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Article

Change Detection in Peri-urban Areas Based on Contextual Classification

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Summary: This paper presents a methodology for change detection in peri-urban areas using high spatial resolution image and lidar data, founded on object-based image classification and a comparison of the classification results from two epochs. The definition of the objects is based on cadastral boundaries obtained from a geospatial database. An exhaustive set of descriptive features is computed, characterising each object for both epochs regarding spectral, texture, geometrical, and three-dimensional (3D) aspects. In addition, contextual features describing the object at two levels are defined. Internal context features describe the relations between different land cover elements within the object, whereas external context features describe each object considering the common properties of neighbouring objects, usually coinciding in urban areas with an urban block. Both the classification and the change detection process are thoroughly evaluated, and the specific contribution of 3D features to the accuracy of the processes is analysed. The results show that 3D information enables to improve the classification results, remarkably increasing the accuracy values of certain classes, and allowing for an enhanced discrimination of building typologies. Moreover, the change detection efficiency is notably improved by a significant reduction of both commission and omission errors.

Zusammenfassung: Dieser Beitrag beschreibt eine Methodik zur Erkennung von Änderungen in Stadtrandgebieten mit Hilfe von räumlich hoch aufgelösten Bild- und Laserscannerdaten, die auf einer objektbasierten Klassifikation und einem anschließenden Vergleich der Klassifikationsergebnisse für zwei Epochen aufbaut. Die Definition der Objekte basiert auf Katastergrenzen aus einer räumlichen Datenbasis. Ein umfangreicher Satz von Merkmalen wird berechnet, der jedes Objekt aus beiden Epochen hinsichtlich seiner spektralen, texturellen, geometrischen und dreidimensionalen (3D) Aspekte charakterisiert. Zusätzlich werden Kontext-Merkmale, welche das Objekt auf zwei Ebenen beschreiben, definiert. Die internen Kontext-Merkmale beschreiben die Beziehungen zwischen verschiedenen Landbedeckungsarten innerhalb eines Objekts, während die externen Kontext-Merkmale jedes Objekt hinsichtlich der gemeinsamen Eigenschaften von benachbarten Objekten beschreiben; letztere sind für Objekte innerhalb eines Gebäudeblocks normalerweise ähnlich. Sowohl die Klassifikation als auch die Änderungsdetektion werden sorgfältig evaluiert, und der Einfluss der 3D Merkmale auf die Genauigkeit dieser Prozesse wird analysiert. Die Ergebnisse zeigen, dass die 3D Information dabei hilft, die Genauigkeit der Klassifikation zu steigern, wobei diese Steigerung für einige Klassen bemerkenswert ausfällt und insbesondere eine verbesserte Unterscheidung von Bebauungsarten erlaubt. Darüber hinaus wird die Effizienz der Änderungsdetektion deutlich erhöht, indem sowohl die Zahl der nicht erkannten Änderungen als auch jene der falschen Alarme signifikant reduziert wird.

1 Introduction

In many developed countries peri-urban areas are undergoing major transformations (Busck et al. 2006). These areas are under a considerable urban pressure that often entails their fast degradation and the abandonment of agriculture for a more profitable use of the land (Allen 2003, Huang et al. 2009). The high dynamics of peri-urban areas produce con-

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tinuous changes of land cover and land use and, consequently, cartographic information is quickly outdated. Detailed and up-to-date cartographic and geographic information is needed for adequate urban management and planning.

Although urban growth has been traditionally monitored by using pixel-based classification techniques (Del Frate et al. 2005, Yuan et al. 2005, Zhou et al. 2008a) or standard change detection methodologies (Kwon et al. 2006, Xian & Homer 2010), many reliable change detection analyses in urban environments have been performed using object-based approaches. In an object-based approach, image analysis is performed by considering objects instead of pixels. An image object, or simply an object, is a group of pixels with common characteristics according to a segmentation criterion (Blaschke 2010). Several works have been presented using automatic segmentation methodologies applied to urban and peri-urban areas (Zhou et al. 2008b, Doxani et al. 2008, Lu et al. 2010, Myint et al. 2011). The segmentation method employed has a considerable impact on the extraction of descriptive features of objects, since the resultant object shapes and properties will differ depending on the algorithm used and the parameters selected (Hay & Castilla 2006).

