Machine learning image classification for urban land use using GEOBIA, texture and landscape metrics

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Abstract

Rapid urban growth in developing countries is causing a great number of urban planning problems. To control and analyze this growth, new and better methods for urban land use mapping are needed. This article proposes a new method for urban land-use mapping, which integrates spatial metrics and texture analysis in an object-based image analysis classification. A high-resolution satellite image was used to generate spatial and texture metrics from the landcover classification using machine learning. The most meaningful spatial indices were selected by visual inspection and then combined with the image and texture values to generate the classification. The proposed method for land-use mapping was tested using a 10-fold cross validation scheme, achieving an overall accuracy of 92.3% and a kappa coefficient of 0.896. These steps produced an accurate model of urban land use, without the use of any census or ancillary data, and suggest that the combined use of spatial metrics and texture is promising for urban land-use mapping in developing countries.

1. Introduction

The global urban population increased from 30% to almost 55% between the years 1950 and 2014 [1]. This urbanization can also be represented as an increase in urban land, which is predicted to occupy an additional 1.2 million square kilometers [2]. This expansion is most likely to happen in developing countries [3, 4], and some do not possess the resources to cope with this growing social phenomenon, thus causing segregation, slums, deficiency of infrastructure, social inequality, and uncontrollable urban sprawl. The problem of land-use mapping is challenging in developing countries as urban areas are more heterogeneous, there is poor resource and budget allocation, and a lack of expertise, as well as corruption [5]. Currently, the processes to obtain land-use and land-cover maps and zoning for urban planning in developing countries are time consuming and costly since they tend to rely on census data [6-7] and in some countries the last major detailed urban land-use maps date back to the 1970s [8], whereas the environment of a city is constantly changing in terms of shape, size and patterns of land cover, land use, and transport. This means that national census information is immediately out of date.

In Mexico, land-cover and land-use mapping must be done mainly by the government through the National Institute of Statistics, Geography and Informatics (INEGI for its initials in Spanish). In the 1980s INEGI started to develop national land-cover mapping through intensive fieldwork and visual interpretation of aerial photography [9]. The classification structure for these maps overly complicated, the classes keep changing with every new administration, the mapping methodology and accuracy levels are unknown. Despite this, they are considered to have good accuracy and are widely used [10]. INEGI continues to update this database every without explaining the methodology or accuracy levels [10-11]. Due to the complexity of urban land use, its production is largely based on visual interpretation of aerial and satellite images and census data, which is subjective, as well as time consuming and costly [11-12]. Recent attention to methodologies based on spatial metrics and machine learning has shown promise for improved accuracies using image data alone [13]. This article proposes a new method for urban land-use mapping, involving spectral, spatial, and textural information from satellite images, which provides good classification accuracy at a high level of detail, without the need for survey or official census data.

1.1. Spatial metrics

Spatial metrics are based on spatial representations of the landscape and identify and quantify the spatial heterogeneity of images using individual patches in the same class or all patches in the whole landscape. These metrics are derived from fractal geometry and are now recognized as essential inputs to automated land-use mapping [14]. Their ability to measure the structure and arrangement of the urban landscape can help to improve the analysis and modelling of urban growth and the changes in land-use over time [15]. These metrics can also represent spatial complexity and configuration in three dimensions: structure (shape, size, number), function (interaction of the spatial elements), and change (fluctuations trough time) [16], which further reduces the uncertainty in class allocation. Although spatial metrics have been used as a post-classification tool to measure, model, and analyze the state or changes in image classification, their values have not been explored as complementary bands in land-use classification. The initial land-cover map was trained for six classes: bare soil (containing natural, construction, and sand), vegetation (any type including trees, shrubs, parks, agriculture, and urban vegetation), water (rivers, canals, and irrigation systems), bright roof (normally thermoplastic covers used in industrial factories and high-income neighborhoods), dark roof (typically red brick, wood, or asphalt), and impervious surfaces (roads, streets, and parking lots). The spatial metrics were selected based on visual analysis of the graphic representations of their numerical values from the initial land-cover map.

