fractal net evolution approach (FNEA) have revolutionized the processing of HR remotely sensed data by offering effective computer-assisted classification techniques that come close to the quality of manual photo-interpretation, whilst being much faster, cheaper and more reproducible (Blaschke et al., 2000; Blaschke and Hay, 2001; Benz et al., 2004; Frauman and Wolff, 2005; Kamagata et al., 2005; Lemp and Weidner, 2005; Liu et al., 2005; Marangoz et al., 2004). Some successful landcover or landuse classifications in urban areas have been obtained with this approach (Burnett and Blaschke, 2003; Kamagata et al., 2005; Moeller and Blaschke, 2006; Moeller, 2005; Puissant, 1998; Puissant and Weber, 2002; Van de Sande et al., 2003). The FNEA incorporates an object-oriented framework and image segmentation techniques. In particular, it utilizes fuzzy set theory to extract the objects of interest, at the scale of interest, by segmenting images simultaneously at both fine and coarse scales and then building image semantics between levels and their elements (Blaschke and Hay, 2001). Carleer et al. (2005) compared four segmentation algorithms from the two main groups of segmentation algorithms (boundary--based and region-based) applied on very high spatial resolution images for different landscapes. In this comparison, urban areas are distinguished into three types: residential, urban administrative zone and urban dwelling zone. For those three types of urban areas, an empirical segmentation discrepancy evaluation based on the number of mis-segmented pixels in the segmented images compared with the visually segmented reference images and on the percentage of misclassified pixels for each reference region demonstrates that region-growing algorithms give the best results (with a mean of only 10.8% of average errors by region for the three urban classes).

Region-growing algorithm description

The region-growing algorithm used in this study for segmentation and image classification was developed by Baatz and Schape (2000) and is proposed in the OBIA solution of Definiens Professional Earth commercial software (previously called eCognition). The bottom-up region-growing segmentation procedure starts at each point in the image with one pixel objects and merges these image objects into bigger ones throughout a pair-wise clustering process. Throughout this process, the underlying optimization procedure minimizes the weighted heterogeneity nh of resulting image objects, where n is the size of a segment and h is a parameter of heterogeneity based on three concepts: colour, smoothness and compactness (Carleer et al., 2005). In each step, the pair of adjacent image objects that are merged results in the smallest growth of the defined heterogeneity. If the smallest growth exceeds the threshold defined by the scale parameter, the process stops. A detailed description of the region-growing algorithm is given in Baatz and Schape (2000), Benz et al. (2004) and Definiens (2007). With this approach, segments not only have spectral properties, but also region-based metrics such as shape, texture, structure, size and context (Baatz and Schape, 2000) that are used in the OBIA for classification or feature extraction.

In this study, we applied OBIA for building extraction and change detection in the context of the urban sprawl monitoring of the Reunion Island in the Indian Ocean.

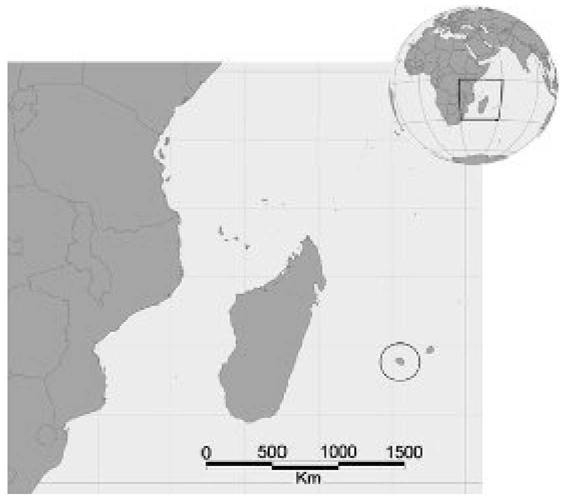

Fig. 1. Localization of the study area: The Reunion Island in the Indian Ocean.

