Neighborhood variations in urban green cover patterns in Bogotá (Colombia) estimated by NICFI-Planet images

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Keywords: Urban vegetation, NDVI, Machine learning, K-means, Google Earth Engine, Environmental justice

Abstract

To achieve a more green city in the shortest possible time, joint work between government and society is necessary and this work intend to contribute with scientific basis to support the expansion of urban greens areas in Bogota DC. We analyzed the spatial and the social distribution of urban greens and their variations inside of Bogotá urban areas, between years 2019 and 2023, based on NICFI-Planet images. The Normalized Difference Vegetation Index (NDVI) was calculated for each monthly cloud-free mosaics over Bogota DC. and a NDVI Maximum Value Composite (NDVI-MVC) image was calculated for both years. The NDVI-MVC images were clustered with the k-means algorithm, generate a binary image with built-ups targets and other urban targets (vegetation and shadows). These images were analyzed with socio-economic data to a better understanding about the social distribution of urban greens. Were observed an environmental injustice, where the benefits of green areas of the human health are allowed for people from middle and upper classes.

1. Introduction

Bogotá DC, Colombia's capital, is located on a plateau with an average altitude of 2,640 meters above sea level. Its areas range from densely populated urban areas to rural regions of great importance for agriculture and biodiversity. This geographic and socioeconomic diversity is reflected in a variety of neighborhoods, ranging from upper-class residential areas to more modest sectors (Alcaldia de Bogotá, 2024).

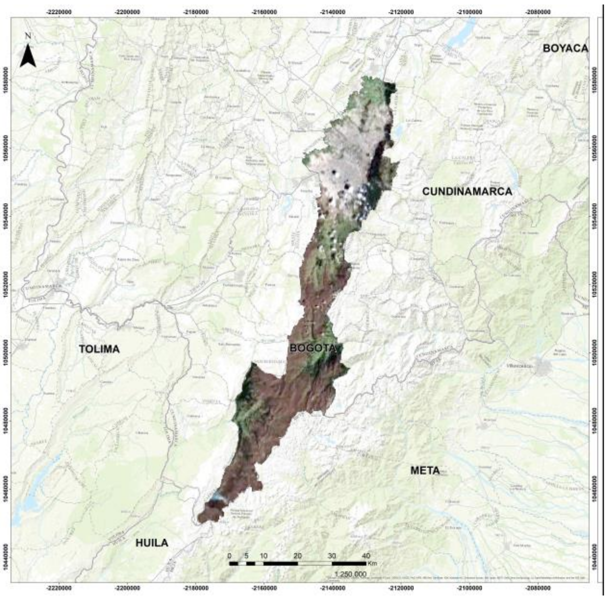

Figure 1. Study area situation map the Bogota DC. Satellite image over a ESRI basemap.

According to the recommendation of the World Health Organization (WHO), every 3 inhabitants should have at least 1 tree in their surroundings, and, in this case, the situation in Bogotá is worrying. The city has approximately 1,534,489 trees, according to data from the National Administrative Department of Statistics, in a population of around 7.8 million inhabitants (Jardín Botánico de Bogotá, 2024). Like many large cities, Bogotá's urban expansion and infrastructure development often result in the loss of green areas. This urban pressure can reduce residents' availability of green spaces, exacerbating social and environmental inequality, as some neighborhoods have access to more green spaces and services than others.

Without accurate knowledge of the city's distribution, density, and health of public vegetation, making informed decisions regarding urban planning, climate change mitigation, and air quality improvement becomes a complex challenge (Corzo, 2007). In the urban environments, the planning of plant communities is conducted in a multifaceted manner to meet various functional requirements, ranging from accessibility to the promotion of biodiversity. These plant communities encompass a broad mix of trees, shrubs, and ground covers. Accurately segmenting these elements into tree and shrub categories serves as a basis for a comprehensive assessment of the state of urban green areas. The management of plant communities in urban environments differs substantially from that in natural forests. These variations include aspects such as plant height, canopy size, trunk morphology, and the shading effect of tree canopies on shrubs below (Miehe, et al., 2015). According to Streiling and Matzarakis (2003), the benefits of understanding urban forestry can be divided into several aspects: the impact of the presence of street trees on indoor temperatures; at the local level, the presence of street trees plays a significant role in moderating temperatures inside buildings by providing shade. These authors found that grouping trees in rows or small groups interspersed with open areas can facilitate nighttime cooling. At the local level, tree canopy characteristics, such as tree density and proximity to other urban structures, influence the plants' ability to remove air pollutants.

