

URBAN DETECTION, DELIMITATION AND MORPHOLOGY: COMPARATIVE ANALYSIS OF SELECTIVE “MEGACITIES”

CPSV, Centre of Land Policy and Valuations, Polytechnic University of Catalonia (UPC), Av. Diagonal 649, 08028

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ABSTRACT:

Over the last 50 years, the world has faced an impressive growth of urban population. The walled city, close to the outside, an “island” for economic activities and population density within the rural land, has led to the spread of urban life and urban networks in almost all the territory. There was, as said Margalef (1999), “a topological inversion of the landscape”. The “urban” has gone from being an island in the ocean of rural land vastness, to represent the totality of the space in which are inserted natural and rural “systems”. New phenomena such as the fall of the fordism model of production, the spread of urbanization known as urban sprawl, and the change of scale of the metropolis, covering increasingly large regions, called “megalopolis” (Gottmann, 1961), have characterized the century. However there are no rigorous databases capable of measuring and evaluating the phenomenon of megacities and in general the process of urbanization in the contemporary world. The aim of this paper is to detect, identify and analyze the morphology of the megacities through remote sensing instruments as well as various indicators of landscape. To understand the structure of these heterogeneous landscapes called megacities, land consumption and spatial complexity needs to be quantified accurately. Remote sensing might be helpful in evaluating how the different land covers shape urban megaregions. The morphological landscape analysis allows establishing the analogies and the differences between patterns of cities and studying the symmetry, growth direction, linearity, complexity and compactness of the urban form. The main objective of this paper is to develop a new methodology to detect urbanized land of some megacities around the world (Tokyo, Mexico, Chicago, New York, London, Moscow, Sao Paulo and Shanghai) using Landsat 7 images.

1. INTRODUCTION

1.1 Overview and motivations

The second half of the twentieth century was undoubtedly the time when there has been a faster urban growth worldwide. The urban population has grown from 750 million in 1950 to 2860 million in 2000, and now represents over 50% of world population. The expansion of the cities had its origin in the model of suburban life began with the generalized use of the car. A lifestyle based on the “American Dream: one single family-home, and one (or more) car (s)”, that means mobility and homeownership. However it has been since the late 70s when it has had a more dramatic development, as a consequence of the crisis of metropolitan areas linked to what is called Post-Fordism economy and some authors have characterized as counter-urbanization (Berry) desurbanization (Berg), edge-cities (Garreau) metapolis (Asher) or diffuse city (Indovina). Despite the diversity of urban development, the increasing consumption of land, the excessive use of land as a scarce resource, it is a constant in the urbanization process in the early twenty-first century.

In this sense, the urban sprawl, the process of gradual spread out of urbanization has become a worldwide phenomenon, especially in the developed world and its environs. The growing consumption of land, as a result of the extension of highway networks in urban areas, seems to have become unstoppable and affects virtually all the contemporary metropolis worldwide.

The literature has discussed deeply the concept of sprawl. Some of these concepts are: Sprawl is the spreading out of a city and its suburbs over more and more rural land at the periphery of an

urban area. This involves the conversion of open space (rural land) into built-up, developed land over time; “Our method of defining sprawl is to characterize it simply in terms of land resources consumed to accommodate new urbanization. If land is being consumed at a faster rate than population growth, then a metropolitan area can be characterized as “sprawling.” If population is growing more rapidly than land is being consumed for urbanization, then a metropolitan area can be characterized as “densifying.”” (Fulton et al. 2001); or “The literature on urban sprawl confuses causes, consequences, and conditions. This article presents a conceptual definition of sprawl based on eight distinct dimensions of land use patterns: density, continuity, concentration, clustering, centrality, nuclearity, mixed uses, and proximity. Sprawl is defined as a condition of land use that is represented by low values on one or more of these dimensions.” (Galster et. alt., 2001). However there is no consensus in defining urban sprawl, because of its complexity and multidimensional character.

Thereby, the research uses the remote sensing to identify, to analyse and to measure the urban sprawl in the selected megacities, using the LandSat7 imagery, with the aim to compare the different morphologies and to understand the urbanization process of the metropolitan areas, and then proceed to get indicators that explain this global phenomenon objectively and accurately.

1.2 General objectives

The overall objective of the paper is to develop an efficient technique of remote sensing for monitoring the contemporary process of urban sprawl. More specifically, it seeks to develop a

fast and suitable system to detect and accurately measure the artificialized land of the great mega-cities through the use of low-resolution satellite images (Landsat 7).