Study area

The French oceanic island of La Reunion (2512 km^2) is located in the Mascarene Archipelago in the Indian Ocean (Fig. 1). While the Piton des Neiges reaches 3070 m in the center of the Island, more than 80% of the total population (almost 800,000 in 2006) live on the coastal lowlands (< 500 m) where most of the economic activities are concentrated. For the last 20 years, this insular environment has been distinguished by fast and strong spatial mutations related to new economic and demographic development. Lagabrielle et al. (2007) showed that urban areas in La Reunion sprawled at a rate of 157 % from 1989 to 2002. Urban sprawl is concentrated on coastal areas and the phenomenon is highly heterogeneous in terms of the mechanism and the resulting urban structure (i.e. dense or dispersed, wellplanned or ad hoc). Consequently natural areas and agricultural areas are being rapidly converted into urban sprawl. Assessing and monitoring urban sprawl became a central problem in La Reunion Island over the last 20 years, and will continue to be so if the population follows predictions of a 25% increase in the next 15 years (1.7% yr^{-1}), rising to 1 million inhabitants in 2030 (INSEE, 2006).

Satellite and aerial datasets

Spot 5 Supermode 2.5 m resolution images were used in this study. Supermode multi-spectral images result from the fusion of a 2.5 m panchromatic (PAN, 0.51–0.73 μm) image and three 10 m multi-spectral images (0.5 – 0.59 μm, 0.61 – 0.68 μm and 0.79 – 0.89 μm). The 2.5 m panchromatic image itself is obtained after interpolation, deconvolution and noise removal of two 5 m panchromatic images acquired simultaneously. One of the big advantages of Spot 5 images compared to other VHR images is the large swath (60 km × 60 km) that allows a complete view of Reunion Island. However, high cloud cover on the windward South - East coast makes it almost impossible to acquire a cloud free image (this part of the island receives more than 14,000 mm of annual rainfall and is characterized by several rainfall intensity world records). To have a full coverage of the island, mosaic was created with the main image acquired on the 07/21/03, along with two images from 05/13/04 and 10/18/02.

We benefited from the “BD Isle” project developed by the Centre National d’Etudes Spatiales (CNES, 2006) to offer free access to a series of Spot 5 images of Reunion Island. Note that even with such a facilitated access to the Spot 5 catalog, there is an interval of 19 months to obtain a full coverage of the Island, which is not satisfactory in an operational context.

For an accuracy assessment of building extraction from the Spot 5 images and in order to develop a combined change detection methodology based on aerial and satellite imagery, we used BD Topo^{R} reference maps from the French National Geographic Institute (IGN). BD Topo^{R} is the 1:25,000 topographic reference in the French territories. It is a 1 m resolution vector database based on a computer-assisted photo-interpretation of 50 cm aerial ortho-photography. The BD Topo^{R} dataset available for Reunion Island is based on 1997 aerial photographs. Such a high quality database is very useful for urban management, however, the updating of BD Topo^{R} generally takes five years (and even more for periphery regions like Reunion Island) and only half of the French territories are currently covered by this database. From this database, we elaborated both a building extraction methodology for the year 2003 (using a composite of the three Spot images) and a urban sprawl change detection method applied to the period 1997–2003.

Object-based extraction methodology

The processing chain of the building extraction is composed of the six following steps: (1) object-based cloud screening, (2) object-based multi-temporal image compositing, (3) tiling with overlap, (4) object-based image analysis for building extraction, (5) object-based image editing and (6) object-based stitching.