In addition, climate change can have a negative impact on the biodiversity and resilience of urban green spaces, as rising temperatures and climate variability can alter these ecosystems. The conservation and improvement of green spaces require adequate funding and resources. Investment in maintenance and restoration is essential to ensure the sustainability of these spaces. It is also necessary to involve the community in managing and conserving green spaces, as a lack of awareness and participation can undermine conservation efforts. Conserving native species and restoring degraded ecosystems should be at the top of the city's environmental conservation agenda. (Mayorga and Lopez, 2021)

Figure 2. Urban landscapes in Bogotá DC (San Cristobal, Candelária, Santa Fé and Engativá neigborhoods).

In particular, the lack of detailed information about public vegetation in a city can limit decision-makers ability to effectively manage natural resources and design policies that promote environmental sustainability and citizens' quality of life (Sorense et al., 1998). To achieve a green city in the shortest possible time, joint work between government and society is necessary, and this work intends to contribute with a scientific basis to support the expansion of urban green areas in Bogota, DC. In-depth environmental education is needed to reintegrate people with nature and increase the number of green areas in Bogotá. Identifying areas where small green squares can be established in densely urbanized areas can increase the density of trees per inhabitant. This work analyzed the spatial distribution of urban greens and their variations inside Bogotá urban areas between 2019 and 2023, based on NICFI-Planet images and k-means unsupervised machine learning algorithm. We also analyzed the spatial distribution of urban greens and their relationship with socioeconomic data and population density.

2. Methodology

The image processing was made with Google Earth Engine (GEE) (Gorelick et al., 2017) in its native Javascript interface, using NICFI-Planet images (Planet Labs, 2024). All the image processing steps are presented in Figure 3. The vegetation maps and the difference map were exported to QGIS for a joint analysis with the neighborhood socioeconomic dataset.

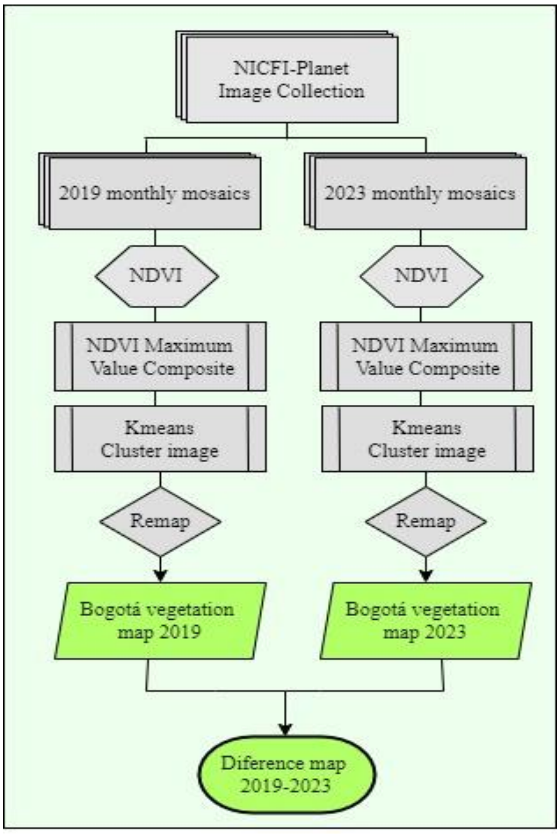

Figure 3. Image processing workflow steps.

NICFI-Planet images are available in monthly cloud-free mosaics, with 4.7 meters spatial resolution and four spectral bands (Blue, Green, Red and Near-infrared) as an image collection at GEE. Through Norway’s International Climate & Forests Initiative (NICFI), Planet’s high-resolution, analysis-ready mosaics of the world’s tropics are available in order to help reduce and reverse the loss of tropical forests, combat climate change, conserve biodiversity, and facilitate sustainable development (Planet Labs, 2024).

The NDVI (Normalized Difference Vegetation Index) was calculated for each monthly cloud-free mosaics over Bogota DC. for years 2019 and 2023. The NDVI uses the red and near-infrared reflectance bands (Equation 1), available in the NICFI-Planet images.