Plot-based image analysis is a specific case of object-based image analysis that uses plot boundaries derived from land-use/land-cover (LU/LC) geospatial databases (i.e. cadastre, agricultural inventories). These boundaries enable the definition of semantic properties better than pixel aggregation algorithms. This methodology is suitable for environments such as urban, suburban and peri-urban areas, where landscape units present unambiguous boundaries. Plot-based approaches have also been employed for change detection in forest (Hall & Hay 2003) and in agricultural areas (Raza & Kainz 2002, Walter 2004, Gamanya et al. 2007), since they allow for an easy integration and relation of image-derived change information with LU/LC geospatial databases.

Buildings represent primitive entities of urban areas (Thomson & Béra 2008), and many change detection studies are focused on comparing detection or classification results corresponding to two different epochs (Hyyppä et al. 2007), or comparing the classification results from one date to historical databases (Vosselman et al. 2004, Vu et al. 2004, Rottensteiner 2007, Champion et al. 2010, Matikainen et al. 2010, Bouziani et al. 2010).

This paper evaluates a plot-based approach for change detection in peri-urban areas by comparing classification results obtained for data from two different epochs, taking into consideration a set of descriptive features extracted from high-resolution multispectral imagery. Additionally, contextual features were considered that correspond to two aggregation levels: internal and external. Lastly, the effect of the use of three-dimensional (3D) descriptive features derived from lidar data on the classification and change detection efficiency is evaluated.

2 Study Area and Data

The study area is located in the north of the city of Valencia, Spain (Fig. 1), having approximately 5,372 ha. The region has undergone important changes in LU/LC for the last decade, including the transformation and urbanisation of large agricultural areas formerly covered by orchards and horticulture crops, and the removal of some industrial and agricultural structures.

Fig. 1: Location of the study area in the north of the city of Valencia.

The objects were defined using the plot boundaries derived from cadastral maps produced by the Spanish General Directorate for Cadastre (Dirección General de Catastro), with a scale of 1:1,000 in urban areas and 1:2,000 in rural areas.

High-resolution multispectral imagery and lidar data were available for both epochs. For the first epoch, QuickBird imagery acquired in February 2004 was available, with 11 bits/pixel radiometric resolution and four spectral bands (visible and near infrared). The multispectral and panchromatic bands were merged using the substitution method based on principal components transformation, obtaining a final spatial resolution of 0.6 m/pixel. The image was georeferenced and orthorectified. Lidar data were acquired in December 2003 by an ALTM-2033 sensor, and a digital surface model (DSM) having a grid size of 1 m was computed. In addition, a manually edited digital terrain model (DTM) was available. The normalised digital surface model (nDSM) was generated as the difference between the DSM and the DTM.

Additional aerial images were acquired in August 2008 in the framework of the Spanish National Plan of Aerial Orthophotography (PNOA), with 0.5 m/pixel spatial resolution, 8 bits/pixel radiometric resolution and four spectral bands in the visible and near infrared domains. These images were orthorectified and georeferenced. Panchromatic and multispectral bands were merged, and mosaicking and radiometric adjustments were applied as a part of the PNOA programme. Lidar data were acquired in September 2009 using a RIEGL LMS-Q680 sensor with a nominal density of 0.5 points/m^2. The DTM was computed by means of the iterative algorithm described by Estornell et al. (2011) that selects minimum elevation points and eliminates points belonging to above-ground elements such as vegetation or buildings.

3 Methodology

Land use classification and change detection were carried out according to the following steps: class definition, sample selection, feature extraction, object classification at both epochs, change detection, and evaluation. A plot-based image classification approach was used, where the objects were defined by the cartographic boundaries of the plots in the cadastral database. The objects were exhaustively described by image-based features, geometrical features describing the shape of each object, and contextual features. Contextual features were defined at two levels: internal and external. Urban change detection – concerning building construction, destruction or use alteration – was performed by comparing the class assigned to each plot at both epochs.

3.1. *Definition of Classes and Sample Selection*

The definition of land-use classes was based on the land cover catalogue of the Land Cover and Land Use Information System of Spain (SIOSE). This database, corresponding to a scale of 1:25,000, was created to homogenize former LU/LC national databases. Based on this catalogue seven classes were defined, and some of them were subdivided into more specific classes for classification purposes. Thus, four building-related classes were defined: *historical*, *planned urban* (subdivided in *closed urban* and *open urban*), *industrial*, and *suburban housing* (consisting of *semidetached housing* and *detached housing*). The rest of the classes were *arable land* and *croplands* (internally divided into *cropland* and *arable land*, depending of the presence of vegetation), *citrus orchard*, and *bare soil*. Fig. 2 shows examples of the classes.