Clouds, cloud edge and cloud shadow object-based screening

The use of a cloud threshold based on a blue band is commonly considered a good cloud screening methodology. However, no blue band is available for Spot 5 images and cloud screening should be based on the green band (0.50 – 0.59 µm). However, the use of a single reflectance threshold is sometimes weak when clouds are located over bright surfaces like metal plates used for roof or coral sand beaches in Reunion Island. To distinguish clouds from bright surfaces (bare soil, coral sand, sugarcane mulch), we based cloud screening on a specific object-based image classification. Object-based cloud screening is based on a coarse multi-resolution segmentation (with a medium object size of 1 ha). Multi-resolution segmentation provided by Definiens (2007) is used to create object primitives. The advantage of multiresolution segmentation is that the scale of resulting image objects is freely adaptable to fit the scale of the task and all image objects resulting from one segmentation level are of a comparable scale. Cloud screening was based on a threshold (in the high values) obtained by expert visual judgment of the mean of the green band pixel values forming each image object. Coarse segmentation avoids the risk of incorrectly filtering out small bright objects in the green band (like buildings) since they are merged at this segmentation level into bigger objects with darker pixels and the resulting objects have a mean green band value that is lower than the screening threshold. This cloud screening methodology should be used precociously for other applications since some large objects from the coral sand beaches are also filtered.

Cloud edges were screened using a “relative border to clouds” fuzzy membership function. All objects having a relative border to clouds (border length of the object in contact with clouds divided by the total length of the object) higher than 0.6 were classified as cloud edges, while objects having a relative border to clouds lower than 0.2 were not. A fuzzy sigmoid membership range was defined in between and objects that have a relative border to clouds between 0.2 and 0.6 receive a membership value to the cloud edge class between 0 and 1, based on the decreasing sigmoid function slope defined.
To detect dark cloud shadow objects, thresholds based on the mean of the three spectral layers were used in combination with a distance threshold to clouds (defined at 700 m in all directions of the clouds). Objects having reflectance lower than the thresholds defined for each band and within a distance to the clouds lower than the screening threshold were considered as cloud shadows.
Finally a quick manual editing was done to correct misclassified objects. We applied this object-based cloud and cloud shadow screening on the three Spot 5 images.

Objec-tbased multi-temporal compositing of Spot 5 images

Identified clouds, cloud edges and cloud shadow objects observed in the 07/21/03 image (least cloud cover image) were substituted by objects from the more recent Spot 5 image (05/13/04) or by objects from the third Spot 5 image acquired on 10/18/02 if objects from the second image were also identified as covered by clouds. The resulting image composite covers more than 95% of Reunion Island, the remainder that was still covered by clouds was mainly in inhabited areas around the Piton de la Fournaise, an active volcano.

Tiling

To accelerate image processing during the finer segmentation used for building extraction, we cut the image into 30 tiles of 2080 × 2360 pixels (5200 m × 5900 m) with an overlap extent of 200 pixels (500 m), so that adjacent tiles have an overlapping area to eliminate border effects during segmentation and classification. The overlap extent must be larger than three times the size of the bigger objects at the highest image object level to guarantee that border effect will be avoided while stitching the tiles together.

Object-based image analysis for building extraction

From a spectral point of view, buildings are seen as roof surfaces of different materials such as brick, copper, aluminum, zinc, slate, bitumen, stone, etc. with a certain slope. Such a complex mix of roof construction and materials leads to difficulties for automatic spectral building extraction (Lemp and Weidner, 2005). In Reunion Island, as in many tropical regions, this problem is less pronounced since most of the houses are covered by white zinc sheeting which has a very high reflectance in the visible channels. The specific spectral properties of roof surfaces in such regions can be used advantageously for automatic building extraction. However, as mentioned above, high reflectance in the visible channels can also characterize other types of land cover like coral sand beach, concrete, sugarcane mulch and lichens on lava flow. To distinguish buildings from other bright objects using spectral, contextual and shape information, we applied OBIA for building extraction to the 30 tiles.

