Land-use Mapping of Valencia City Area from Aerial Images and LiDAR Data

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Abstract - **Land-use classification of urban environments is usually limited by the number and complexity of the considered classes and the capability of the selected methodology for the efficient discrimination of these classes. Thus, this paper analyses and assesses the performance of a contextual object-based classification methodology in urban environments considering a comprehensive land-use legend, including several complex urban land-uses** –*historical buildings, urban buildings, open urban buildings, semi-detached houses, detached houses, industrial/warehouse buildings, religious buildings, commercial buildings, public buildings, gardens and parks*–**, and agricultural classes** –*arable lands, citrus orchards, irrigated crops, carob-trees orchards, rice crops, forest, greenhouses*–**. Object-based approach was achieved by using cadastral plot limits for object definition. An exhaustive set of object-based descriptive features were computed informing about the spectral, texture, structural, geometrical, three-dimensional and contextual properties. Classification was performed by means of decision trees algorithm combined with boosting multi-classifier. The overall accuracy reached classifying the urban area of Valencia reached 84.8%, which is a significantly high value when considering a large number of complex urban classes.**

Keywords - Object-based classification; high spatial resolution imagery; LiDAR; urban areas; mapping

I. INTRODUCTION

Urban areas are dynamic and changing environments both in land covers and land uses. This entails that cartographical information referred to cities becomes rapidly obsolete. An efficient urban management requires an accurate and up-to-date knowledge about the land cover situation and evolution in urban and surrounding areas. This enables a wide range of applications including physical planning –viewshed analysis, impact assessment, environmental issues–; economic planning –accessibility, location analysis, transport studies –; social planning –population and other socio-demographic distributions, urban structures–; or forecasting models –diffusion and urban growth– [1].

Traditionally the process of creating land-use/land-cover (LU/LC) maps of urban areas involves field visits and classic photo-interpretation techniques. These methodologies are expensive, time consuming, and also subjective, requiring skilled operators. Remotely sensed data and digital image processing techniques help to reduce the volume of information that needs to be manually interpreted, satisfying current demands for continuously precise data for an automatic, systematic and efficient territorial and urban management.

Image classification processes to produce land-cover maps in urban areas can be considered straightforward when compared to the complex process of deriving information on urban land use [2], since the land use is an abstract concept that represents a socio-economic criterion referring to the dominant activity of a place, and may include category subdivisions with differing levels of detail [3]. The definition of an extensive land-use legend enables a deeper and better knowledge of the "*actuality*" of the urban scenario, but it also entails additional difficulties in the discrimination of classes, since a large number of complex land-use classes generally lead to reach limited results.

When considering high spatial resolution imagery, object-based approaches are generally used to classify land uses in urban areas, where objects can be defined using automatic segmentation methods or –most commonly– by means of urban blocks or plot limits derived from existing cartography. Moreover, plot-based image classification allows to directly relate the information extracted from the remotely sensed data to LU/LC geo-spatial database objects.

Reference [4] considered eleven complex land use/land cover classes, but without assessing the quality of the methodology. Reference [5] obtained discrete accuracy values when classifying eight different urban land uses; [6] obtained an accurate result considering five classes of urban development, and [7] differenced six land uses reaching medium accuracy values. The definition of a contextual framework through a multi-resolution analysis permits to increase the classification accuracy of urban environments considering several classes, as demonstrated in [8].

The addition of three-dimensional information using LiDAR (Light Detection and Ranging) data allows to increase the number of classes in the legend, and to reach higher accuracy values. Therefore, [9] obtained high accuracies when classifying a suburban area distinguishing between land uses and other additional land-cover classes to fully complete the area. Reference [10] considered nine different complex urban land uses reaching unbalanced

accuracies due to the extreme differences in the number of per-class samples. In the same sense, [11] defined ten land use classes to completely classify the city of Brussels including different housing typologies, but no accuracy assessment was presented. Combining three-dimensional information and context-based descriptive features [12] attained accurate results distinguishing between five complex urban classes plus two agricultural classes.

The aim of this paper is to analyse and assess the performance of a contextual object-based classification methodology using high spatial resolution multispectral imagery and LiDAR data when classifying urban environments considering a comprehensive land-use legend containing a large number of classes, including several complex urban land-uses and agricultural classes. This paper is organized as follows. Section 2 describes the area where the study was performed and the data employed. Section 3 describes the object-based classification methodology and the accuracy assessment followed. Section 4 reports and analyses the results. Section 5 presents the conclusions.

