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# Extraction of Buildings from QuickBird Imagery for Municipal Use – the Relevance of Urban Context and Heterogeneity

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**Abstract.** Lisbon is both a historical and modern city having a dynamic landscape, where increasingly diverse urban forms and materials coexist. This complex reality is possibly causing the feature extraction process from imagery to become more challenging. This study tests the semi-automated extraction of buildings from a QuickBird image in urban areas with different characteristics, and explores the impact of the heterogeneity of these features in the extraction process. Spatial metrics are used to characterize types of buildings present in the study areas. Results show that the study areas display different levels of heterogeneity even for the same type of building and suggest that the extraction may be affected by the spatial configuration of target features.

**Keywords.** QuickBird, feature extraction, spatial metrics, Lisbon

## Introduction

A spatial component is associated with the majority of municipal activities, namely in urban planning and management. The high frequency and scope of spatial changes in cities demand ways of expediting the production and updating of large-scale geographic information, as required by Portuguese legislation. For that purpose, current and future very high spatial resolution satellite imagery (VHR), due to their availability, wide coverage, and cost, may be an advantageous alternative to classical data sources and methods, i.e., aerial photography and photogrammetry.

The nature of this recent data source, volume of data, and expanding range of applications has been driving the development of advanced semi-automated geographic object-based image analysis (GEOBIA) [1] methods for efficient feature extraction. There are now several commercial-off-the-shelf software packages which are increasingly user-friendly. Still, to be operationally adopted by municipalities, feature extraction should be reliable, have clear procedures and parameters to facilitate insertion into a mapping work-flow, and conform or approach quality standards typical of large-scale mapping. Therefore bringing GEOBIA approaches into the operational mapping domain remains a challenge and should probably be a 'hot' research topic in the field in addition to the four topics recently listed by Blaschke [2].

At the same time, the overall urban environment is becoming more complex and heterogeneous, possibly turning the feature extraction process more challenging. While much research has focused on developing, adapting and applying these approaches, less attention has been devoted to the interplay of spectral data source (imagery), feature extraction methods, and geographic characteristics of the area under analysis.

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Originating in landscape ecology, spatial metrics can be employed to measure the heterogeneity of landscapes at different spatial scales based on categorical patches or elements. Herold et al. [3] have computed spatial metrics for land-cover objects (including buildings) to analyze and differentiate urban land uses in a coastal area of California, USA.

The work presented in this paper takes place in the context of the exploration of VHR satellite imagery and new methods as an alternative source of geospatial information for large scale mapping to assist urban planning and management in Lisbon, Portugal. The present effort aims at testing the semi-automated extraction of different building types from areas with diverse characteristics, and studying the impact of the heterogeneity of these features and the urban context in the extraction process.

## 1. Study Area and Dataset

Lisbon is both a historical and modern city having a dynamic and complex landscape. Three study areas were selected in different parts of the city, to represent the diversity of urban character. The areas have a square shape and the same size of 64 ha (800 m X 800 m) (Figure 1).