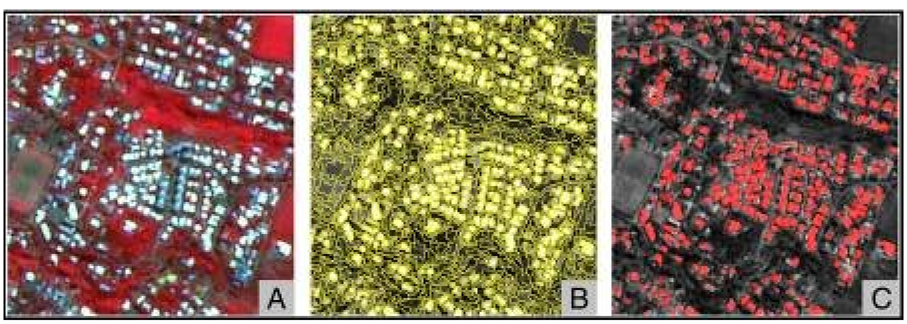

Fig. 2. Second image object level and automated classification. A. Spot 5 supermode[R] 2.5 m image. B. Multiresolution segmentation. C. Building extraction (buildings in red). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Building extraction from Spot 5 images was done in three steps: creating a hierarchical network of image objects using the multi-resolution segmentation, classifying the derived objects by their physical properties and describing the semantic relationships of the network's objects in terms of neighborhood relationships or being a subor super--object. Image objects resulting from the coarse segmentation used for cloud screening were used as the first level of the hierarchical network. A second level was created with a much finer multi-resolution segmentation to reach building objects' scale (with a medium object size of 330 m^2). A class hierarchy defining the class descriptions is built on this two level hierarchical network. Class descriptors are a combination of fuzzy membership functions used to describe intervals of feature characteristics wherein the objects do belong to a certain class or not by a certain degree of membership. A class is described by combining one or more class descriptors by means of fuzzy-logic operators and/or by means of inheritance.

On the first level, large bright objects such as sugarcane mulch and coral sand beach were identified based on fuzzy rulesets using the following spectral features of the image objects: mean in the green channel, mean in the red channel, ratio in the green channel, and standard deviation in the red channel. Those features were chosen according to an expert visualization of the different features of the objects obtained from the segmentation. Features that helped in identifying visually the large bright objects from the other objects were retained. The expert visualization defined also the boundaries of the fuzzy membership functions for each feature. A layer mean value and standard deviation were calculated from the layer values of all pixels forming an image object, while the ratio of the green layer is the green layer mean value of an image object divided by the sum of all spectral layer mean values. A minimum area threshold of 3000 m^2 also described large bright objects.

On the second level, a first building class was described by fuzzy membership functions of the mean in the green channel, and the mean in the red channel. A second class was created to complete missing buildings not identified by the first class description. This class was defined with a membership function of the feature ‘mean difference to neighbor of the green layer’. For each neighboring object, the green layer mean difference was computed and weighted with regard to the length of the border between the objects (if they were direct neighbors) or the area covered by the neighbor objects (if the neighborhood was defined within a certain perimeter (in pixels) around the image object in question).

Both building classes’ descriptions are also defined with a maximum object area and look at the superobject classification from level 1. If an object from level 2 has a superobject classified as a ‘large bright object’, then it is not considered as a building in level 1. Finally, the two buildings classes were merged into one class. Fig. 2 shows the second image object level and the classification result before manual editing. We observe that some sugarcane fields are classified as buildings.

Object-based manual editing

Misclassification during building extraction resulted mainly from the inclusion of areas such as sugarcane mulch and bright rocks. Also, because of the size threshold, big buildings like factories or supermarkets were often not considered as buildings, but as large bright objects. Object-based classification is a semiautomatic technique, but offers powerful manual editing capabilities. Intelligent selection of classified objects in a specific area using polygon selection and specific class filters accelerate and improve manual editing. To finalize classification, one hour of manual editing was allocated per tile.

Object-based stitching

Building extraction results were exported as Shapefile[R] into a GIS. Stitching of the resulting polygons was done by making a manual selection of the polygons having a border effect on each overlapping tile and by deleting these polygons. Manual selection inside overlapping areas was done using a rectangle selection of two thirds of the overlapping area on the first image and of one third on the second tile to delete all unreliable polygons. The tiles were then merged and the topology was corrected on the overall shapefile using Arc Info[R].