II.   STUDY AREA AND DATA

This study was performed in the administrative area of the municipalities of Valencia and Paterna, located in the Mediterranean coast of Spain (see Figure 1.). Valencia is the largest city and capital of the Valencian Community, having 809,267 inhabitants in 2010 [13]. Valencia is a compact city composed by a central historical area surrounded by buildings of different typologies, depending on the date of construction. The northern area is covered by citrus orchards and horticulture crops, while the natural park of *l'Albufera* presents extensive rice crops and forests, and is located in the southern zone. Paterna is a contiguous municipality located in the metropolitan area of Valencia with a population of about 65,921 inhabitants [13], presenting large extensions of low-density suburban housing and several industrial and commercial areas.

The limits of the plots were provided by vectorial cadastral cartography in shapefile format, produced by the Spanish General Directorate for Cadastre (*Dirección General de Catastro*). This cartography presents a scale of 1:1,000 in urban areas and 1:2,000 in rural areas.
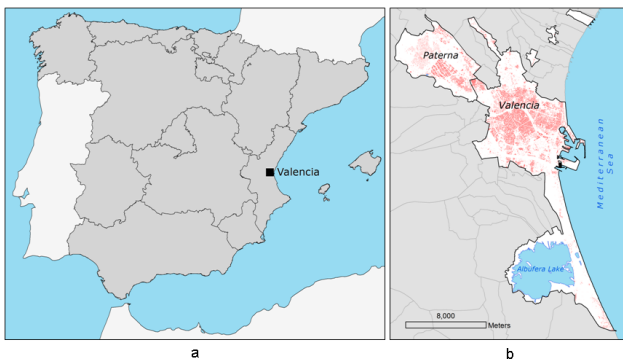

Figure 1.   Location of Valencia in Spain (a) and representation of the two municipalities considered in this study: Valencia and Paterna (b).
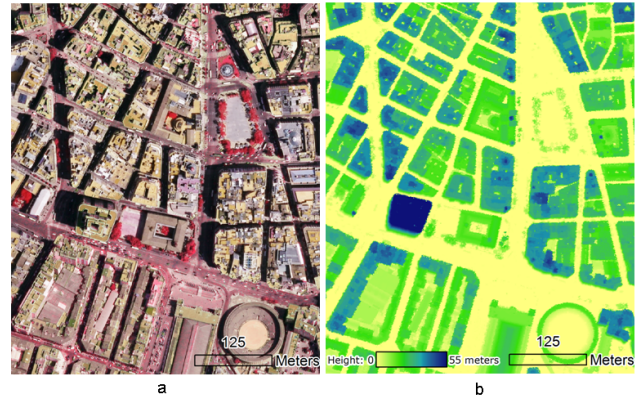

Figure 2.   Detail of a high spatial resolution image in colour infrarred composition (a), and digital surface model created with the LiDAR data (b), depicting a zone in the urban centre of Valencia.

Imagery and LiDAR data were acquired in the frame of the Spanish National Plan of Aerial Orthophotography (PNOA). The images were collected in August 2008 and they have 0.5 m/pixel spatial resolution, 8 bits radiometric resolution and four spectral bands: red, green, blue and near infrared. The images are distributed orthorectified and georreferenced, panchromatic and multispectral bands fused, mosaicking and radiometric adjustments applied, as part of the PNOA project. An example of the multispectral imagery employed is show in Figure 2. a.

LiDAR data were acquired in September 2009 with a nominal density of 0.5 points/m^2 using a RIEGL LMS-Q680 laser scanner device. A normalised digital surface model (nDSM), i.e., the difference between the digital surface model (DSM) and the digital terrain model (DTM), representing the physical heights of the elements present over the terrain, was generated from LiDAR data. The DTM was computed by means of an algorithm that iteratively selects minimum elevation points and eliminates points belonging to any aboveground elements, such as vegetation or buildings [14]. Figure 2. b shows an example of the nDSM of the centre of Valencia.

III.   METHODOLOGY

Land use classification was carried out in five steps: class definition; sample selection; descriptive feature extraction; object classification; and evaluation. Object definition was done using cadastral plot limits, and these objects were exhaustively described by different types of image derived features: three-dimensional features computed from LiDAR data, structural features derived from the semivariogram graph, geometrical features, and context-based features. Classification was performed by means of C5.0 decision tree algorithm combined with the boosting technique. The classification accuracy was assessed by analyzing the confusion matrix.