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \tag{1}$$

where NDVI = Normalized Difference Vegetation Index
NIR = Near-infrared band reflectance
R = Red band reflectance

For both years, the NDVI Maximum Value Composite (MVC) image was calculated to eliminate cloud pixels and the vegetation seasonality related to temperature and precipitation. A MVC image is calculated considering, for each pixel, its maximum value for all the time series. For NDVI time-series images, the MVC technique allows the elimination of cloud effects; once, for the cloudy pixels, the NDVI is negative, and higher NDVI values eliminate the vegetation seasonality, which is related to the most vigorous vegetation season (Holben, 1986).

The NDVI-MVC image was clustered for both analyzed years using the K-means algorithm (MacQueen, 1967). The k-means is an unsupervised learning algorithm that is used to identify groups (or clusters) in a dataset. The K-means extracts regions from a satellite image using a minimum Euclidean distance decision rule and for each region is assigned a cluster, based on the training dataset (Usman, 2013). The number of clusters must be defined a priori by the analyst and the training sample area. For these analyses, b, other NDVI-MVC images were clustered in six groups. To training the algorithm, the training area was the same of the area of interest, the entire Bogotá DC. The result was a clustered image where each pixel was given a number to identify its cluster.

A binary image was built by remapping these six clusters to represent areas with builds-up and areas with no builts-up (trees, grasses and shadows), based on the visual inspection of the Google Satellite basemap. The variations between years were observed by comparing the both clusters images for the years 2019 and 2023. We using a difference-image calculate using both annual images to better identify the local changes among the neighborhoods. The actual green cover distribution pattern was analyzed based on the neighborhood borders and also considering the population density and incoming levels.

3. Results and Discussion

Considering Bogota's recent situation, analyzed with the image of 2023 (Figure 4), a pattern of urbanization was verified, where there is no space left for trees, regardless of the income level of the analyzed neighborhoods. In central neighborhoods, parks and squares comprise the city's structure. At the same time, there are no trees along the roads in these neighborhoods and a large part of the city, similar to Bogota's landscapes presented in Figure 2.

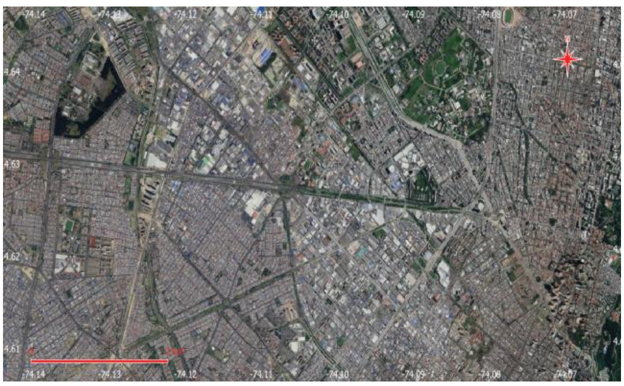

Figure 4. The urban central area of Bogota, DC, observed in a Planet RGB image of December 2023, presents a highly dense urban pattern.

In some central areas like Kennedy and Puente Aranda neighborhoods few variations were observed when we compared the binary images for 2019 and 2023 (Figure 5). These two neighborhoods are different in some aspects like total area, average incoming and the relationship between green areas and inhabitants (Table 1), but in both are in the central area, and cannot expand their borders to rural areas, so this is the main cause to not observed temporal and spatial variations in this neighborhoods.