Results and accuracy assessment for building extraction

The BD Topo[R] database from IGN was used as a reference to evaluate the quality of the urban object extraction. Both extraction and reference datasets were in vector format. However, a direct comparison of our results with this reference data is limited by several factors: the difference in resolution; co-registration errors; the fact that the reference data is five to seven years older than the Spot 5 images used in our study; that there can be more than one reference building in one extracted polygon due to extraction methodologies; finally, extraction of buildings in dense urban areas is limited in our method because the rule-set defined for classification is oriented for zinc sheet and other highly reflective roofs, while dense downtown areas are likely to contain a large variety of roof materials that are not highly reflective (a specific classification ruleset dedicated to such areas could solve this limitation).

Figure (3) presents the results of the urban object extraction for the whole island in comparison with BD Topo [R] with focus on urban areas at different scales to give a more detailed look. First, observations show that the quality is not homogeneous and there are major discrepancies in dense urban areas that are composed of different kinds of buildings, whereas less dense areas composed of individual housing areas are better. In total, 92,121 polygons were extracted from the Spot 5 images. Using the estimation of INSEE (2006), 54,000 new houses would have been built between 1997 and 2003 (9000 houses/ year). If we add this estimation to the number of buildings in 1997 given by the BD Topo [R] dataset (189, 195), we obtain 243, 195 buildings on the overall Island for the year 2003. This means that each extracted polygon would represent a mean of 2.6 buildings since they do not separate adjacent buildings. When comparing our results to the reference data (after converting both datasets into 2.5 m resolution raster files), we observe a very low Kappa of 0.16 and only 18.4% of positive identification of reference buildings. Further analyses showed that 97.95% of reference buildings are situated within a 50m buffer zone around the center of the extracted building polygons, which suggests that urban areas are globally well identified and that errors of classification could in fact come mainly from the co-registration errors and the differences in resolution of the data sources and the shape of the resulting polygons. Hereafter, we present another method of accuracy assessment based on the vector files that gives a better evaluation of the added value of the building extraction.

We exported into a vector format the resulting polygons of the building extraction. Using these vectors, different parameters can be estimated to evaluate the quality of urban object extraction: the number of buildings, a building's area, its shape, the exact location of its center, and its main orientation. Again, it is important to consider that our results differ from the reference database based on a computer-assisted photo-interpretation of 50 cm aerial ortho-photography (Fig. 4): there can be more than one reference building in one extracted polygon with consecutive impacts on comparative area, center location, shape and direction; the perimeters of extracted polygons are naturally saw-toothed being derived from rasters, while the vectors from the reference database are constituted by straight lines, and the reference polygons delineate entire buildings when our method identifies only the highly reflective part of the roof that may also merge with adjacent reflective objects like cars or bright pavement. Consequently, only the number of buildings, the total built-up area and the intersection area between extracted and reference buildings were considered for the accuracy assessment.

Our purpose here is to check the capacity of this methodology to monitor urban sprawl, and so it was decided to concentrate the accuracy assessment on the estimation of the extraction quality in lowdensity areas with individual houses that characterize the major part of the urban sprawl.
Extraction accuracy was calculated on 20 separate test sites with a total of 7344 buildings (Fig. 3). Test sites were selected around the island based on the criterion of areas that were characterized by lowdensity suburban development with mainly individual residential areas within mainly post -1997 built-up areas.