Training samples were collected by assigning classes to objects (cadastral plots) by visual photointerpretation, applying two main criteria: the representativeness of samples selected per class; and the homogeneity of the spatial distribution of samples in the study area. A restricted randomization scheme (Chatfield 1991) was applied consisting of a random sample selection followed by a monitored sample reallocation and selection in order to maintain a minimum number of samples per class, to obtain a representative sample of each class, and to represent the changes in the area. As a result, 1458 training samples were selected (see sample number distribution for both ep-

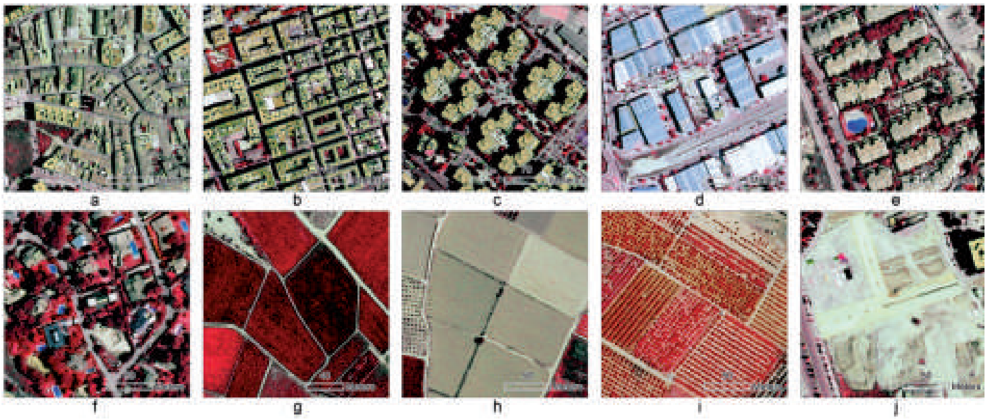

Fig. 2: Examples of the classes defined: historical (a), closed urban (b), open urban (c), industrial (d), semidetached housing (e), detached housing (f), cropland (g), arable land (h), citrus orchard (i), and bare soil (j).

ochs in Tab. 1). A total of 128 objects (8.8 %) of the samples corresponded to urban changes, concerning building construction, destruction, or use change.

3.2. *Feature Extraction*

Descriptive features were extracted attending to three different object aggregation levels: object-based, related to internal context and related to external context (Fig. 3). Object-based features describe the properties of each object (plot) considered as a single unit. They were computed using the object-based feature extraction software FETEX 2.0 (Ruiz et al. 2011). These descriptive features provide information about spectral, textural, geometrical, and 3D properties. Spectral features inform, through the intensity values of the pixels contained in the plots, about the objects' overall spectral behaviour in the different spectral bands used. Mean, standard deviation, as well as minimum and maximum of the intensity values of the pixels for all available bands and an NDVI image were computed for each object (NDVI = normalized difference vegetation index). Texture features quantify the spatial distribution of the intensity values in the analysed objects. The following descriptive features were derived: histogram kurtosis and skewness, descriptors derived from the grey level co-occurrence matrix (GLCM) proposed by Haralick et al. (1973), edgeness factor (Sutton & Hall 1972), and semivariogram-based descriptive features (Balaguer et al. 2010). Three-dimensional features were derived from the nDSM computed from lidar data, each object being characterised by the mean, standard deviation, and maximum values of the heights. Geometrical features describing the dimensions of the objects and their contour complexity were computed: area, perimeter, compactness (Bogaert et al. 2000), shape index and fractal dimension (Krummel et al. 1987, McGarigal & Marks 1995).

Some of the context-based features were based on the area covered by buildings and vegetation inside each object, since this distri-

Tab. 1: Number of samples per class used in both dates.

Classes	Dates	
	2004	2008
Historical	213	213
Urban	234	298
Industrial	105	98
Suburban housing	222	256
Arable land and croplands	277	259
Citrus crop	235	182
Bare soil	172	152
Total	1458	1458

bution is strongly related to the different urban typologies. Building and vegetation masks were obtained using an automatic building detection technique consisting of applying a multiple-threshold based approach, as described in Hermosilla et al. (2011). Buildings and vegetation correspond to the sub-objects inside the plots.