1.3 Specific objectives

The specific objectives can be summarized as follows:

- The first aim of this paper is to delimitate the study area of the selected cities. A “window” of 45,000 square kilometres of each megacity will be studied in a detailed level.
- The second aim of this paper is the classification and interpretation of archived satellite images for the identification of land covers. Rural and artificialized land (including roads and urban green) will be classified. Urban texture analysis plays an important role in image segmentation and object recognition for improving objects extraction and classification.
- Another goal of the paper is to delimitate, measure and understand the urban continuum inside and outside the administrative boundaries. The morphological analysis of conurbation will serve to identify the core city from the surrounding countryside and to compare the different structures of the studied megacities.
- Comparison between the different models of urbanization. This stage is directed towards analyzing from a morphological perspective the process of spatial occupation of the megacities. Landscape indicators will be used to define the pattern of urbanization of each megacity. Urban sprawl, monocentrism vs. polycentrism, fragmentation and others aspects of the urban structure will be studied to compare the selected megacities.

Finally, our aim in this paper is to generate an indicator to present geometric properties and intrinsic morphology of urban settlements based on their characteristics and fundamental forms, and to develop a strategic urban model that guides sustainable development of selective “Megacities”, using innovative technologies such as Remote Sensing, Geographic Information Systems (GIS) and WEBGIS.

2. METHODOLOGY

2.1 Analysed data

Data sources are based on satellite images from Landsat 7 ETM+ and the GLS (Global Land Survey) 2000 Collection brought together, which provides multispectral images of 30 meters, plus a 15 m panchromatic image, in Geotif format.

2.2 Land Use Classification Efficiency According to Per-Pixel Based Approaches

The complexity of image classification techniques can range from the use of a simple threshold value for a simple spectral band to complex statistically based decision rules that operate on multivariate data. Classification approaches can be implemented to classify the total scene content into a limited number of major classes or can also be implemented to distinguish one or more specific classes of terrain (such as water bodies, artificialized land or other types). Pixel-based approaches have been developed and are widely used in remote sensing image processing and classification. Supervised

classifications, such as Maximum Likelihood, Minimum Distance, Mahalanobis Distance, and Parallelepiped Classification, have been used.

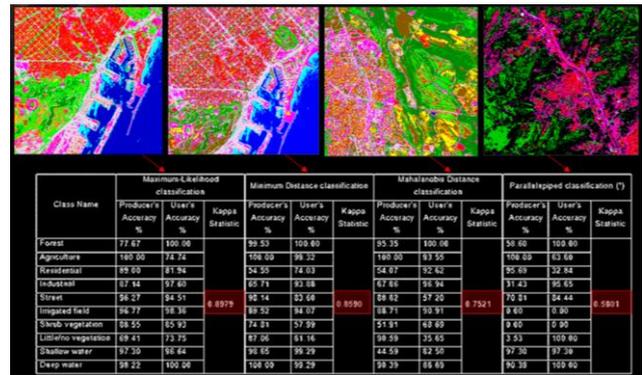


Figure 1. Per pixel classification approaches

A number of issues have to be taken into consideration when selecting a suitable classifier:

- Different training strategies may produce different classifications results. The training size, the image resolution, and the degree of autocorrelation inherited in each class influenced the performance of different training strategies.
- The size of the training set is important in influencing supervised classification results when the single-pixel training strategy is applied. The number of pixels required to extract training statistics vary for different classes with different spatial structures. For spectrally homogeneous classes, a small number of training pixels may be sufficient. But for spatially heterogeneous classes, a relative large number of pixels are likely to be required in order to extract representative statistics.
- Single-pixel may be implemented to avoid autocorrelation effects, but not always lead to more accurate classification results than other training approaches involving contiguous pixel selection. For spectrally homogeneous classes, the single-pixel training approach may be preferred. But for spatially heterogeneous classes, small-block training has the advantage of easily capturing spectral and spatial information and saves the analyst interaction time.
- Using an overlay tools as an additional process increases the classification accuracy for all classes and tends to reduce the differences of classification results caused by training strategies at all levels when the pixel-base classifier is used.