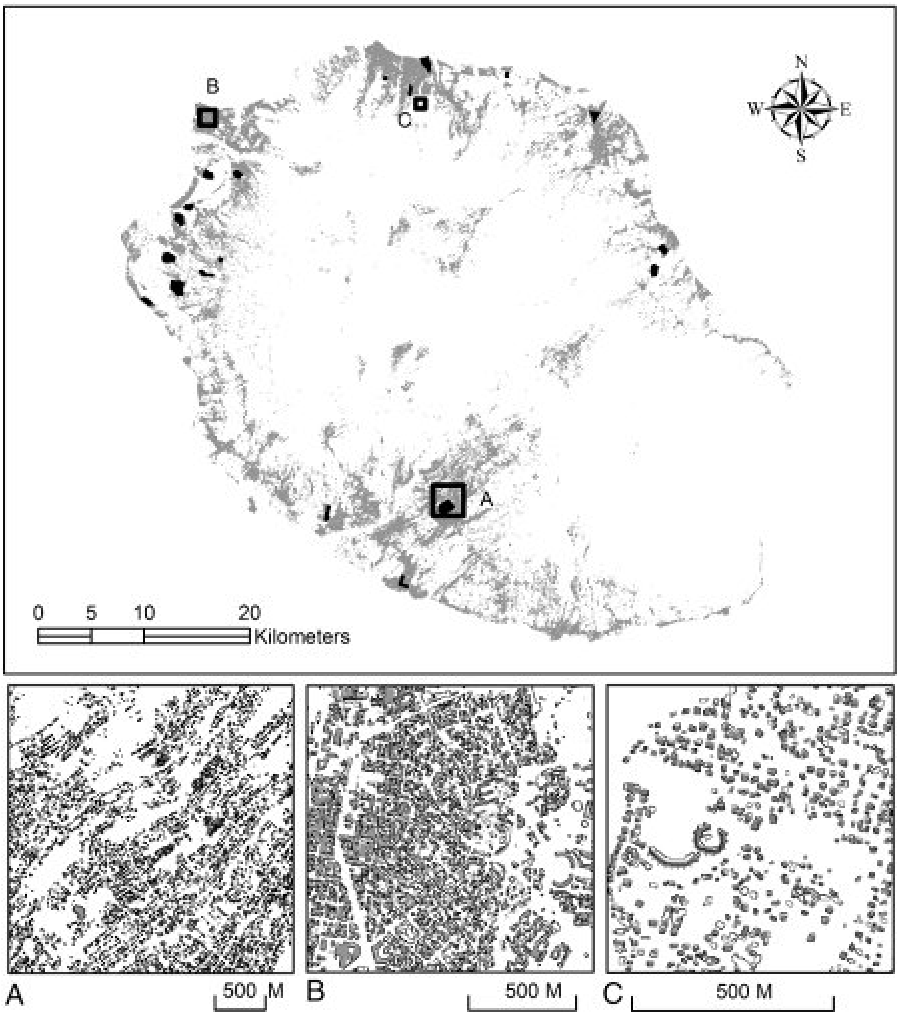

Fig. 3. Extraction of buildings in Reunion Island from a 2002/2003/2004 Spot 5 composite. Test sites for accuracy assessment are in black. Zoom on Le Tampon (1:10,000), Le Port (1:5000) and Saint Denis (1:2500): Extracted buildings are shown in black and reference buildings from BD Topo in gray.

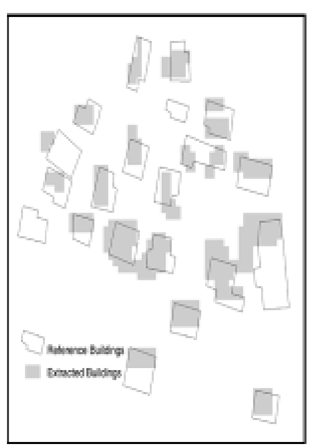

Fig. 4. Examples of extracted polygons and reference buildings.

To avoid some of the limitations coming from the inherent differences between the reference data and the extraction results, a manual photo-interpretation was done using both the BD Topo^{R} database and the Spot 5 images to eliminate those houses built after 1997 from our building extraction result (without eliminating the misclassified polygons: i.e. buildings extracted, but considered as inexistent by photo-interpretation on the Spot5 image).

Since extracted polygons correspond to more than one reference building, the number of buildings correctly extracted was calculated using the area intersection between reference and results (Table 1). We consider that if a reference building is covered by more than 25% of an extracted building, then it was correctly
identified.