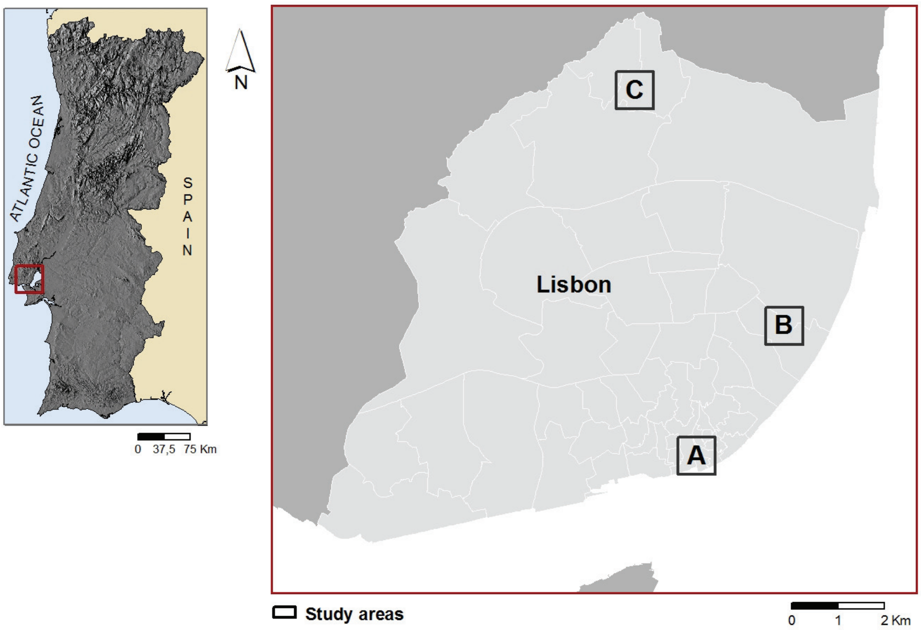


**Figure 1.** Location of the study areas.

Study area A (Baixa) is located in the slow-changing old historical district (i.e., downtown): the street network is dense and most of the area is built-up. Study area B (Madre) is located in the oriental part of the city and has a very heterogeneous land use, including built-up, parks, agriculture and vacant land; buildings' functions range from residential (single and multi-family housing), to industrial, utilities, and schools. Study area C (Alta) is a new residential area under development, with on-going construction of parks, roads, and apartment buildings.

The three study areas are quite distinct, with their current urban morphology and majority of buildings originating in different periods (Table 1).

**Table 1.** Main periods (centuries) determining current urban layout of the study areas.

| Study Area | Urban Morphology | Majority of Buildings |
|---|---|---|
| A-Baixa | $\leq 18^{th}$ | $18^{th}$, $19^{th}$ |
| B-Madre | $\leq 19^{th}$, $20^{th}$ | $20^{th}$ |
| C-Alta | $21^{st}$ | $21^{st}$ |

The spatial database includes spectral, altimetric, and planimetric data sets. A QuickBird (QB) image was acquired in April 14, 2005 with an off-Nadir angle of 12.2º. The image has a spatial resolution of 2.4 m in the multispectral mode and 0.6 m in the panchromatic mode, and a radiometric resolution of 11 bits. Altimetric data included a normalized Digital Surface Model (nDSM) for 2006 obtained from LiDAR with 1 m resolution. Planimetry included a detailed reference map of building outlines and types of roofs produced by an independent interpreter using visual analysis of the imagery and ancillary data.

Pre-processing of data has included orthorrectification and pansharpening of imagery in PCI Geomatica and production of the nDSM grid. All data sets were geometrically corrected to a common projected coordinate system (PT-TM06/ETRS89). Still, there was some mis-registration between the QuickBird and the nDSM data sets on building's roofs due to the significant off-Nadir angle of the image. For more details on this stage see Santos et al. [4].

## 2. Methodology

The approach involved extraction of specific classes of buildings and its quality assessment, computing spatial metrics for each study area and building class, and analyzing the results.

### *2.1. Feature extraction*

Since our goal was to analyze the heterogeneity of building features in the study areas, and satellite imagery capture their roof, a typology of buildings' roofs was defined based on their main material and its tone/color/reflectance, the primary elements in image analysis [5]. The following building classes were defined: 1-Red tile roof, 2- Dark tile roof, 3-Light tin roof, 4-Dark tin roof, 5-Fibrocement roof, 6-White roof, and 7-Other roofs.

Extraction of building classes (polygons) from the imagery was performed using Feature Analyst 4.2 (VLS), as an extension for ArcGIS (ESRI). Feature Analyst (FA) is a *GEOBIA* application that conducts an internal "hidden" segmentation of the image that allows classifying and extracting only those features belonging to the class of interest. Building classes were extracted independently using the pansharpened QuickBird image as main input, and the nDSM as ancillary elevation. Although individual adjacent buildings can be identified visually in the image and used as training areas, due to the combined limitations of extraction algorithms and image spatial resolution, FA can only retrieve building blocks of the same class. Building blocks equal buildings for non-contiguous buildings.