Among the most frequently used classification algorithms, the maximum likelihood method is generally preferred (Campbell 1998, Avery & Berlin, 1992). It becomes the most commonly used classifier due to its higher accuracy levels. It is generally accepted that this is the more accurate form of classification if compare to parallelepiped and minimum distance algorithms (Curran 1985). In our experience, the overlay of maximum likelihood and minimum distance classifications allow good performance in per pixel-analysis.

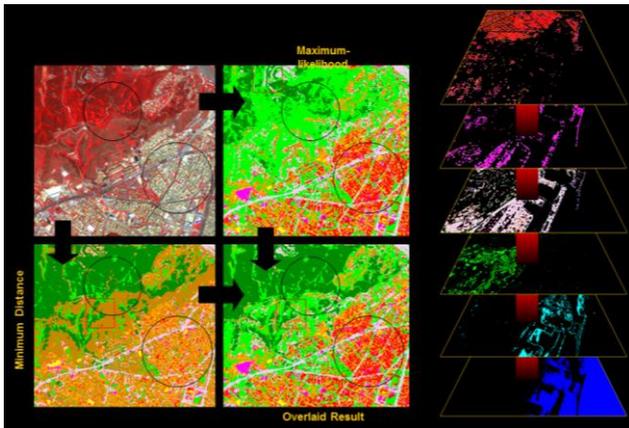


Figure 2. Overlay classifications

2.3 Texture Analysis to Improve Per-Pixel Image Classification

Nevertheless, classification errors caused by similar reflection (wave length) dramatically affect the separation between built-form and non-built-form areas. It is rare that the classification accuracy greater than 80% could be achieved by using per-pixel classification algorithms (Atkinson and Tate, 1999). In this context, texture analysis can be a good indicator of the presence of buildings and other objects and they are usually easier to detect than the often-complex multi-textured objects which cause them.

In general, texture analysis approaches are used for recognition and distinction of different spatial characteristics of spatial arrangement and frequency of tonal variation related to patterns or phenomena contained in the digital image or the sensor image. In this sense, texture image analysis is one of useful approaches for urban class extraction and separation (Wang and Hanson 2001, Herold, 2003). Zhang (1999), for example, combined multi-spectral classification and texture filtering for building detection in the urban area, and suggested that this approach increases classification accuracy.

Previous works related to texture image have been carried out into three categories: development and improvement of texture extraction algorithms, comparison between texture extraction schemes, and domain application of extracted texture images. These types of researches are similar to other cases in digital image processing, such as image classification. The main methodologies applied are those related to structural, statistical, stochastic and space-frequency models (Tuceryan & Jain 1998).

Statistical methods analyse the spatial distribution of grey values by computing local features at each point in the image and deriving a set of statistics from the distributions of the local features (Ojala & Pietikäinen 2004). Statistical methods can be classified into first-order (one pixel), second-order (two pixels) and higher-order (three or more pixels). Most frequently used texture analysis is Grey Level Co-occurrence Matrix (GLCM) based on second order statistic.

Our research group has developed extensive experience in the use of per pixel and texture analysis in classification of high resolution imagery (Alhaddad, Burns & Roca, 2007). The study of historical images for monitoring urban sprawl (Alhaddad, Roca & Burns, 2009) has led us to use GeoGraphic Imager

plugin, which allows to georeference old images, and, thus, exploit the capabilities of Photoshop software for image processing (Morgan & Coops, 2010; Yang, 2009; Gamache, 2007; Gleason, 2007; Peterson & Kelso, 2004).

This methodology, using low resolution images (as Landsat 7) to detect artificialized land of megacities can be summarized as follows:

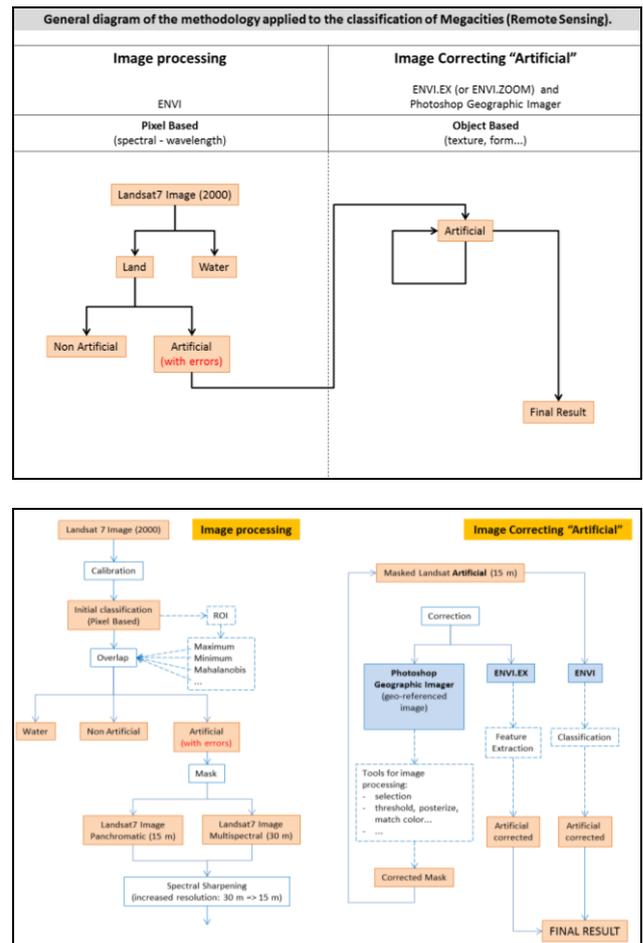


Figure 3. General Diagram of the Methodology

3. ANALYSIS OF THE RESULTS

3.1 Built-up Land of Mega-Cities

The above methodology, applied to the eight mega-cities (Tokyo, Mexico, Chicago, Moscow, New York, London, Sao Paulo and Shanghai), allows the delineation of the built up land, as shown in the fig. 4, referring to the pre-established windows of 45,000 sq. km.

The built-up area overcomes the 5,000 sq. km in New York, Tokyo and Chicago. In London, Sao Paulo and Shanghai is between 4,000 and 5,000 sq. km. Finally, Moscow and overall Mexico City has a lower built-up area, 3,000 and 2,000 sq. km respectively. The above results suggest, if they are correlated with information on population and economic structure of those metropolises, a higher level of urban sprawl in the USA and Japan than in Europe and Latin-speaking America.

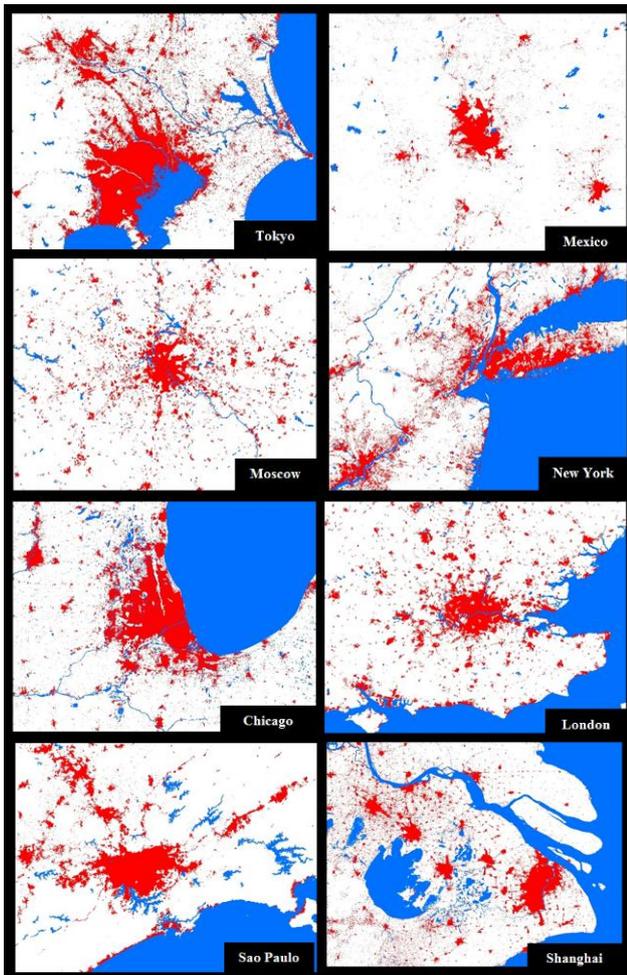


Figure 4. Mega-Cities Built up Area

The different patterns of urbanization in the selected mega-cities, especially those related with urban sprawl, in addition to the low resolution of the satellite images used (30 m pixel), cannot guarantee us optimum results regarding the detection of the built up area. It is necessary a further development to measure accurately the urban sprawl on a global scale.