Table.1

Cumulative frequency of the percentage of intersected area between reference and results

%	*Reference/Result*	*Result/Reference*
75–100	*3324*	*1687*
50–100	*5072*	*4361*
25–100	*6103*	*5215*
0–100	*7344*	*5758*

The 1st column shows how the extracted polygons cover the reference data and the 2nd column shows how the extracted polygons are covered by the reference data.

This arbitrary threshold was fixed to take into account the co-registration errors, the differences in resolution, and the fact that automatic extraction does not delineate entire buildings as manual photo-interpretation does.
Using this threshold, 83.1 % of the 7344 reference buildings were identified and only 9.4 % of the extracted polygons were inexistent reference buildings. Across all 20 sites, the total built-up area is estimated at 187 ha, which is only 6.8 % more than the 174.2 ha of the built-up area from the reference data. This last result must be considered with caution, since it could express the fact that the missing parts of the buildings were not extracted because they were in the shadow or they were covered by a different roof material. This error could be counterbalanced by the merged adjacent objects like cars or bright pavement.
The results show that the extraction of buildings from Spot 5 images using an object-based methodology has limitations for defining the shape and the number of buildings, but gives a good estimation of the location and the size of the built-up area and of the urban structure morphology. The data produced should not serve as reference data for technical management and basic mapping (except in places where recent aerial survey is unavailable), but could be of great value for planning in urban sprawl areas where up-to-date information is lacking because of the rapid pace of house construction and residential development. However, if urban sprawl is the only process of interest, it is useless and time consuming to extract existing buildings already mapped in previous databases. Also, the manual editing applied on a limited number of polygons would be more efficient. For those reasons, we developed a methodology for extracting only the new buildings in the sprawling areas.

Object-based urban sprawl change detection

Based on the existing rule-set, we built an extraction methodology specific to the urban sprawl between 1997 and 2003 using the BD Topo^{R} dataset as a reference. Compared to the 1997 BD Topo^{R} dataset, the previous resulting map is composed of existing urban buildings in 1997 and urban growth extracted from Spot 5 imagery. As defined by Wilson et al. (2003), urban growth itself can be divided into three categories: infill growth for converted areas surrounded by urban areas, expansion growth for converted areas on the fringe of urban areas and outlying growth for converted areas occurring beyond existing developed areas. Urban sprawl is the sum of the expansion and the outlying growth. So we can define buildings composing urban sprawl as the buildings not present in 1997 and not surrounded by existing buildings. Based on this definition, our extraction rule-set was modified by adding two simple rules:

– New buildings do not intersect with existing buildings from BD Topo^{R} 1997.
– New building centers are more than 35 m distant from the center of extracted polygons that intersect with BD Topo^{R}. Using a distance feature is faster and more efficient than using a density feature, while still giving a good approximation.

Results and discussion for the urban sprawl change detection

Fig. 5 shows urban sprawl from 1997 to 2003. From the 92,121 previous polygons, 7342 were identified as new buildings that formed part of the sprawl. If we consider that on average each polygon extracted from a Spot 5 image contains 1.3 buildings (by comparing our previous extraction to the BD Topo^{R} in the 20 low-density housing sites), between 1997 and 2003, 9544 buildings were built in sprawling areas, amounting to 1590 houses per year. The total built-up area represents 149 hectares without taking into account streets, roads, gardens, intra-urban open spaces, and conversion to impervious areas that together would amount to a much larger surface. If we compare those results with the potential need for new housing defined by INSEE (2006) at 9000 houses/year until 2010, it means that less than a fifth of the new houses are being built in sprawling areas. Assuming that each building is surrounded by an area of 0.6 ha (mean area estimation of space consumption for one building in dispersed habitat areas in La Reunion (Croizer and Beaudemoulin, 2006)), and that 9544 new buildings were built in six years from 1997 to 2003, then the urban sprawling rate is 954.4 ha/per year. Such a rate is higher than the previous estimation from Lagabrielle et al. (2007) based on Spot 1 and Spot 4 images. This study estimated that urban area sprawl increased at a rate of 707 ha/per year during 13 years from 1989 (5863 ha) to 2002 (15,058 ha).