1.2. Random Forests

Random Forests works as an ensemble learning algorithm based on decision tree classifiers, bagging, and bootstrapping. The algorithm is based on decision trees working as classifiers. Each tree is trained by bootstrapping, using different samples from the training data. Also, each tree is trained using a random subset of the predicting variables (in this case, the spectral bands of the satellite image). Random Forests uses many decision trees, where each tree casts a vote, and the prediction of the class is decided by the majority vote. [17] The Random Forests algorithm was selected because it is fast and can handle many features without affecting the overall accuracies.

1.3. Geographic object-based image analysis (GEOBIA)

GEOBIA segmentation extracts meaningful objects usually existing at various scales within a satellite image. Since different physical features recognizable for urban land cover and land use vary greatly in size, the segmentation must be processed at different resolutions. The multiresolution segmentation adopted in this study requires the setting of the input parameters scale, shape, compactness, and band weight. The scale parameter is the threshold of variance and is weighted against the shape and compactness parameters, which controls the extension and border of the objects. By increasing the scale parameter, larger objects will be extracted from the image as the spectral heterogeneity increases. The setup for multiresolution segmentation parameters is created on a trial-and-error basis through visual analysis [18].

1.4. Texture metrics

Texture in remote sensing describes the variations between the values of the intensity of the light reflected to the sensor. These spikes in intensity can be measured and provide valuable data about the different objects that form urban areas. Texture metrics include mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment, and energy. For the texture analysis, the grey-level co-occurrence measures for the eight spectral bands were extracted [19].

2. Methodology

The method used a WorldView-2 multispectral image with eight spectral bands (coastal blue, blue, green, yellow, red, red edge, near-infrared 1 and 2) and a spatial resolution of 0.5 m acquired in September 2014. The method first combines GEOBIA, texture metrics, and Random Forests to obtain a land-cover map, extracts spatial indices from derived land-cover map, and finally integrates all derived data to produce the urban land-use map using Random Forests for classification (Figure 1). The method is validated using a 10-fold cross-validation approach.

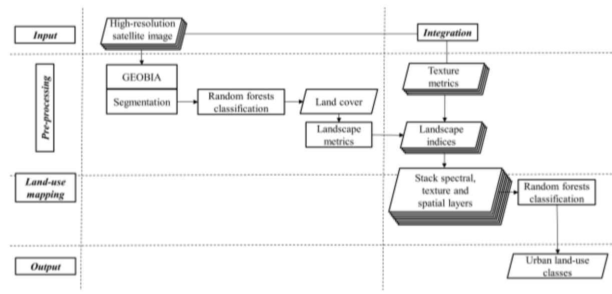

Figure 1: Method workflow.

2.1 Study area

The study area is in the northern border town of Mexico, Ciudad Juarez, Chihuahua, a manufacturing town with over 1.3 million inhabitants. The city is located between 31° 47′ N and 31° 07′ N and between 106° 11′ W and 106° 57′ W. The city’s area is approximately 3561 km2 with an urbanized core of 353 km2, of which the study area comprises 378 km2. Historically the city follows the standard Latin American model: a concentric grid pattern of primarily low-rise buildings with irregular settlements on their urban periphery.

3 Results

In this bottom-up multiresolution segmentation algorithm, the number of homogenous objects is large at higher scales, whereas smaller objects are realized at lower scales, which results in longer processing time. The parameters to adjust were scale, shape, and compactness. After various experiments and visual analysis, it was decided to use the values 75, 0.3, and 0.5, respectively, giving weight only to the spectral bands.

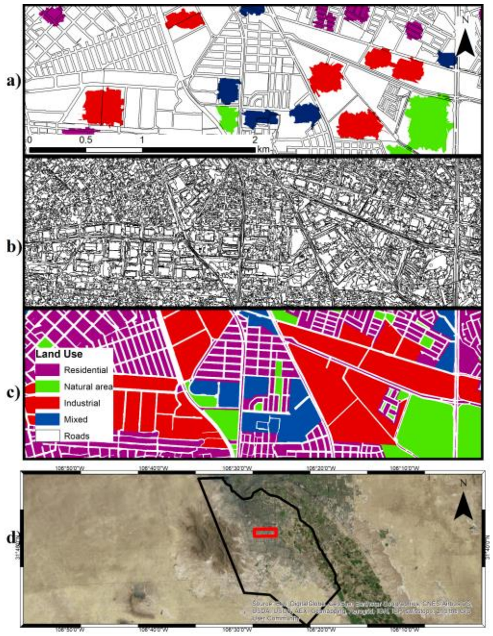

Figure 2: Training, segmentation, and ground reference.