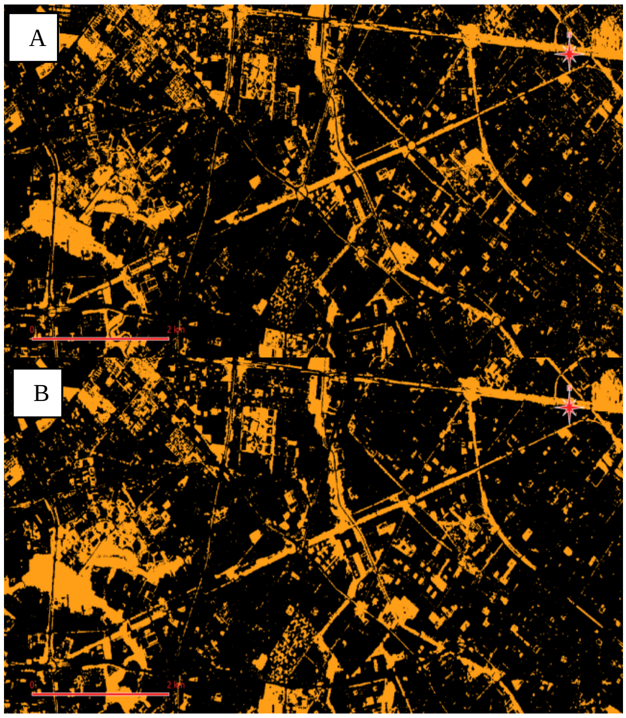

Figure 5. Binary images over Kennedy and Puente Aranda neighborhoods for 2019 (A) and 2023 (B). The black color represents the urban built-ups and the orange color represents vegetation (trees and fields) and urban shadows.

Neighbor-hoods	Population	Total area	Average incoming	Green area/inhab
Antonio Nariño	111,637	4.99	901,701	6,8
Barrios Unidos	243,874	11.92	1,650,303	15,7
Bosa	681,234	24.22	678,968	5,4
Candelaria	24,088	1.83	1,335,213	11,9
Chapinero	139,701	35.78	2,766,693	9,4
Ciudad Bolivar	733,859	130	666,385	14,3
Fontibon	891,530	36.06	1,103,348	11,0
Kennedy	395,122	33.32	1,395,651	6,8
Los Martires	1,092,110	38.72	907,997	4,3
Puente Aranda	99,423	6.53	993,703	8,6
Rafael Uribe Uribe	257,242	17.24	875,304	6,1
San Cristobal	374,246	13.44	760,153	7,9
Santa Fe	402,554	48.83	711,523	11,7
Suba	109,195	44.82	1,040,478	9,8
Sumapaz	1,124,692	101.07	1,492,606	-
Teusaquillo	153,133	14.2	2,825,050	18,8
Tunjuelito	217,139	10.79	788,122	12,6
Usaquen	503,767	65.54	1,974,102	12,3
Usme	457,302	122.63	646,542	27,4

Table 1. Total population, total area (hectares), average incoming (Colombian pesos) and green areas per inhabitant (m^2/inhab) for the Bogota neighbourhoods (Alcaldia de Bogotá, 2024).

Despite Planet images' high spatial resolution, the available visible and near-infrared spectral bands prevent a quantitative analysis once we cannot correctly separate the urban greens from other urban targets, like shadows and pavements. An analysis of the relationship between green areas and a number of inhabitants found that the poorest neighborhoods, located on the city's borders, like the Usme neighborhood, have a more significant number of green areas per inhabitant than other neighborhoods in the city's central location (Table 1). These neighborhoods, when compared to the traditional slums that exist in large cities in different countries, tend to have a more significant number of trees per inhabitant. But, when only the urbanized part is analyzed, these same neighborhoods can be seen to lack tree vegetation as in other areas of dense urbanization in different cities worldwide (slums/favelas). It can be observed in Figure 6, where we can find a similar slum pattern without green spaces or even isolated trees among the built-ups. In this location, people need to go to peripheral non-urban areas to take advantage of vegetation benefits in their health, which are well documented by researchers (Mwendwa and Giliba, 2012; Chiabai et al., 2020; Javadi and Nasrollahi, 2021).

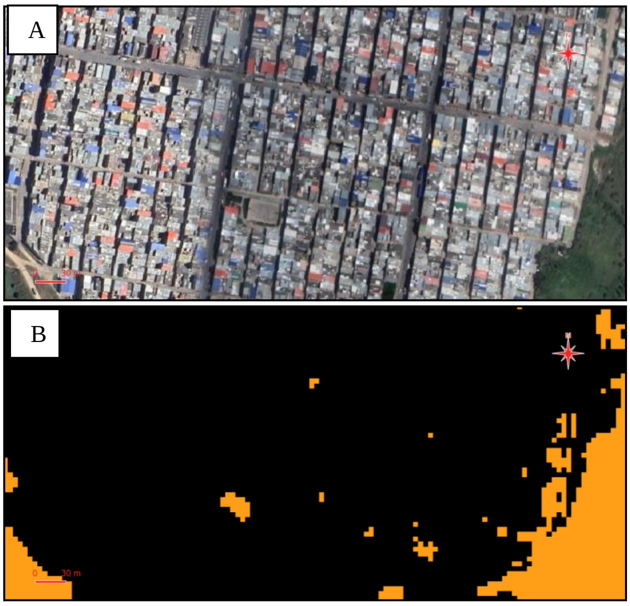

Figure 6. (A) - Google satellite basemap over Usme neighborhood urbanized area. (B) – Binary image for the same area for 2023. The black color represents the urban built-ups and the orange color represents vegetation (trees and fields) and urban shadows.