Internal-context features describe an object by characterising the internal sub-objects of the plots. Both 2D and 3D features describing the buildings inside each object were computed. The 2D features consist of the built-up area and the percentage of built-up areas in an object. The latter feature – usually referred to as building coverage ratio (BCR) or sealed surface (Yoshida & Omae 2005, Van de Voorde et al. 2009, Yu et al. 2010) – is computed as described in (1):

$$BCR = \frac{A_{Building}}{A_{Object}} \cdot 100 \qquad (1)$$

where $A_{Building}$ is the built-up area, and A_{Object} is the area of the considered object. Buildings were also characterised by a set of 3D features describing their heights, using the mean, standard deviation, and maximum values from the nDSM. Similarly to (1), the percentage of surface covered by vegetation within an object was defined, and additionally a set of statistical descriptors of height and status of vegetation sub-objects (mean and standard deviation of nDSM and NDVI, extracted only from groups of vegetation pixel) was computed.

Due to the hierarchical structure of urban landscapes, the analysis and exploration of their various aggregation levels result in a precise analysis of the relations of objects (Bruzzone & Carlin 2006). Features based on external context provide information about the properties of the urban blocks. An urban block is the area surrounded by public roads or streets and it may be subdivided into any number of plots. In the Spanish urban cadastral maps, streets are not represented by polygons. This enables to delimit the urban blocks by iteratively merging adjacent plots. Urban blocks significantly determine the appearance of urban environments, influencing spatial experience and defining local particularities related to a spatial identity (Laskari

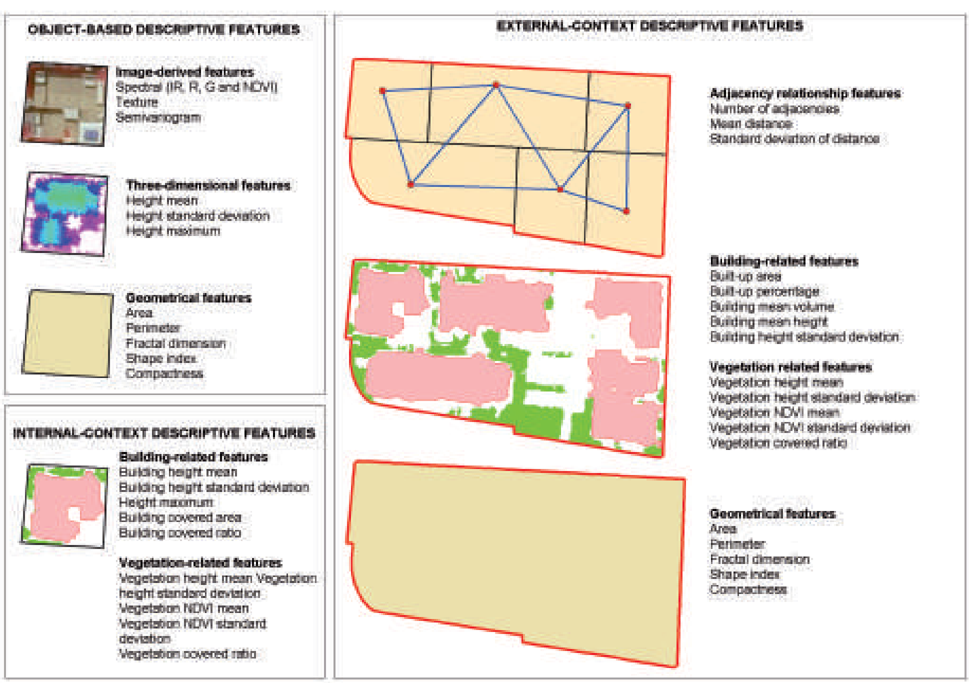

Fig. 3: List and graphic examples of the features computed.

