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Special article

Understanding multi-temporal urban forest cover using high resolution images

Aline Canetti[a], Marilice Cordeiro Garrastazu[b], Patrícia Póvoa de Mattos[b,*], Evaldo Muñoz Braz[b], Sylvio Pellico Netto[a]

[a] Federal University of Paraná, Av. Pref. Lothario Meissner 900, 80210-170, Curitiba, PR, Brazil
[b] Embrapa Florestas, Estrada da Ribeira Km 111, Caixa Postal 319, 83411-000, Colombo, PR, Brazil

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ABSTRACT

Urban forests offer city residents a better quality of life. They also act as barrier and filter to pollutants resulting from human activities. Mapping the distribution of forests in urban areas is therefore important for good urban planning. Currently, high resolution images are considered useful tools to quantify forested urban areas for large scale urban development. The objective of this work was to evaluate multi-temporal urban forest area changes over different land-use classes, using available high-resolution images obtained from different satellites. The municipality of Araucaria (Paraná State) was chosen as study area because it is a large industrial zone of southern Brazil. The effects on the forests within this municipality caused by the increase in human activities between 2005 and 2012 were determined using high resolution images (5 m). We recorded a reduction of 22.8% in the forests surrounding urban areas of the municipality, as a result of deforestation of 791 ha and plantation of only 251 ha. The utility, commercial and residential zones which are more crowded the areas of highest population density were those which showed the greatest loss of tree cover. Object-based classification accuracy using images from different satellites was sufficient to quantify the evolution of tree-cover over the studied period.

1. Introduction

There is a growing recognition that urban forests improve urban quality of life in many ways, offering benefits that meet local needs (Küchelmeister, 2000). Through the physiological processes of trees, forests act as air filters and have a direct influence on temperature and other climatic variables involved in air pollutants dispersion (Murphy et al., 1977; Lima, 1980; Brack, 2002; Walton et al., 2008).

Preservation of forests in urban and industrial areas is therefore of fundamental importance. Generally, industrial areas are associated with environmental impact, such as smoke, construction and noise. Predomination of asphalt and concrete in those areas increases summer heat by raising air and soil temperature which consequently reduces moisture in tropical and subtropical regions. The limited space of exposed soil makes it more difficult for precipitation and air to percolate into soil, which reduces nutrients necessary for plant growth. This increases as soils become compacted by the transit of heavy vehicles and heavy machinery damages plant roots, trunks and branches (Poracsky and Scott, 1999).

The role of ecosystems has become especially relevant with increasing human impact and environmental pollution. The environmental and economic values of forests and their sensitivity to pollution make them indicators of environmental changes, which allow modelling general tendencies of the whole biosphere affected by human activity (Juknys et al., 2002).

To predict consequences of a marked increase in urbanization on quality of life requires an understanding of the evolution over time of a number of variables. For example it is important to understand the relationship between the expansion of urban areas and the distribution of remaining forest cover. One way of modelling changes and their consequences is to study variations in municipal green areas at a global level, examining different urban areas in various parts of the world (Fuller and Gaston, 2009).

Tree cover may be mapped by different methods when using images. Some authors use remote sensing for this purpose (Myeong et al., 2001; Sawaya et al., 2003; Walton et al., 2008; Buccheri Filho and Nucci, 2011; Myint et al., 2011; Eduardo et al., 2013; Nagi, 2014) and others field inventories (Banks et al., 1999; Harder et al., 2006).

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* Corresponding author.

E-mail addresses: alinecanetti@ufpr.br (A. Canetti), marilice.garrastazu@embrapa.br (M.C. Garrastazu), patricia.mattos@embrapa.br (P.P.d. Mattos), evaldo.braz@embrapa.br (E.M. Braz), sylviopelliconetto@gmail.com (S. Pellico Netto).

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Modern technologies that allow highly accurate monitoring of urban green areas are also being used. For example, unmanned aerial vehicles (UAVs) can obtain information about urban tree cover from a different perspective (Kulhavy et al., 2016) with low-cost and high resolution (Kalantar et al., 2017). Another tool still being evaluated is the terrestrial light detection and ranging (LiDAR). This technology is being tested to classify and map tree species from images (Korpela et al., 2010; Wegner et al., 2016), It also allows measurement of the leaf-area index and carbon storage (Alonzo et al., 2016; Klingberg et al., 2017). These technologies have the potential to considerably increase the information related to forest structure in urban environments.

The advantages of aerial images are the wider areas covered at each pass and their affording an easy comparison of historical data sets. Moreover, they provide a wider ranging assessment of urban forests than forest inventories, which concentrate on measuring trees on public access sites (Nowak et al., 1996). Especially in urban areas, monitoring the vegetation is more complex due to high variation in land use (Myeong et al., 2001; Weber and Puissant, 2003). With the advance of technology, there is an increasing use of satellite images, as they are highly effective tools for large scale monitoring (Walton et al., 2008; Myint et al., 2011; Sexton et al., 2013).

The objective of this work was to evaluate multi-temporal urban forest area changes over different land-use classes, using available high-resolution images obtained from different satellites. These results will place Araucaria in a growing list of municipalities that monitor urban forest cover that will be helpful to guide planners in creating environmental policies in their cities.