The training parameters that resulted in the best extraction in FA are listed in Table 2. Not all classes were present or significant enough (i.e., having more than 10 features) for extraction in each study area. Extracted features were not generalized or squared up prior to accuracy assessment.

**Table 2.** Parameters used for feature extraction.

| Study Area | Building Class | Training Features | Pattern | Width | Aggregation |
|---|---|---|---|---|---|
| A-Baixa | 1 | 49 | Manhattan | 13 | |
| | 2 | 49 | Manhattan | 13 | 11 |
| | 3 | 4 | Manhattan | 9 | 70 |
| | 5 | 4 | Manhattan | 9 | 70 |
| | 6 | 3 | Manhattan | 11 | 90 |
| B-Madre | 1 | 24 | Manhattan | 5 | 10 |
| | 3 | 1 | Manhattan | 5 | 100 |
| | 4 | 5 | Manhattan | 9 | 70 |
| | 5 | 7 | Manhattan | 5 | 100 |
| | 6 | 2 | Manhattan | 5 | 10 |
| C-Alta | 1 | 7 | Manhattan | 13 | 200 |
| | 5 | 4 | Manhattan | 13 | 200 |
| | 6 | 6 | Manhattan | 9 | 80 |

For assessing the quality of the feature extraction stage, and in the absence of a compatible and updated official map, a reference map of building blocks was created by an independent interpreter using visual analysis and manual digitizing over the pansharpened image. All the discernible buildings were digitized and classified as belonging to one of the seven classes, without limits of size or shape.

Quality assessment was exhaustive (i.e., by census) and conducted independently for each class using ArcGIS 9.3 (ESRI). It was based on analysis of spatial overlap between classified and reference map for each building class, in vector format: percent overall accuracy is obtained by dividing the area of intersection of both datasets by the area of union, while the proportion of non-overlapping features from the reference map stands for error of omission and the proportion of non-overlapping features from the classified map stands for error of commission. Because the extracted datasets for different classes can overlap, an object-based overall accuracy for study areas can be obtained by computing an average among classes weighted by the actual number of features (in reference dataset).

### *2.2. Spatial metrics*

Although some metrics are highly correlated to one another and can be redundant, a large set of spatial metrics (Table 3) was computed as patch-based indices for each building class in the reference dataset in order to characterize the buildings present in the study areas and assemble a database. The metrics are used to quantify the spatial heterogeneity at the building class level, and at the landscape level using overall values for each study area.

Calculating metrics for typologies of building roofs represents a one-level increase in the urban analysis scale when compared with the generic class “buildings” analyzed by Herold et al. [3].

**Table 3.** List of spatial metrics computed.

| Indicator | Acronym | Units |
|---|---|---|
| Number of features | NoF | Number |
| Percentage of features | No % | Percent |
| Feature density | Fdens | no. per ha |
| Percentage of landscape | PL | Percent |
| Mean feature size | AREA MN | $m^2$ |
| Area standard deviation | AREA STD | $m^2$ |
| Shape Index | SI | -- |
| Perimeter-Area Ratio | PAR | m per $m^2$ |
| Fractal Dimension | FD | -- |
| Nearest Neighbor Mean Euclidian Distance | ENN MEAN | m |
| Richness | R | -- |
| Diversity Index | Div | -- |
| Evenness Index | Eve | -- |
| Dominance | D | -- |

The metrics were calculated in ArcGIS 9.3 in vector format for the reference building blocks. The more complex indicators were computed using the V-LATE 1.1 extension tool [6]. Shape Index, Perimeter-Area Ratio and Fractal Dimension give indications about landscape configuration, while Richness, Shannon’s Diversity and Evenness Indices, and Dominance are examples of landscape composition indicators. More details on these metrics can be found in O’Neill et al. [7] and Herold et al. [3].

