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Original article

Relationship between densification and NDVI loss. A study using the Google Earth Engine at local scale

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ABSTRACT

Latin American cities are amongst those with the highest rates of urbanization in the world. This process has involved their territorial expansion as well as the densification of some of its neighborhoods, in mainly central areas. This is the case of the city of Santiago del Estero (Argentina) that increased its population by 33% between 1991 and 2010 with the consequent transformations of the local space. In this context, this study analyzes the evolution of vegetated areas and densification of the central area of the city using satellite data. We analyzed two indices: normalized difference vegetation index (NDVI) and Urban Index (UI) time-series data, for the 1992–2011 year period, using the Google Earth Engine for processing Landsat 5 TM images. We found that the NDVI showed a decreasing trend in the timelapse under consideration, while the UI performance registered the opposite trend. The mean NDVI decreased from 0.161 (1992) to 0.103 (2011) while the UI mean increased from 0.003 to 0.036 in the same timelapse. Further, the NDVI has a strong negative correlation with UI (R-squared = -0.862). The results are consistent with the census information that recorded an important demographic and housing growth for the entire city in this period.

KEY WORDS: vegetation cover loss, densification, NDVI, Google Earth Engine, Santiago del Estero, Argentina

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1. Introduction

Rapid urban sprawl is a major contributory factor for environmental change in many parts of the world. Latin America and the Caribbean is the most urbanized region in the developing world and is characterized by accelerated growth. One of the key developments that shaped Latin American cities is the migration of people from the countryside to the city, a phenomenon that has generated regional imbalances in most countries of the region (VARGAS-BOLAÑOS ET AL., 2020). Hence, in addition to presenting high rates of urbanization, Latin American cities also display new urban peripheries, usually without planning, resulting in several issues that have characterized the cities of this part of the world: environmental impact, diseconomies, and a decrease in the quality of life of the local population. Although urban growth is referred to as necessary for a sustainable economy, uncontrolled urban growth can cause several problems, such as loss of open spaces, landscape modification, environmental pollution, traffic congestion, pressure on insufficient infrastructure, and other social and economic problems (NOLÈ ET AL., 2013). Moreover, in this region, urbanization is one of the main anthropogenic factors that has produced the reduction of green areas and the replacement of pre-existing habitats in cities of Latin America (BERKOWITZ ET AL., 2003).

To address this context, FERRO (2001) argues that urban planners may consider diverse approaches: new developments planned in the suburbs (a practice that responds to a "traditional" form of growth), new cities in the area, or the reuse of existing space through densification projects. As a substitute to "traditional" urban sprawl, there is a "densification" approach through the re-ordering of large areas that are well located, but that have deteriorated, or are misused or vacant. In Latin America, the outcome is an amalgam of growth where the middle and upper residential areas have practically disappeared due to increasingly smaller high-density buildings, or from the edification of new constructions that replace homes in old residential neighborhoods. As opposed to, the lower strata that do not have the resources to access the formal housing market, and are located in the most distant peripheries, in informal urbanization lots where they build homes "progressively". Consequently, the central areas of the cities have been condensing with great force, appealing to the tertiary sector, and creating at the same time, an area of commercial activity and services, to which is added the construction of residential buildings. Hence, while the central areas are densified, the single-family neighborhoods on the periphery are also growing in a process that does not necessarily occur in a planned manner. From the urban economic perspective, MATTOS, (2016), DEL RÍO (2017) and BENSÚS TALAVERA (2018) maintain that this densification course is associated with an intense exploitation of the urban land in areas of high construction demand, closely linked to the real estate market.