2. Material and methods

Araucaria generates one of the largest tax incomes in the state of Paraná. It was chosen for the present study because it is a large industrial zone in south of Brazil, with recent history of industrialization. It has undergone significant development as a result of tax incentives introduced in the 1970s, and industry now constitutes the largest part of the municipal economy (Negrelli, 2004). For this work we analysed the urban area of Araucaria (Fig. 1).

Araucaria is part of the Curitiba metropolitan area, in Paraná State, Brazil (49°23′52"S and 25°35′06"W). The climate is subtropical warm-temperate (Köppen, 1936), always humid, ranging from warm summers to cold winters, with occasional frost. The mean annual temperature is 16 °C and highest rainfall occurs in January and lowest in August. The relative air humidity is near 80% throughout the year (Paranö, 2015).

To estimate changes in forest cover over time, high resolution imagery was used. These images can be compared to historical data sets and are available for a wide area in Brazil, allowing them to be used to replicate this study in other municipalities. Spot 5 images with 5 m precision were obtained for 2005, provided by the department state for urban development (SEDU/PR). The images supplied were compositions already fused on 3 bands pansharpened. RapidEye images were obtained for 2012, from the Geocatalog collection of Environment Ministry. Both images were received orthorectified; Rapideye images were pre-processed. The conversion of raw digital number (DN) values to top-of-atmosphere (TOA) reflectance data was processed using the Raw data module of Impactoolbox software (Simonetti et al., 2015).

Image classification was performed using segmentation and classification tools available in ArcGis 10.5 with object oriented approach. For segmentation, spectral composition of bands was needed, which was carried out on both images (RGB-543 for RapidEye and RGB-321 for SPOT 5). For mean-shift segmentation, spectral, spatial and minimum segment size detail parameters were tested for both images, looking for the best segmentation for each one. The images were segmented into objects and training segments samples were selected for image classification by support vector machine algorithms. We selected segments to achieve at least thirty thousand pixels for each land-use class (nearly 0.01% of total image area) following the recommendation of Nagi (2014).

We considered five classes: remaining forests, comprising areas showing predominantly forest cover; Low vegetation complex areas, that were predominantly agriculture or pasture areas; soil, represented by soil without expressive vegetation coverage or completely exposed; impermeable surfaces, comprising buildings, paved and asphalted surfaces; water, characterized by water bodies of at least 5 m width, due to image-spectral resolution.

Image classification accuracy was determined using confusion matrices generated by an overlap of georeferenced points randomly selected on Google Earth historical images of 2005 and 2012 (30 for each land-use class) and the relative segments on both classified images. The matrices were used to express the number of pixels correctly classified according to the accuracy test carried out by the map's publisher. In addition, another classification accuracy test was carried out by cross validating with training samples. In this test, selected segments were compared to classes identified by the software.

Forested areas were selected and separated on each image, and we compared 2005 and 2012 images by map algebra (raster calculation). It was possible to quantify additional and deficit of forested areas in the period. The areas were also classified according to municipality urban zoning (Fig. 1).

Tree cover percentage from the total area of Araucaria was calculated using classified maps. Green area per inhabitant percentage was calculated for 2005 and 2012 using census demographic data. Municipality growth projection was obtained from the Araucaria geometric growth rate (2.37) (IBGE, 2010). Demographic data for each studied year was divided by forested area obtained by classified images.

3. Results

The best parameters obtained for SPOT 5 mean-shift segmentation were 18, 10 and 16, and for RapidEye were 20, 8 and 12 for spectral, spatial and minimum segment size detail, respectively. Accuracy test of SPOT 5 imaging and classification through superposition with Google verification points in the field resulted in 87.4% of global exactitude and 84.3% on Kappa index, while for RapidEye global exactitude was 87.3%, showing a Kappa index of 84.2% (Table 1). Global exactitude of SPOT 5 and RapidEye classifications by cross validation were, respectively, 93.2% and 95.5% and Kappa index were 91.3% and 94.2% (Table 2). Soil and impervious surface were the most confused classes but classification accuracy for remaining forests was higher than 90% for both images in both tests.

Nett tree cover reduction can be observed in Araucaria from 2005 to 2012. A reduction of 541.73 ha of continuous tree vegetation was detected, representing 22.82% of existing forests in 2005 (Table 3). This resulted from forest replanting of 250.84 ha and a deficit of 790.97 ha in the same period.

Variation of trees cover in Araucaria in 7-years period is presented in Fig. 2. Trees cover replanting and deficit areas are shown along with those that did not present variation in the period.

In 2005 approximately 30% of Araucaria area was covered by forests. Seven years later it was reduced to 24%. Green area per inhabitant reduced from 199 m^2 in 2005–154 m^2 in 2012, representing a reduction of approximately 25%.

The municipality environmental protection zone (Brasil, 2012) shows the greatest proportion of remaining forests in 2012, with nearly half of total forested area (41.91%). The industrial zone presents the second largest area, with approximately 30% covered predominately with trees. Residential, utility and commercial zones are those with proportionally less tree-cover, with no more than 20% of forested areas.

Between 2005 and 2012 there was a reduction of forest cover in all zones, but the greatest reduction was observed in commercial and residential zones (nearly 30%). Suppression of forested areas was more pronounced in utility and commercial zones, but the utility zone also included the greatest area of reforestation (Table 4). The most