A.   Definition of classes

Land-use class definition was performed based on the specifications of the Land Cover and Land Use Information

System of Spain (SIOSE) database. The legend was composed of seventeen classes, discriminating between ten urban land use classes and seven agricultural classes. The samples (plots) were collected by using a restricted randomization scheme [15], consisting on a random sampling selection, to ensure the spatial homogeneity of the samples, followed by a redistribution and addition of some samples in order to maintain the appropriate number of samples according to the variability into each class. The urban classes defined were: *historical buildings* (264 samples), *urban buildings* (225), *open urban buildings* (142), *semi-detached houses* (90), *detached houses* (153), *industrial/warehouse buildings* (139), *religious buildings* (30), *commercial buildings* (24), *public buildings* (173), including schools, universities, sport facilities and civic and governmental buildings, and *gardens and parks* (57). The agricultural classes defined were: *arable lands* (92), *citrus orchards* (141), *irrigated crops* (81), *carob-trees orchards* (63), *rice crops* (74), *forest* (39) and *greenhouses* (43). Examples of the defined classes in colour infrared composition are shown in Figure 3.

B. Object-based descriptive feature extraction

Object-based features describe each object as a single entity based on several aspects that reflect the variety of information used, and these were computed using the object-based image analysis software FETEX 2.0 [16]. The computed features provided information regarding spectral, texture, structural, geometrical, three-dimensional and context based properties.

Spectral features provide information about the intensity values of objects in the different spectral bands. Statistical descriptors were computed for each plot in the available bands and in the NDVI image. Texture features quantify the spatial distribution of the intensity values in the analysed objects. Texture was characterized by means of kurtosis and skewness, the descriptors derived from the grey level co-occurrence matrix proposed by [17], and the edgeness factor [18]. Structural features provide information of the spatial arrangement of different elements in the object, in terms of randomness, and these were derived from the semivariogram graph [19] [20]. Geometrical features describe the dimensions of the plots and their contour complexity. Three-dimensional features were derived from the nDSM computed using LiDAR data.

Context was described by characterizing the higher and lower aggregation levels of the plots. Thus, internal context features describe an object attending to the land cover types of the elements contained within the object (denoted as sub-objects). In this case, buildings and vegetation, which were extracted by applying a multiple-threshold based approach, as described in [21]. External context is defined characterizing each object by considering the common properties of adjacent objects that combined create an aggregation higher in hierarchy than plot level, such as urban blocks in urban areas. This context is described by means of specific building-based, vegetation-based, geometrical and adjacency features [12].

Figure 3. Examples of the considered classes: *historical buildings* (a), *urban buildings* (b), *open urban buildings* (c), *semi-detached houses* (d), *detached houses* (e), *industrial/warehouse buildings* (f), *religious buildings* (g), *commercial buildings* (h), *public buildings* (i), *gardens and parks* (j), *arable lands* (k), *citrus orchards* (l), *irrigated crops* (m), *carob-trees orchards* (n), *forest* (o), *rice crops* (p), and *greenhouses* (q).

C. Classification and accuracy assesment

Classification was performed using decision trees constructed with the C5.0 algorithm [22] combined with the boosting technique. The process of building a decision tree begins by dividing the collection of training samples using mutually exclusive conditions. Each of these sample subgroups is iteratively divided by using the gain ratio as a splitting criterion until the newly generated subgroups are

homogeneous, i.e., all the elements in a subgroup belong to the same class or a stopping condition is fulfilled. The gain ratio criterion employs information theory to estimate the size of the sub-trees for each possible attribute and selects the attribute with the highest expected information gain. The algorithm is based on searching partitions to obtain purer data subgroups, which are less mixed than the previous group from where they were derived. This is iterated until the original data set is divided into homogeneous subgroups.

The evaluation of the classification was based on the analysis of the confusion matrix [23], which compares the class assigned to each evaluation sample with the reference information, defined by photointerpretation. The overall accuracy of the classification and the kappa index were computed, as well as the producer's and user's accuracies for each class, that respectively expose the classification errors of omission and commission. In order to maximize the efficiency of the evaluation process, in terms of the number of samples, the *leave-one-out* cross-validation technique was employed. This method uses a single observation from the original sample set as validation data, using the remainder observations as training data. This is iterated 1590 times, until each observation in the sample set is used once as validation data.

IV. RESULTS AND DISCUSSION

The cartographic representation of the classification, depicting the centre of Valencia is shown in Figure 6. where the different urban structures are distinguished: historical centre, planned areas, industrial, civic and transportation facilities, parks, etc. The overall accuracy of the classification was **84.8**%, and the kappa coefficient **0.83**. These are sound results, especially considering the large number of classes defined (17) and the structural similarities between some classes, e.g., *semi-detached houses* and *detached houses*.