This lack of space allocated for urban vegetation can be observed in recent urban expansions in the Usme (Figure 7) and also in the Ciudad Bolivar (Figure 8) neighborhoods, where significant reductions in green areas were observed in regions of recent urbanization between 2019 and 2023. This same pattern was observed in other peripheral city neighborhoods, where spaces are densely occupied, and green areas for collective use, such as squares and parks, are not allocated.

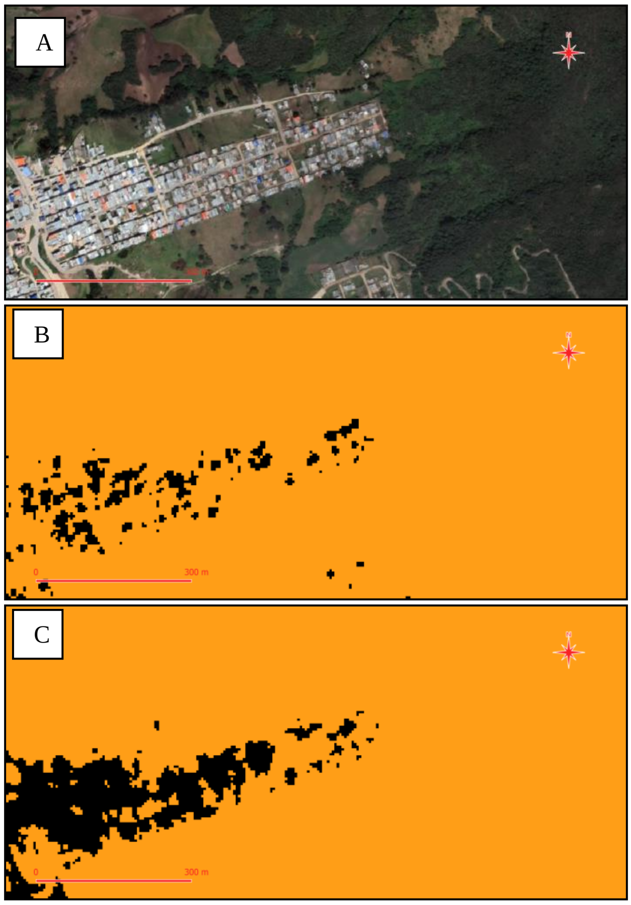

Figure 7. (A) - Google satellite basemap over a recent urban expansion area in Usme neighborhood. For the same area (B) – a binary image for 2019 and (C) – a binary image for 2023. The black color represents the urban built-ups and the orange color represents vegetation (trees and fields) and urban shadows.

In Ciudad Bolivar, we can observe the increase of the built-up in the urban area (Figure 8), where the remaining urban green area was replaced by small houses inside the existing glebes, usually to attend to people from the same families due to recent marriage. In both cases, Usme, as well as Ciudad Bolivar neighborhoods, have low average incoming and their urban pattern, without trees along the streets and inside the glebes, with no public gardens or parks, can be characterized as an environmental injustice, when the benefits of green areas of the human health is denied to the people due to its the economical conditions (Wolch et al. 2014).

A few cases of an increase in the amount of vegetation were observed on wide roads built recently in the city where the planted trees had an increase in volume, and this identification was possible to be observed on NICFI-Planet images between the five years analyzed. Some vegetation increases were also observed in upper-class residential areas between 2019 and 2023, like Teusaquillo neighborhood where the buildings are more spaced. We can identify some new trees along the streets and inside the yards in this king of neighborhoods.