3.2 From “built-up” to “artificialized” land

The development characterized with a scattered urbanization, especially when it is surrounded by urban green areas, can hardly be detected with accuracy, because of the lack of high resolution sensors. So, it is necessary to move on from the built up area to the concept of *artificialized land*, which is the land impacted by the urbanization. This concept seems to be better to understand and explain the magnitude of the process of urban sprawl in the contemporary metropolises.

For this purpose, once obtained the final dataset of built-up areas, we aim to measure the degree of physical continuity of urban settlements grouping the patches of the built up areas between buffers of 100 meters. That built-up land, grouped at 200 meters and aggregated in continuous urbanization, offers a relatively accurate image of artificialized land of the mega-cities, such as shows the accuracy analysis that has been done. It also allows the identification of the central continuum of each window, and helps to understand the structure and morphology of the studied world capitals.

Mega-Cities	Built-up Area	Aggregate (Total)	Aggregate (Central)
Chicago	5.170,86	6.562,34	4.847,75
Tokyo	5.257,05	7.481,97	4.904,78
México DF	2.042,84	4.562,39	1.296,67
London	4.433,02	6.330,16	2.383,10
New York	5.022,22	9.104,47	6.913,74
Sao Paulo	4.368,92	4.997,80	2.265,37
Moscow	3.322,68	4.265,05	1.354,79
Shanghai	4.470,51	7.287,49	1.967,79

Table 1. Land Consumption

Table 1 shows, the total of the artificialized land and the built up area for each window of the metropolises, and also the artificialized land for the central continuum of each metropolis. New York stands out with more than 9,000 sq. km of urbanized land, followed by Tokyo, Shanghai, Chicago and London, as the metropolis with highest level of land consumption. In contrast, Moscow, Mexico City and Sao Paulo have lower levels of land consumption, and thus of sprawl.

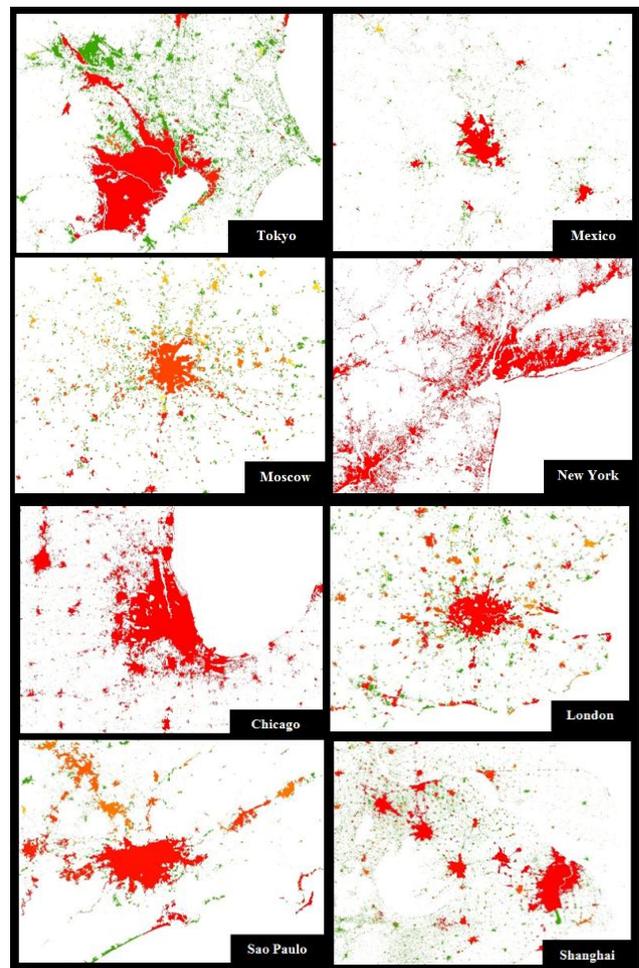


Figure 5. Central Continuum of Mega-Cities

3.1 Sprawl and Landscape Indicators

The results obtained allow studying comparatively, in addition to the degree of land consumption, the morphology of the urbanization of the world's megacities. The subdivision of the windows of 45,000 sq. km in a grid composed of cells of one sq. km, enables the construction of various landscape indicators, such as the artificialized Index (the percentage of total area occupied by urbanized land), the fractal dimension, the dominance index, the entropy or the MECI of each cell. These indicators allow us to understand the similarities and differences between landscapes of different mega-cities, and then characterize the typology of urban sprawl process.

