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Pattern of urban forest changes in a volcano neo-tropical city

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Abstract

Urban forests are a key component of nature-based adaptation strategies; therefore, their monitoring and management is fundamental to urban management in the 21st century. This research identified and estimated land cover changes in an urban space located in the neo-tropical Andean valleys. To achieve this objective, we set out to quantify over a five-year period (2013-2017) the land cover changes with emphasis on impervious cover, forest fragments, urban trees, and urban green areas. Thus, we identified the spatial variations of urban vegetation over the five-year period using SPOT 6 and 7 images, applying an object-based classification and a transition matrix. We found an increase in the impervious category and the loss of urban vegetation, represented by the sum of the categories: forest, green areas and shrub-shrub. In parallel, we observed an increase in forest and urban woodland that compensated for the losses in the categories of shrubs and green areas. Quantifying the spatio-temporal variations of urban forests more accurately and at an appropriate scale generates timely information for the design policies aimed at achieving environmental justice in the city; and also will determine the transition to sustainability cities in the 21st century.

Keywords: urban forest, object-based classification, SPOT, land cover changes

Introduction, scope and main objectives

When studying land use and land cover changes in urban and hyper-urban areas, finer scales of information are required to accurately identify fragments of other coverages, such as forest, trees, green areas, soils, etc. In that sense, optical images such as SPOT have proven to be a solution for better understanding urban phenomena (Weber & Hirsch, 1992; Sertel et al., 2015; Li et al., 2019). Moreover, they now have a historical record that allows them to overcome the challenges of time scale to quantify changes.

In this context, this study aimed to identify and estimate land cover changes in an urban space. This information provides tools to address the challenges of urban sustainability and green infrastructure design. To achieve this goal, we set out to quantify over a five-year period (2013–2017) the changes in land cover with an emphasis on impervious cover, forest fragments, urban trees, and urban green areas.

Methodology/approach

To determine the temporal changes in urban forest cover and climate variability in recent years, we first quantified changes in forest cover and urban green areas over a five-year period (2013–2017) using high-resolution imagery in a mountain city: Quito at 2,815 m.a.s.l. (Figure 1).

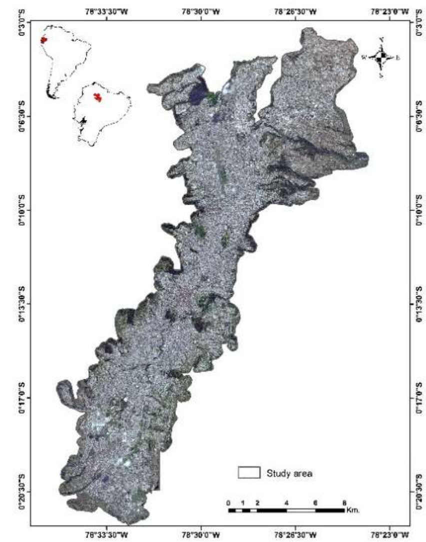

Fig. 1. Study Area: Quito hyper urban gradient

We classified two images: SPOT 6 sensors (PMS 1503537, ORT 2956463201, June 23, 2013) and SPOT 7 (PMS 1512376, ORT 2956433101, December 16, 2017). The resolution of this type of image (*cell: 1.5*1.5*) provides a suitable scale for the identification of green areas and urban forests (Andersson et al., 2009; du Toit et al., 2011). The two images were divided into five segments to facilitate classification. From these images, a land use classification process was initiated, which included three phases: atmospheric correction with the ATCOR tool - Ground Reflectance Workflow (Geomatica, 2019); mosaic generation with the OrthoEngine tool (Geomatica, 2018a); and finally, a classification process based on objects through the Object Analyst tool (Geomatica, 2018b).

This last tool was applied on high resolution images and performed an object-based image analysis. First, it segments an image for classification, then an analysis phase determines the classification process and, it is characterized by the extraction of statistical and geometric features from the object/polygon layer. Statistical features are a function of image pixels within an object and SPOT bands. Whereas the geometric features: circular, elongated compact and rectangular are calculated by analyzing the boundaries of the polygons created in the segmentation process (Geomatica, 2018b; Bonilla-Bedoya et al., 2020).

Then, we generated a grid over the SPOT. This was useful to distribute the land cover classification training polygons. The classes considered were forest component, grassland, impervious, agriculture, shrubs and herbs, soil, and water. For the evaluation, a new class sample was generated that considered approximately 25% of the total area of each land cover. These data were used to cross-check a confusion matrix and errors of omission and commission to derive a validation kappa index.

The land cover classification for 2013–2017 and a cross-tabulation matrix allowed the total change of the coverage categories to be quantified. This process considered both the net change and the swap in addition to the gross gains and losses (Pontious, 2004; Alo & Gilmore, 2008; Bonilla-Bedoya et al., 2014). In addition, this enabled the visualization of differences between the systematic or random transitions among the different categories that make up the urban landscape (Pontious et al., 2004; Alo & Gilmore, 2008).

source

Results

Classification of the SPOT images (2013, 2017) yielded a mean kappa index calculated from the five sections into which each image was divided (Table 1). The categories of impervious cover, forest, green areas, and shrub-herb dominate the urban landscape of this city. The most important processes of loss, gain, and exchange in the landscape occur in these categories (Table 2). In addition, our results demonstrate an increase in the impervious category and the loss of urban vegetation, represented by the sum of the categories: forest, green areas, and shrub-herb (Figure 2). However, in parallel with this change, we observed an increase in forests and urban woodland that compensated for losses in the shrub-herb and green areas categories (Table 3)

Table 1. Mean and standard deviation of the Kappa Index considering the five classification sections 2013-2017.