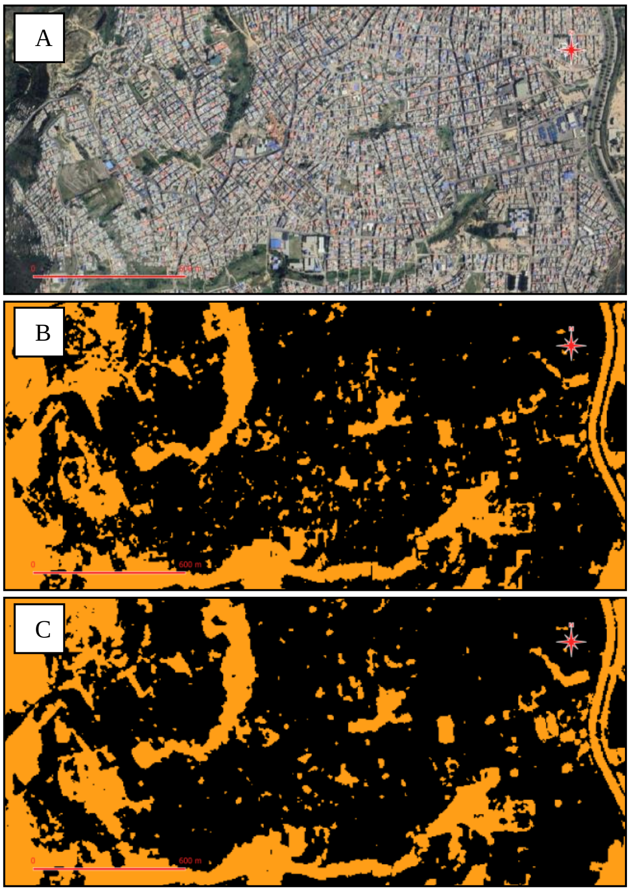

Figure 8. (A) - Google satellite basemap over a recent urban expansion area in Ciudad Bolivar neighborhood. For the same area (B) – a binary image for 2019 and (C) – a binary image for 2023. The black color represents the urban built-ups and the orange color represents the vegetation (trees and fields) and the urban shadows.

4. Conclusion

The monthly NICFI-Planet images and the k-means unsupervised machine learning algorithm can provide maps to analyze the spatial distribution of urban greens in a diverse city like Bogota DC, in Colombia. These maps can be explored in association with socioeconomic data to understand urban greens' social distribution better. In this case, we can observe an environmental injustice, where the benefits of green areas for human health are allowed for people from the middle and upper classes. For these situation in the Bogota,DC. different strategies need to be adopted to increase the benefits to plants for all, like converting spaces in small urban parks and creating a culture of garden pots in the periphery areas.

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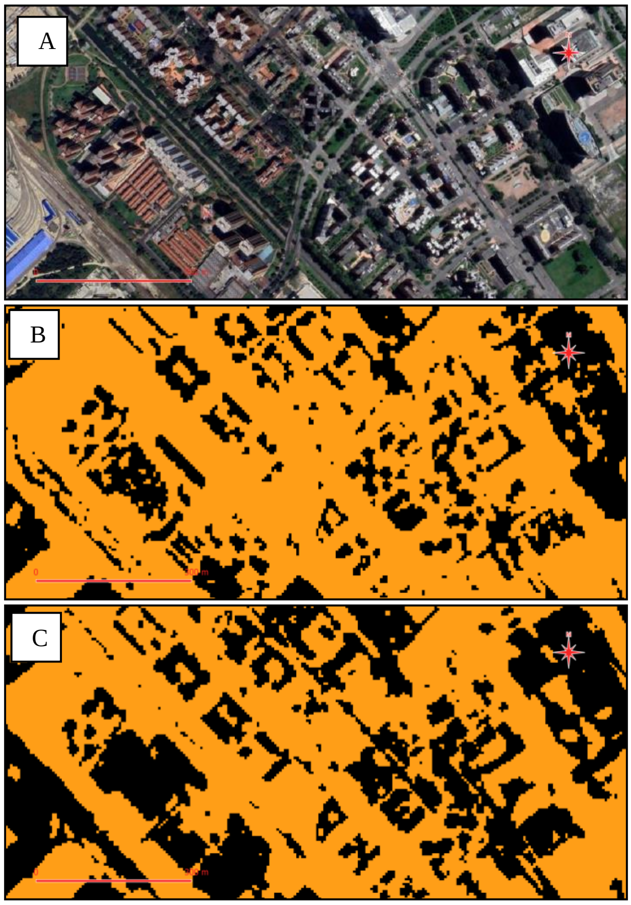

Figure 9. (A) - Google satellite basemap over a recent urban expansion area in Teusaquillo neighborhood. For the same area (B) – a binary image for 2023 and (C) – a binary image for 2019. The black color represents the urban built-ups and the orange color represents the vegetation (trees and fields) and the urban shadows.

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