Densification is usually more noticeable in specific neighborhoods/parts of a city as recent studies indicate (DARCHEN & POITRAS, 2018; TILLIE ET AL., 2018; TREIJA ET AL., 2018; SKREDE & BERG, 2019; ANDERSSON ET AL., 2020; LI ET AL., 2021; EGGIMANN ET AL., 2021; CELLUCI & SIVO, 2021; among others), and is viewed as an answer to the uncontrolled urban sprawl, however, compared to urban growth, densification has some environmental merits, but is not without negative environmental impacts (NÆSS ET AL., 2020; COPPOLA, 2012). Dense cities are a logical choice for an increasingly urbanized world, where worries about environmental sustainability and urban growth are significant (UN HABITAT, 2012). Among their many benefits, dense cities, in addition to helping to preserve rural land, also reduce greenhouse gas emissions (LIBERTUN DE DUREN AND COMPEÁN, 2016). Densification is viewed as an appropriate measure to cope with fast urban growth that aims to limit the expansion of the constructed area on the outskirts by expanding additional living space within already built areas (BERNDTSSON ET AL., 2019) and can be seen as an opportunity for sustainable urban development, as it fosters resource efficiency and transportation, while undeveloped land outside the city could be retained as a natural environment (EMILSSON & SANG, 2017). Although vegetation cover loss is prevalent, densification does not always indicate a reduction in greenness. In certain instances, more vegetation in urban areas has emerged from planning and the drive for more sustainable cities, such as the cases of Taipei (WANG ET AL., 2018) and Singapore (GAW & RICHARDS, 2021). On the other hand, most case studies in Argentina demonstrate the opposite results (MERLOTTO ET AL., 2012; PAOLINI ET AL., 2016; FERRELLI & BUSTOS., 2015; ARBOIT & MAGLIONE, 2018). Therefore, in most cases, this process usually involves the loss of green spaces with negative environmental impacts such as the alteration of wind and temperature patterns (PAULEIT ET AL., 2005; FONTENELLE ET AL., 2015; LEMONSU ET AL., 2015).

Land-use changes are the most notable indicator of the human footprint and are considered to be the most important factor of biodiversity loss and land degradation. The effect of land-use change varies by region and geographic location (ZURQANI ET AL., 2019). Generally, in developed countries there is effective territorial planning, while, in Latin America, it is more anarchic, coexisting urban planning measures with growth areas without any control. Given that cities in this region will continue to expand and densify, the study of changes in urban land cover and their impacts on urban vegetation is of fundamental interest (FERRELLI ET AL., 2018).

Tracking urban land cover change, through the interpretation of satellite imagery, can be an extremely valuable tool for urban planners in detecting the effects of environmental change (HUANG ET AL., 2009). At present there are numerous satellite platforms that record terrestrial information, which is disseminated in different repositories. This results not only in a wide variety of data, but also makes it imperative to handle these large volumes of information more efficiently. Due to the high volumes of data captured and archived regularly and over a long period, changes in land use can now be measured not only in two-time snapshots, but continuously over many time intervals (JIANYA ET AL., 2008). Satellite imagery is rapidly being utilized to construct diverse maps of land surface features, such as vegetation, snow, water, and built-up land characteristics, automatically and semi-automatically (FIROZJAEI ET AL., 2019). More specifically, Landsat sensors have been instrumental in observing geographic phenomena, with datasets going back decades (LI JIAN & ROY, 2017).

Time series analysis of changes in land cover allows researchers to understand the general trends and dynamics of land-use changes over complete time series rather than a simple increase, or decrease, between two points in time. Hence, modeling vegetation change rates as well as built-up area evolution can be done more accurately using a time series provided by satellite imagery (Trombetti et al., 2008). Historically, the large volumes of data provided by continuous satellite monitoring represented a technical challenge for interpretation and analysis. The processing of large time series datasets has been made accessible thanks to recent technological advances in computing, in particular the creation of Google Earth Engine (GEE). In this context, access to historical and current remote sensing data using Google Earth Engine's geospatial technology represents a significant improvement in monitoring and evaluating land-use change over time (Zurqani et al., 2019).

Vegetation greenness and built-up land are the two most important factors for studying urban variations. The NDVI reflects the health and density of the vegetation, while the built-up indices refer to constructed areas. The NDVI and built-up indices have also been evaluated as predictors and factors in urban land change (Grover & Singh, 2015). Due to the variability and spectral closeness of built-up areas and bare land, using this type of index is particularly difficult. Hence, several indices for mapping built-up and other land cover types in urban areas have been used in various studies, including the Normalized Difference Built-Up Index (NDBI) (He et al., 2010), Index-based Built-Up Index (IBI) (Xu, 2008), Urban Index (UI) (Kawamura et al., 1996), Normalized Difference Bareness Index (NDBaI) (Zhao & Chen, 2005), and Bare soil index (BSI). The spectral performance of built-up land and other properties related to wavelengths of the electromagnetic spectrum in terms of absorption, or reflection, serve as the foundation for the development of these indices (Firozjaei et al., 2019), although each one has its own set of potentials and drawbacks. NDBI and UI, for example, have the limitation of mixing to some degree built-up and bare land areas, but on the other hand, are easy to implement (Sinha et al., 2016). Moreover, recent studies have demonstrated that using built-up indices, such as NDBI and UI- recurring to the SWIR 1/SWIR 2 bands, are more effective at detecting built-up areas, as they possess higher reflectance values, allowing them to be readily distinguished from other land uses. Therefore, UI, like NDBI, is a relevant indicator for urban studies since it gives accurate information regarding land change across time and can be calculated quickly from satellite data (Xi et al., 2019) and, unlike NDVI, which is dependent on and varies with climatic conditions, these built-up indices remain more constant throughout the year in any climatic conditions around the world (Kumari et al., 2020).