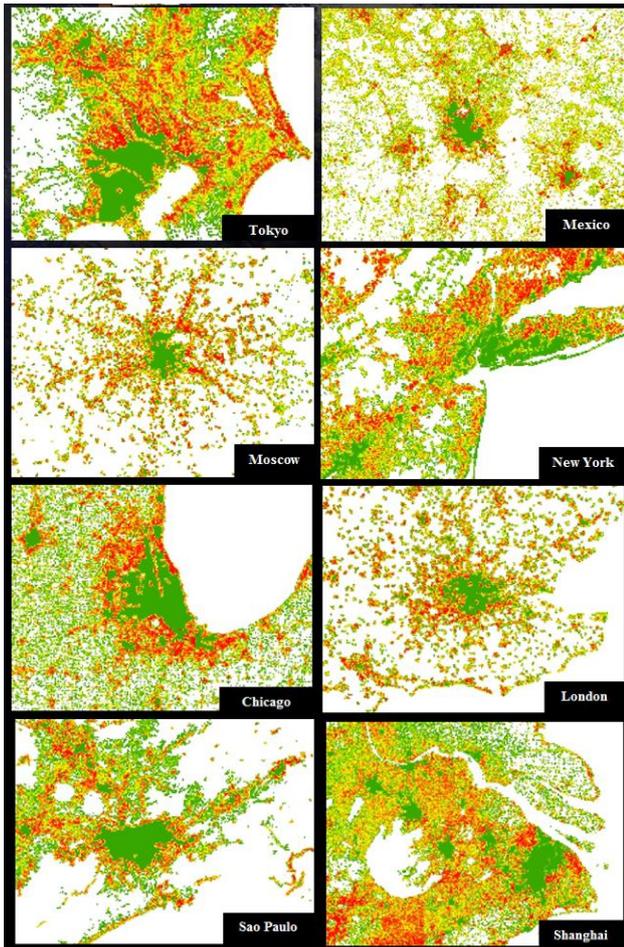


Figure 6. The Urban Entropy

The spatial distribution of the entropy of the patches of *artificialized land* in the areas studied shows how there is a greater fragmentation of urbanization in the metropolitan periphery (red color in the images, see figure 6) while in urban centers, subcenters and rural areas (green in images) the entropy or complexity is lower.

The explanatory models of the spatial distribution of entropy show a clear quadratic structure, maximum at the intermediate distances that characterize significant urban sprawl processes.

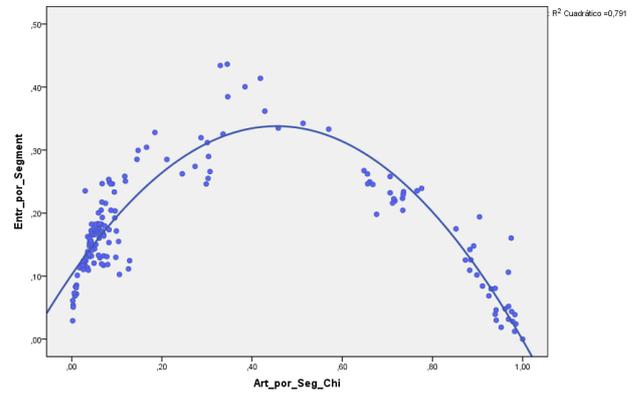


Figure 7. Spatial Distribution of the Urban Entropy of the Artificialized Land of Chicago according to the distance to CBD.

4. CONCLUSIONS

Monitoring urban sprawl using remote sensing is fundamental to understand the contemporary process of urbanization on a global scale. As a result of this research, among others, our center of research on Land Policy and Valuations is developing a platform called GLOBUS to observe the global urban sprawl (<http://www-cpsv.upc.es/GLOBUS>), and its purpose is to continue studying and analyzing the process of urban sprawl in a representative sample of most populated metropolitan areas, intermediate cities and singular small cities with the hypothesis that the process of urban sprawl is a phenomenon which is not limited to the developed world and it is a global scale process. The urban trend to sprawl brings negative effects on sustainability and social inclusion. The Global Observatory should be an extra tool to make decisions on urban plans and policies for our cities in the XXI century.

Finally, the paper present here demonstrates how useful are the methodology developed for monitoring the sprawl, starting from using Landsat 7 imagery with low resolution for doing the per-pixel classification and texture analysis. Also the methodology represents a fast and suitable system to detect and measure accurately the *artificialized land* of the mega-cities as proves the accuracy index greater than 90% in all the studied metropolises.

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