Analysing the per-class user's and producer's accuracies (see Figure 4.) it is remarkable the high performance achieved for agricultural classes, presenting values higher than 90% in the case of *arable lands*, *citrus orchards*, *carob-trees orchards*, *rice crops*, *forest*, and slightly lower for *irrigated crops* (with values around 88% for both accuracies) and the user's accuracy of the class *greenhouse* (84%). Among the urban classes, the lowest accuracies and the most unbalanced values were obtained for classes *commercial buildings* and *religious buildings*. The stu confusion matrix –graphically represented in Figure 5. – shows that *commercial buildings* had a poor performance and presented several misclassifications with *industrial/warehouse* and *public buildings* classes. *Religious buildings* class producer's accuracy reached a very low value (37%) due to the confusion with classes *urban* and *public buildings*. Medium user's and producer's accuracy values (70%) were achieved for *public buildings* and *semi-detached houses*. *Public buildings* presented a high degree of confusion with most of the building-related classes, due to their heterogeneity, and the fact that these buildings usually have significant morphological differences, producing
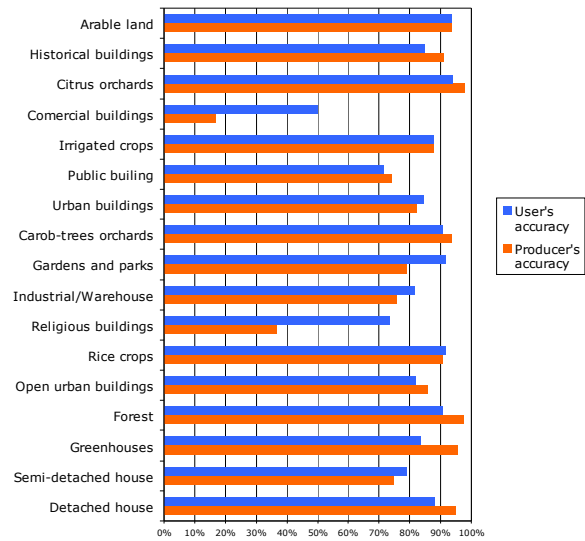

Figure 4. Classification user's and producer's accuracies for each defined class.
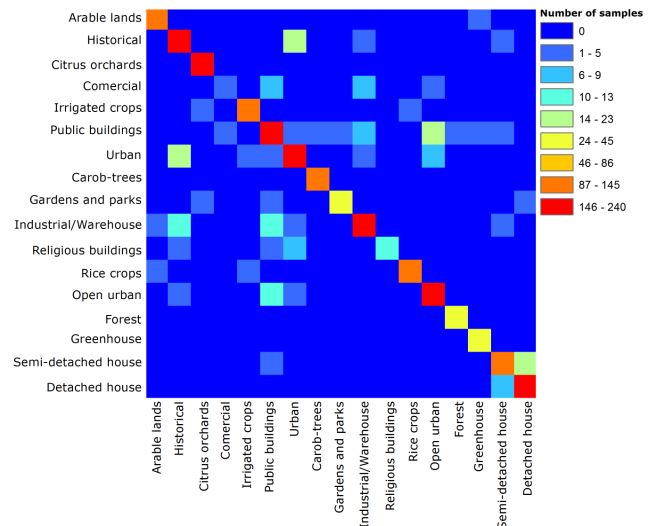

Figure 5. Graphic representation of the confusion matrix of the classification. Rows represent reference class and collums show classified data.