## 3. Results and discussion

### *3.1. Feature extraction*

In study areas A and B five classes were extracted, while in study area C only three of the four present were extracted. Figure 2 illustrates results of extraction for buildings with tile roofs in study area A.

Results of quality assessment (Table 4) show that accuracies for same building class varied among the study areas. Accuracies were generally low for all classes other than buildings with tile roofs, and lowest for buildings with white roofs, especially in study area A. Some roof types, while being semantically different for a human interpreter, are not sufficiently distinct spatially and spectrally for an automated classification. Most roof types are spectrally similar to patches of urban features such as roads and bare ground [3], and there is not sufficient contrast between the object and its background, a requirement for its correct detection [8].


**Figure 2.** Example of extracted features in study area A-Baixa.

The best extraction of buildings with tile roofs was obtained in study area C, where their boundaries are more regular (lower FD) and their ENN MEAN is greatest.

**Table 4.** Results of quality assessment.

| Study Area | Bldg. Class | Overall Accuracy | Error Omission | Error Commission |
|---|---|---|---|---|
| A-Baixa | 1 | 70,1 | 26,1 | 6,8 |
| | 2 | 70,1 | 26,1 | 6,8 |
| | 3 | 36,8 | 40,9 | 50,6 |
| | 5 | 26 | 70,7 | 31,2 |
| | 6 | 19,2 | 56,3 | 74,5 |
| B-Madre | 1 | 73,2 | 22,1 | 7,5 |
| | 3 | 43,5 | 56,5 | 4,8 |
| | 4 | 46,8 | 32,6 | 39,6 |
| | 5 | 46,3 | 51,6 | 10,2 |
| | 6 | 67,9 | 27,1 | 9,2 |
| C-Alta | 1 | 83,6 | 6,0 | 11,7 |
| | 5 | 46,8 | 6,5 | 51,6 |
| | 6 | 29,9 | 32,2 | 65,1 |

Buildings are generally undermapped in study area B (higher omission error), and overmapped in study area C (higher commission error). In study areas A and B some buildings are partially covered by trees and in B there are shipping containers that are misclassified as buildings.

### *3.2. Spatial metrics*

**Table 5.** Spatial metrics for each building class by study area.

| Bldg. Class | Study Area | NoF | Fdens | PL | Area MN | Area STD | SI | FD | ENN MEAN |
|---|---|---|---|---|---|---|---|---|---|
| Red tile roof | A-Baixa | 181 | 2,8 | 33,4 | 1180 | 1873 | 1,65 | 1,6 | 4,8 |
| | B-Madre | 345 | 5,4 | 9,6 | 178 | 231 | 1,32 | 1,7 | 4,5 |
| | C-Alta | 33 | 0,5 | 3,2 | 627 | 523 | 1,44 | 1,56 | 22,9 |
| Dark tile roof | A-Baixa | 13 | 0,2 | 1,3 | 643 | 621 | 1,5 | 1,61 | 61,4 |
| | B-Madre | 7 | 0,1 | 0,1 | 108 | 106 | 1,19 | 1,76 | 84,5 |
| Light tin roof | A-Baixa | 23 | 0,4 | 1 | 288 | 335 | 1,27 | 1,59 | 37,3 |
| | B-Madre | 31 | 0,5 | 0,7 | 148 | 365 | 1,35 | 1,93 | 37,8 |
| Dark tin roof | A-Baixa | 2 | 0,03 | 0 | 125 | 96 | 1,5 | 1,79 | 774,6 |
| | B-Madre | 20 | 0,3 | 0,7 | 214 | 375 | 1,34 | 1,78 | 23,5 |
| Fibrocement roof | A-Baixa | 56 | 0,9 | 2,8 | 323 | 623 | 1,31 | 1,65 | 16,1 |
| | B-Madre | 161 | 2,5 | 4,8 | 192 | 535 | 1,39 | 1,79 | 13,1 |
| | C-Alta | 11 | 0,2 | 1,8 | 1037 | 704 | 1,59 | 1,56 | 51,3 |
| White roof | A-Baixa | 16 | 0,3 | 0,5 | 199 | 265 | 1,46 | 1,71 | 68,4 |
| | B-Madre | 32 | 0,5 | 0,8 | 169 | 228 | 1,26 | 1,76 | 39,2 |
| | C-Alta | 13 | 0,2 | 1,4 | 671 | 1373 | 1,58 | 1,68 | 40,5 |
| Other roofs | A-Baixa | 5 | 0,1 | 0,1 | 150 | 94 | 1,22 | 1,77 | 221,8 |
| | B-Madre | 3 | 0,05 | 0,1 | 125 | 84 | 1,23 | 1,81 | 260,8 |
| | C-Alta | 4 | 0,1 | 0,2 | 326 | 408 | 1,29 | 1,64 | 213,7 |