UI was developed as a built-up index in the 1990s to generate data and analyze the situation and sprawl pattern of built-up areas using remote sensing data (Kawamura et al., 1996). The UI normalizes the NIR and SWIR 2 bands, making use of the inverse correlation between NIR and SWIR brightness in constructed areas. This procedure is based on the fact that urban and bare ground areas have low reflectivity in the NIR band but relatively high reflectivity in the SWIR bands (Do et al., 2021). The UI is computed by using the bands 7 and 4 from Landsat Thematic Mapper (TM) imagery. It is very similar to NDBI and is probably the most used built-up index, with the difference being that it uses SWIR2 instead of SWIR1.

Although the growth and densification of cities are two processes that coexist in Latin American cities, most of the research focuses on urban sprawl, with fewer articles analyzing the densification at intra-urban scale. Consequently, the initial purpose of this research is to use The GEE to process the large free satellite datasets that are available for the long-term monitoring of NDVI and UI in a case study focused on the downtown neighborhood of the city of Santiago del Estero, in a period comprising the years 1992 and 2011. The reason for the selection of this timelapse is not arbitrary since it comprises, approximately, the last three censuses carried out in the country (1991, 2001, 2010) which provided data, albeit partially, on demographic growth as well as on the number of houses in the city. The downtown neighborhood is the central area that has been more patently affected by the densification process throughout the city in the last decades. To better contextualize this land-change scenario, information on population and housing units from these three census periods was obtained from the National Statistical and Census Institute (INDEC) web page. Unfortunately, there is scarce disaggregated data available on that web page, with the exception of the 2011 census.

2. Study area

Santiago del Estero is the capital of the homonymous province in northern Argentina. With a surface area of 2,116 km^2 and a population of 252,192. It is the country's tenth largest city, and it is located 1,042 kilometers north-northwest of Buenos Aires. Santiago del Estero is placed in a transition zone between the temperate climates of the Pampas, and the subtropical climates of the Chaco region and according to the Köppen classification, it has a hot semi-arid climate (BSh).

The annual precipitation of 695 mm is concentrated mostly from November to March with the occurrence of frosts between May and August and the average annual temperature is 21.5 °C (ROGER ET AL., 2016).

It is not possible to know exactly the population of the downtown (central) neighborhood of the city of Santiago del Estero. However, in the period 1991-2010 (Table 1) the number of inhabitants residing in the city increased by 33%, ten more percentage points than the national average. On the other hand, housing also registered a significant increase in the Capital department (where the city of Santiago del Estero is located and comprises 94% of the population) with an increment of 85% in the same period. The central neighborhood of the city has a perimeter of 5.10 km and an area of 1.55 km^2. In its interior, 25 census blocks are located totally or partially (each of them contains approximately 200 houses) (Fig. 1). This area contains 1965 pixels which are sufficient to carry out a microscale study.

An inventory of the street trees carried out by ARIAS & CELEMIN (20218), indicates how the vegetation is located, mainly to the central-south and south-east of the study area, as the abundance increases from the interior to the bordering avenues of the neighborhood. It also registered the location of green spaces, where only two occupy an entire block, out of the 98 blocks in the neighborhood (Fig. 2). It is an area where concrete predominates, with few green spaces and trees (Fig. 3).