General landscape and class-level metrics were created. Of the total of 114 indices that were analyzed by visual interpretation, only 27 were selected for the final classification. These indices were selected by visual interpretation of their values to see which ones typified different types of land use.

Once all the spatial and textural data were collected, they were grouped together to create a new image with the eight original bands from the WorldView-2 image. This was achieved by transforming all these metrics to images and then layer stacking them into a single stack before reapplying land-use classification using the training data set shown in Figure 2(a). This data set contains 150 objects per class, with 4 basic urban land-use classes: industrial zones (including big bright roof and impervious objects bigger than 10,000 m^2), mixed use zones (bright roof and impervious objects like parking lots with any kind of vegetation), natural areas (comprising water, vegetation, and bare soil objects typical of areas in protection, mountains, water canals, agriculture, and the desert), and residential zones (small dark roof objects lower than 500 m^2 and bright roof objects smaller than 1500 m^2), distinguishing between low and high income was possible based on the density of impervious class, where a disorganized pattern is characteristic of unplanned neighborhoods and irregular settlements that are typically habited by low-income population whereas a more compact and grid pattern denotes a higher social level with addition of vegetation areas like private parks. A subset of the image after segmentation is shown in Figure 2(b).

Ground reference of land-use data from a subset of the city were manually identified as the training data set for the whole city (Figure 2(c)). In this case a total of 176 columns exists in the attribute table of this image.

The attributes consist of the 64 texture metrics, 8 spectral bands, 27 spatial metrics (spectral and spatial bands including their mean, standard deviation, and skewness values), and a variety of 7 object attributes (border index, compactness, roundness, border length, asymmetry, density and number of pixels).

The final classification was implemented with a random forest scheme of 350 trees, each constructed while considering 20 random features. For this classification a cross-validation approach was implemented to test the accuracy of the land-use mapping. The 10-fold cross-validation obtained an overall accuracy of 92.3% and a kappa coefficient of 0.896. The final land-use map for the city of Juarez, Mexico is shown in Figure 3.

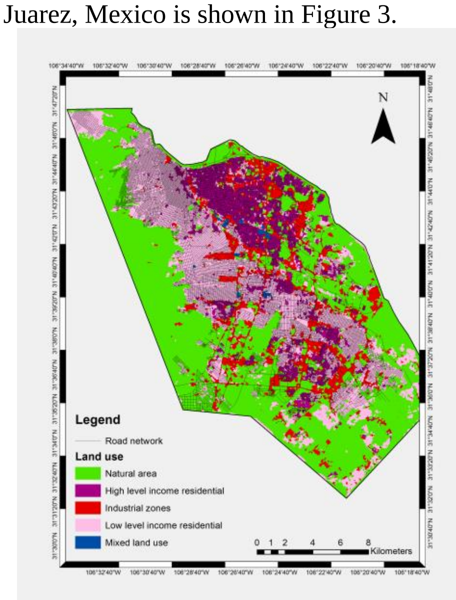

Figure 3: Urban land use of the study area.

4. Conclusion.

This article presents a new method for urban land-use classification using high-resolution satellite images. Its strength lies in the integration of spectral, spatial contextual, object-based and texture information used as input features to automated classification of urban land use in cities of the developing world. The method can provide land-use data at whole city scale from remotely sensed images without the aid of census or survey data. The proposed method was tested in Ciudad Juarez, Mexico, using a WorldView-2 high-resolution satellite image. The results created a model of urban land use for the city with accuracy of 92.3% and 0.896 of kappa coefficient. This method can be used operationally by urban planners to solve land allocation and zoning issues and provide a foundation for the urban development department of the local government database.

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