et al. 2008). Urban block entities have been commonly employed in urban environments to define a higher hierarchical context (Bauer & Steinnocher 2001, Herold et al. 2003, Wijnant & Steenberghen 2004, Novack et al. 2010, Huck et al. 2011). Two-stage approximation methods are frequently employed. Initially, the main land-cover types are detected and this information is afterwards analysed in the spatial context defined by the urban blocks to determine land use. Hermosilla et al. (2012) showed that the specific addition of external context features derived from urban blocks increases the classification accuracy of different typologies of urban plots. Applying this methodology, all the plots contained in the same urban block are described with the same external context features. Thus, external context is described by considering the spatial relations of adjacent objects by means of building-based, vegetation-based, geometrical and adjacency features. Adjacency between objects was characterised based on the graph theory (Laurini & Thompson 1992) by using the number of neighbours with surrounding objects, as well as the mean and standard deviations of the centroid distances between adjacent objects. The shape, size, and number of buildings per block are often related to their socio-economic function and determine the area and volume for an urban block. Therefore, the land use of an urban block may be indicated by the quantitative observations related to the buildings present in it (Yoshida & Omae 2005). Thus, urban blocks were also characterised by the built-up area and the built-up percentage. The height distribution of the buildings contained in an urban block was described using the height mean and standard deviation values obtained from the nDSM. Features related to the volumetric information of buildings were also considered. Thus, the mean volume was computed as the total volume of buildings divided by the number of buildings contained in the block. In a similar manner to the internal context features, vegetation distribution was characterised using the vegetation cover ratio, as well as the mean and standard deviation values of the nDSM and NDVI obtained only from the vegetation area masked within the super-object. Finally, the geometrical properties of the urban blocks were described using the features area, perimeter, compactness, shape index, and fractal dimension.

3.3. *Classification, Accuracy Assessment and Change Detection*

In order to evaluate and quantify the effect of the 3D features in the change detection process, two classifications were performed per epoch: with and without using lidar-derived features. Classification was carried out using decision trees constructed with the C5.0 algorithm (Quinlan 1993), combined with the boosting technique. This algorithm divides the sample set by using mutually exclusive conditions, until homogeneous subgroups are generated, i.e., all the elements in a subgroup belong to the same class, or a stopping condition is satisfied. The stopping condition defined in this work is the minimum number of training cases that must follow each node. It was fixed to 5 cases, constraining the degree to which the initial tree fits the training data.

In order to maximize the efficiency of the number of available samples, the accuracy of the classification was assessed using leave-one-out cross-validation. This method uses a single observation from the original sample set as validation data, and the remaining observations as training data, iterating until each observation in the sample set is used for validation once. The evaluation of the classification was based on the analysis of the confusion matrix, which compares the class assigned to each sample to the reference class obtained by photointerpretation. From the confusion matrix, the user's and producer's accuracies per class were computed, measuring the commission and omission errors, respectively (Congalton 1991).

Changes were detected by comparing the classes assigned to each plot in the classifications of both epochs. The change detection process was focused on urban changes concerning building construction, destruction or use change. Changes produced between agricultural classes were not considered in this study. Although many land-use transitions are theoretically possible, there are limitations by law and by nature which may

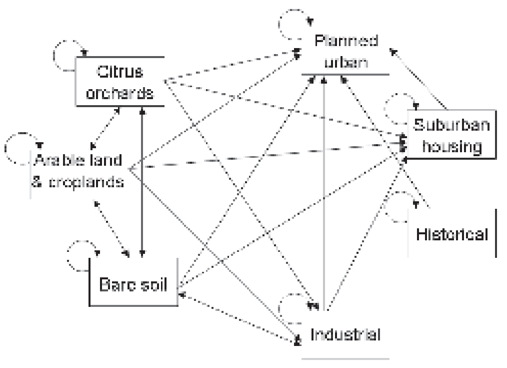

Fig. 4: Land-use transition diagram, showing the possible changes and hiding the restricted land-use transitions.

be used to improve the change detection process (Pakzad 2002). Following these criteria, a knowledge-based land-use transition diagram was designed to formulate the possible land-use changes that are likely to occur in the study area (Fig. 4), restricting unlikely land-use changes. Therefore, when a change that does not fulfil the land-use transition diagram is detected, it is directly removed and considered as no change. These unlikely transitions would necessarily require the revision by a human operator before being fully accepted or rejected in a LU/LC geospatial database updating process.

The LU/LC differences found between the classification results of both epochs enable the detection of the actual LU/LC changes occurring in the territory, but also reveal classification errors. The result of the change detection process is shown in the matrix of Tab. 2. The change detection efficiency is defined by adding the correctly detected changes to the correctly detected unchanged objects. Detectable errors are given when unchanged plots are wrongly detected as changed, whereas undetectable errors are produced when plots where changes occurred are detected as unchanged. The combination of detected changes and detectable errors composes the number of plots that would be manually reviewed in an updating process.

Tab. 2: Distribution of cases and errors in the change detection assessment.