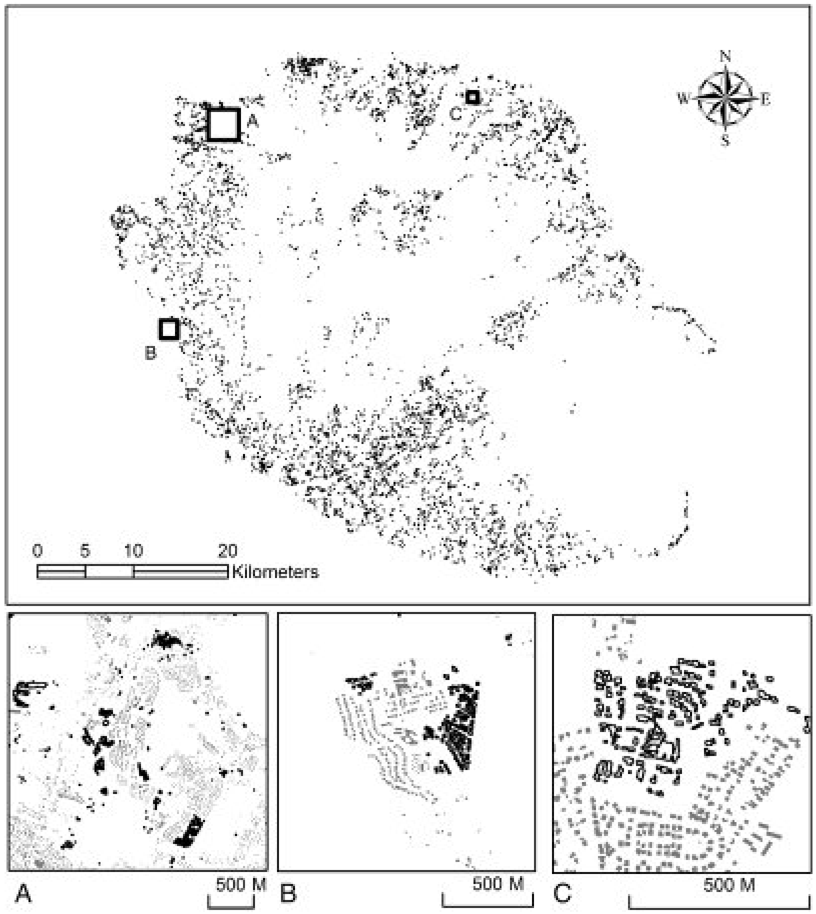

Fig. 5. Extraction of buildings in urban sprawling areas from 1997 to 2003 in Reunion Island. Zoom on Le Tampon (1:10,000), Le Port (1:5000) and Saint Denis (1:2500). Buildings from 1997 BD Topo R are shown in gray (only for zooms) and new buildings in urban sprawl areas in black.

Thus, the lower resolution of Spot 1 and 4 images (20 m) in the previous study would have led to an overall underestimation of the urban sprawl at a regional scale. This is mainly due to the underdetection of buildings in mixed urban–rural fringes.

Conclusion

This paper presents a building extraction methodology optimized for urban sprawl monitoring. The methodology was applied on Spot 5 full scenes of the ISPRS in the Indian Ocean. The methodology is based on the OBIA concepts and on image segmentation. The bottom-up region-growing algorithm used for segmentation gave satisfactory segments for a building extraction on 2.5 m resolution Spot 5 images. The limitation of the extraction came from the limit of the image resolution that makes it possible to identify only the brightest part of the buildings (mainly the white zinc roofs for Reunion Island). Contextual and scale information was used to identify buildings from other bright objects such as coral sand beach or sugarcane mulch. The extraction methodology was adapted for urban sprawl change detection using an existing GIS urban database. The application of the extraction methodology to the urban sprawl monitoring of the Reunion Island demonstrates its potential to provide estimations of the urban sprawl with a convenient temporal resolution at a regional scale.

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