Land cover	Kappa index	
	2013	**2017**
	mean±sd	*mean±sd*
Agriculture	0,95±0,07	0,810.08
Forest	0.89±0.11	0,92±0.06
Green areas	0.87±0.16	0,72±0.18
Impervious	0.90±0.20	0,94±0.04
Shurb and herbaceous	0.75±0.17	0,65±0.39
Soil	0.87±0.10	0,72±0.14
Water	0.80±0.45	0,69±0.47

Table 2. Gain, Loss, Total Change, Interchange, Absolute value of net change of Quito City (2013-2017)

Land cover	**Gain (%)**	**Loss (%)**	**Total change (%)**	**Interchange (%)**	**Absolute value of net change**
Agriculture	1.00	2.41	3.41	2.00	-1.41
Forest	8.49	4.54	13.03	9.09	3.94
Green areas	4.39	6.20	10.59	8.79	-1.80
Impervious	9.54	5.26	14.80	10.51	4.28
Shrub and herb	4.60	9.01	13.61	9.21	-4.41
Soil	1.29	1.89	3.17	2.58	-0.60
Water	0.04	0.05	0.08	0.07	-0.01

Table 3. Systematic transitions in the gain and loss function.

Year 2013	**Year 2017**	**Gain (Observed minus expected)**		**Loss (Difference divided by expected)**	
Forest	Agriculture	0	0	0.04	0.51
Forest	Green areas	0.09	0.16	0.26	0.62
Forest	Impervious	-1.19	-0.43	-1.8	-0.53
Forest	Shrub and herb	1.38	2.06	1.42	2.25

Forest	Soil	-0.06	-0.36	0.01	0.08

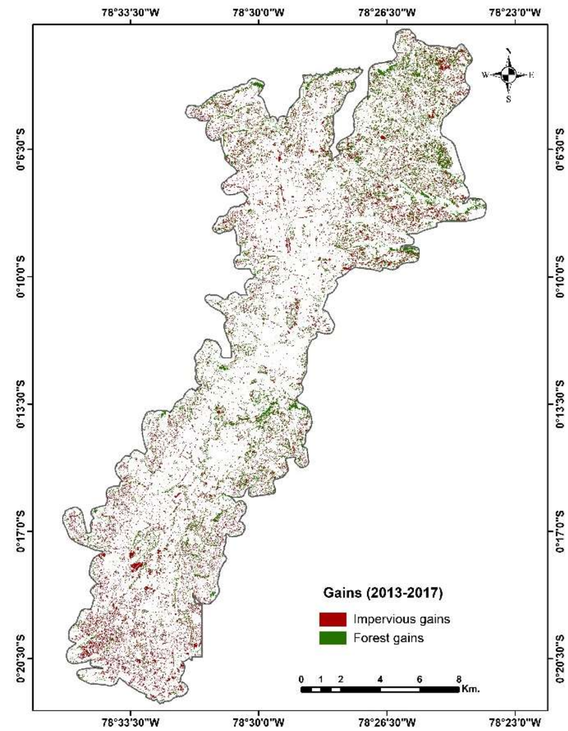

Figure 2. Gains: Forest and impervious cover categories

Discussion

We estimate land cover changes (2013-2017) of a mountain city (Bonilla-Bedoya et al., 2020). Remote sensing methods applied to SPOT images allowed, compared to other sensors, to present information at a fine and precise scale for urban research (Liang et al., 2012). It allows to identify, in relatively recent periods, variations in land cover and land use in urban landscapes.

The loss of urban vegetation, represented by the sum of forest, green areas, and shrub-grass categories is complemented by an increase, over time, in tree cover and urban fragments at the expense of shrub and green area categories. These dynamics in urban cover change indicate the pressure exerted by hyper-urban infrastructure on the few spaces that could be allocated to hyper-urban greenery.

However, this methodology for understanding the dynamics of green infrastructure in the city could be enhanced by assessing forest stand conditions and forest components in urban and peri-urban areas by integrating new approaches, such as those involving airborne laser scanning (LiDAR) data (Alonso et al., 2016).

Conclusions/ wider implications of findings

Remote sensing and geographic information systems applied to the study of land use, land cover, and forest change along urban-rural-natural gradients are essential tools for planning initiatives. The conversion of urban land use and land cover affects the environmental conditions of a city and the wellbeing of its citizens.

Understanding the spatio-temporal variations of urban forests more accurately and at an appropriate scale are challenges that aim to accurately quantify urban forest ecosystem services. This approach could make a difference in the value of contemporary urban land.

Acknowledgements

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