		Classification	
		Unchanged	Changed
Reference	Unchanged	**Coincidences**	**Detectable errors**
	Changed	**Undetectable errors**	**Detected changes**

4 Results and Discussion

Classification overall accuracy values obtained for both epochs with and without considering 3D data are shown in Tab. 3. The classification performance without considering lidar data is approximately 90 %, while the subsequent addition of 3D descriptors results in an increase of the accuracy of about 5 %.

Analyzing the specific per-class accuracy values shown in Fig. 5a, the *bare soil* class shows the lowest user's and producer's accuracies without considering 3D data. This can be attributed to the high variability of this class, which includes a diversity of agricultural and non-agricultural plots, such as abandoned agricultural or un-built areas. In the same sense, the class *industrial* also has low accuracy values, especially when compared to the other building-related classes. Due to the similar spectral and textural properties of *industrial* and *bare soil*, these classes were occasionally confused, notably affecting their respective errors. For the rest of the classes, high user's and producer's accuracies were obtained for both epochs.

Although the inclusion of 3D information from lidar data has a limited effect on the overall accuracy (about 5 %), some classes noticeably improve their user's and producer's accuracies (Fig. 5b). Especially remarkable is

Tab. 3: Classification overall accuracy values achieved for both epochs with and without considering 3D features, for a total of seven LU/LC classes (as in Fig. 5).

Date	Overall accuracy	
	Without lidar	With lidar
2004	90.3 %	94.5 %
2008	89.2 %	94.5 %

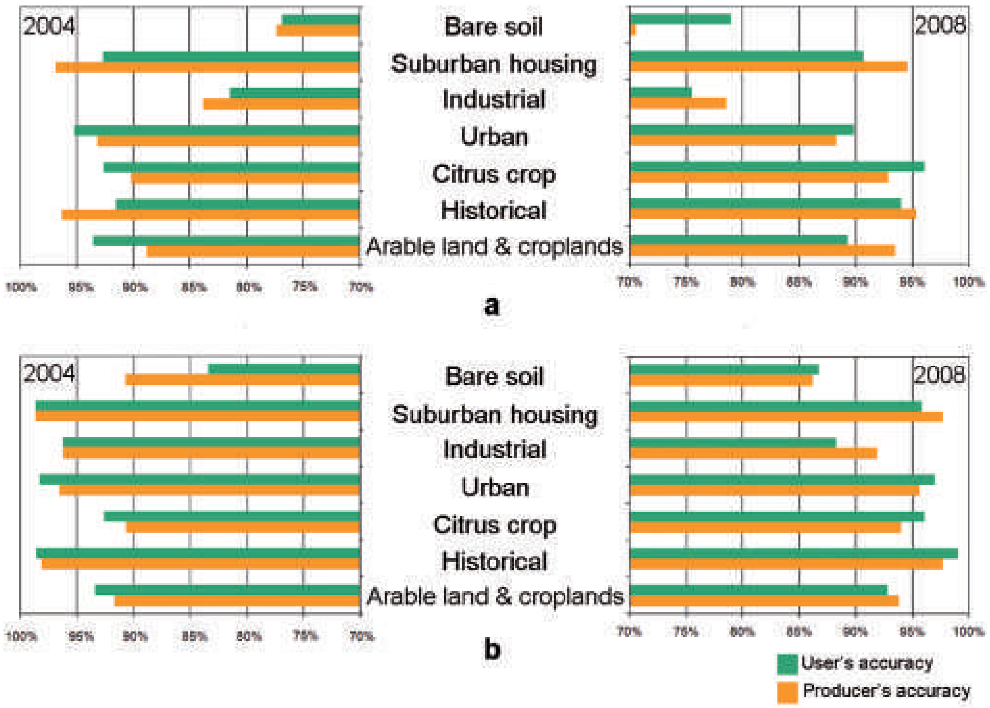

Fig. 5: Per-class user's and producer's accuracies in both dates without (a) and with three-dimensional data (b).

Tab. 4: Change detection assessment concerning urban-related changes considering the land-use transition diagram shown in Fig. 4.

		Without lidar data		With lidar data	
		Unchanged	Changed	Unchanged	Changed
Reference	Unchanged	**87.8 %**	**3.7 %**	**90.6 %**	**0.9 %**
	Changed	**1.9 %**	**6.7 %**	**0.4 %**	**8.1 %**

the case of class *industrial*, where misclassifications are significantly reduced when using 3D information. *Bare soil* has a more modest improvement of the accuracy values, due to confusion with *arable land* and *croplands*. The accuracies of *historical*, *urban* and *suburban housing* classes increase when 3D information is added, even though their values were already particularly high, producing more balanced user's and producer's accuracies per class. Finally, *citrus* accuracies do not increase when 3D information is added, probably because of the correct characterization provided by the texture and semivariogram-based features used.