Some of the spatial metrics obtained for each building class in each study area are shown in Table 5. Results reveal that most values vary widely between study areas for the same feature class. The widest variations occur for buildings with red tile roofs, the most prevalent in Lisbon. Metrics for fibrocement roofs also display significant variation: their presence is much more significant in study area B (due to industrial land use), although their average size is quite smaller than in the other areas; the Shape Index indicates that these buildings are more compact in A-Baixa than in C-Alta (new area, long building blocks), while their boundaries are more irregular in B (higher FD).

**Table 6.** Overall accuracy and spatial metrics for buildings in each study area (landscape).

| Study Area | Overall Accuracy | R | Div | Eve | D | NoF | AREA MN | AREA STD | SI | ENN MEAN |
|---|---|---|---|---|---|---|---|---|---|---|
| A-Baixa | 54,8 | 7 | 0,62 | 0,32 | 1,33 | 296 | 847 | 1559 | 1,53 | 24,3 |
| B-Madre | 62,1 | 7 | 1,15 | 0,59 | 0,80 | 599 | 180 | 350 | 1,33 | 13,2 |
| C-Alta | 64,8 | 4 | 1,14 | 0,82 | 0,25 | 61 | 690 | 826 | 1,49 | 44,3 |

Overall accuracy and metrics for each study area (Table 6) show that the area with highest accuracy (C) also has the highest Evenness, the lowest Dominance, and the largest mean distance between buildings (ENN MEAN). The area with the lowest overall weighted accuracy (A) has the least compact buildings (SI) and the largest variation in their sizes, although in the composition metrics it displays the lowest Diversity, Evenness, and highest Dominance.

The small size of buildings in study area B probably contributes to their undermapping (omission). Results suggest that the success of extraction may be more related to spatial configuration of features than to spatial composition of the landscape.

## 4. Conclusions

The present work is an exploratory attempt at assessing the heterogeneity of feature types and studying the relevance of the urban context in the framework of semi-automated extraction of buildings from VHR satellite imagery for the purpose of urban planning and management. The analysis uses spatial metrics at the level of the building block and is focused on distinct types of roofs of buildings present in the study areas. Results show that the spatial metrics vary for same semantic class of building in different study areas, which display different levels of heterogeneity. Results also suggest that the spatial configuration of target features may be a determinant factor for the success of automated extraction.

Although the extraction's accuracy is not linearly related to the heterogeneity of features, the complexity and heterogeneity of such an historical and dynamic city make the automated extraction of buildings very challenging. Extraction of buildings having similar roofs is further complicated by the different solar illumination of roof gables at time of image acquisition.

Future developments include the addition of other diverse study areas (D and E were selected) as well as more quantitative analysis of spatial metrics. Also, the additional land cover context should be considered. Socio-economic variables from the census will be added to the spatial analysis to further characterize the different areas.

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