misclassifications. Some particular public building plots containing covered sport facilities were erroneously assigned to *industrial/warehouse buildings* and viceversa. *Semi-detached houses* were especially confused with *detached houses*, due to their obvious structural similarities. *Gardens and parks* presented unbalanced accuracies, due to the misclassification with *citrus orchards* and *public buildings*. Other building-related urban classes achieved better classification performances with slight confusions between them, being especially significant for the pair of classes *historical* and *urban*, as shown in the confusion matrix (Figure 5.).
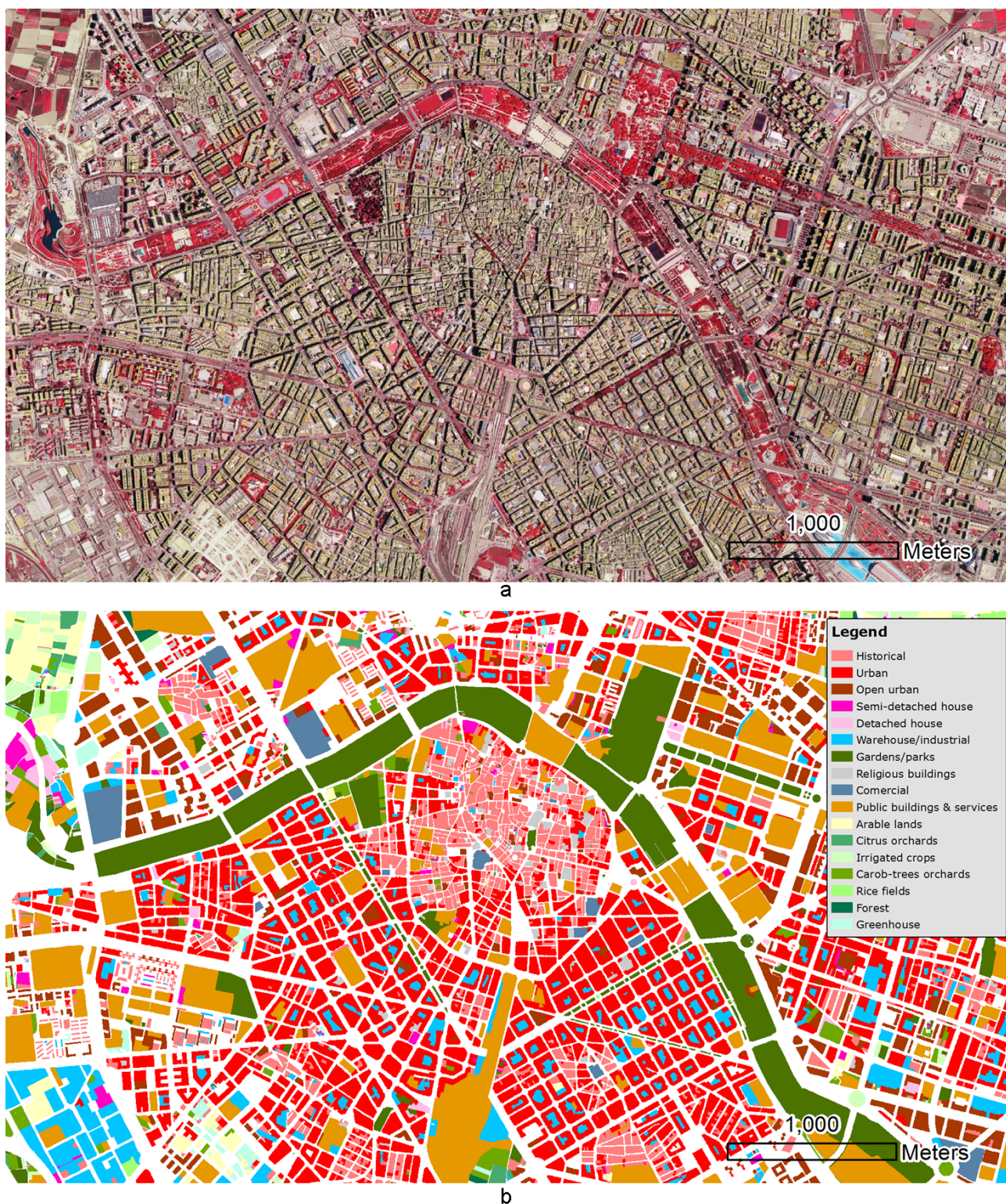
Figure 6.   Thematic map composition showing the classes assigned to each plot of the urban centre of Valencia (a) and colour infrared composition of the same area (b).

V. CONCLUSIONS

In this paper, the performance of a contextual object-based classification methodology in urban environments was analysed and assessed, when considering an exhaustive land-use legend that includes several complex urban land-uses. A set of object descriptive features was extracted to characterise intrinsic properties of the plots –spectral, texture, geometrical, and three-dimensional–, and their context attending to two levels: internal –referred to internal covers in the plot–, and external –related to common properties of plots contained in the same urban block–.

The results showed the high potential of the proposed methodology to correctly and accurately discriminate and assign land use to a large number of different building typologies, and simultaneously a variety of agricultural land uses. Most of the agricultural classes were satisfactorily assigned. In general, urban classes were accurately classified. However, very heterogeneous building typologies concerning commercial, religious and public uses obtained a low performance, since the difficulty found to distinguish these classes from other urban building typologies. Additionally, due to the similarity of some classes, they presented minor mutual misclassifications, for example different typologies of suburban buildings, or planned urban areas and historical areas.

The proposed object-based classification methodology provides new tools that may increase the frequency, efficiency and detail level of urban studies, being useful for systematically mapping cities, urban landscape characterisation, automatic land-use change detection and updating LU/LC geospatial databases.

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