The change detection results are shown in Tab. 4. When 3D data are not considered, the detection efficiency is 94.5 %, obtained as a result of adding correctly detected changes plus correctly detected unchanged objects. The percentage of detectable errors is 3.7 %, and the percentage of plots that would be manually revised to be confirmed as actual changes is 10.4 %. There is a significant rate of undetectable errors (1.9 %), mostly due to misclassifications of *bare soil* for one of the epochs.

Additionally, buildings under construction, which were considered as *bare soil* samples, are finally classified as one of the building-related classes. Moreover, the shadows of neighbour buildings affect the classification negatively, increasing the number of undetectable errors.

When 3D features derived from lidar data are used, both detectable and undetectable errors are reduced by approximately 75 %, enabling the change detection efficiency to achieve up to 98.7 %. Thus, the number of plots to be manually reviewed using photointerpretation and field visits would decrease from 10.4 % to 9 %, mostly corresponding to plots with actual changes. Height information has been shown to be critical to satisfactorily discriminate between building typologies and buildings from *bare soil*, correcting most of the detectable and undetectable errors, and improving the performance of the change detection process. Fig. 6 shows an image detail of the study area and the change detection represented for the selected samples with and without considering 3D data, where the significant reduction of undetectable errors and the increase of detected changes are perceptible.

For comparative purposes, Tab. 5 shows the change detection assessment results when the land-use transition diagram (Fig. 4) is not considered. Contrasting these results with the results presented in Tab. 4 it is noticeable that the restriction of unlikely changes enables to reduce the detectable errors by 35 % to 45 % with and without lidar data, respectively, and to increase the coincidences. Undetectable errors practically remain invariable, and the amount of detected changes is slightly reduced.

5 Conclusions

In this paper, an object-based classification methodology for building change detection in peri-urban areas is presented and evaluated. Objects are defined by using cadastral plot boundaries, allowing the direct relation of the information derived from imagery to the information present in LU/LC databases. A comprehensive set of descriptive features

Fig. 6: Detail of study area in colour infrared composition for years 2004 (a) and 2008 (b); and maps showing change detection results of samples without considering (c) and considering (d) 3D features.

Tab. 5: Change detection assessment concerning urban-related changes without considering the land-use transition diagram.

		Without lidar data		With lidar data	
		Unchanged	Changed	Unchanged	Changed
Reference	Unchanged	**84.8 %**	**6.7 %**	**89.8 %**	**1.4 %**
	Changed	**1.9 %**	**6.9 %**	**0.5 %**	**8.3 %**

characterising each object was extracted at both epochs (2004 and 2008). These features described the particular properties of the objects – spectral, textural, geometrical, and three-dimensional –, and their context at two levels, internal – related to those elements inside the plot –, and external – related to the common properties of plots sharing a superior aggregation level. The specific effect of 3D features on the efficiency of the classification and change detection processes has also been evaluated. In our experiments, this information was derived from lidar data, however, similar results can be expected when using stereo images as the source of 3D information.

The results showed that, although 3D information only produces a slight improvement of the overall classification accuracy, it notably increases the specific accuracy values of some classes, allowing for a particularly enhanced discrimination of building typologies and bare soil. In the change detection process, the use of 3D information produces a notable reduction of both detectable and undetectable errors, remarkably diminishing the number of plots that would be reviewed by human operators in a changing detection procedure, in order to confirm the veracity of the detected changes. As a consequence, the overall change detection efficiency considerably improves (from 94.5 % to 98.7 %).

Although this change detection methodology has been tested in a peri-urban area, it could be adapted for being applied to different scenarios, by selecting a specific set of representative samples of those areas and their particular object class catalogues. In future work, the reduction of sample collection tasks could be further studied by using only samples collected on the initial date, or even directly obtained from the original LU/LC geospatial database to be updated, assuming that the proportion of changes is low compared to the unchanged areas.

In summary a methodology based on automated descriptive feature extraction from 3D data, high spatial resolution imagery and context information using an object-based approach is presented, which may be used to increase the efficiency and reduce photointerpretation and field tasks in many LU/LC geospatial database change detection procedures.

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