Table 1. Increment of population and housing units (1991-2010) (Source: INDEC, 1991, 2001, and 2010 Census)

Year	Population in Santiago del Estero city	Housing Units in Capital Dep.
1991	189 947	42 241
2001	230 614	53 711
2010	252 192	78 281
1991-2010 Variation	32.77 [%]	85.32 [%]

Fig. 1. Study area location

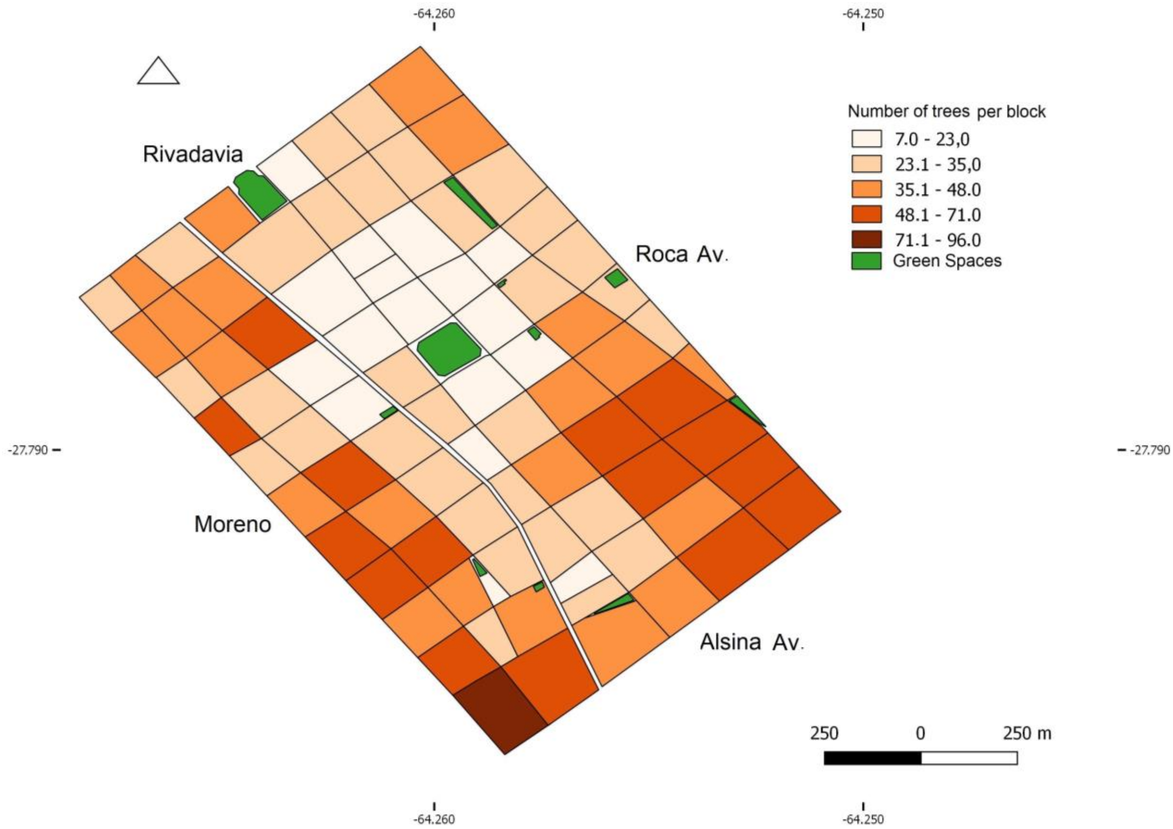

Fig. 2. Tree abundance and green spaces in the study area

Fig. 3. Street photo in the study area (-27.7912; -64.2572), Arias, 20/04/2022

Given the capacity of the GEE to create visual information continuously, a video was made with the monthly evolution of the NDVI in the 1991-2011 period, as a way to provide a better visual interpretation of the study area and of the spatial distribution of vegetation greenness. For this, a script was created with Landsat 5 TM 32-Day NDVI Composite data. Video available at: https://drive.google.com/file/d/1x31fiqykxCBinbeI0FefnYknnq9pMK_x/view?usp=sharing

3. Methods

The GEE catalogue for the Landsat 5 TM was used in this investigation. This satellite was a low-Earth-orbit platform launched on March 1, 1984, and administered jointly by the USGS and the National Aeronautics and Space Administration (NASA). The USGS Earth Resources Science and Observation Center collected and distributed Landsat 5 TM data (EROS). Landsat 5 TM was formally deactivated on June 5, 2013, after 29 years in space.

GEE provides online access to archived Landsat data, including Landsat 5 TM from 1991 to 2011. We used the "LANDSAT/LT05/C01/T1_SR" catalogue that contains atmospherically corrected surface reflectance images from the Landsat 5 TM sensor. These images contain 4 visible and near-infrared (VNIR) bands and 2 short-wave infrared (SWIR) bands processed to orthorectified surface reflectance, and one thermal infrared (TIR) band processed to orthorectified brightness temperature. The VNIR and SWIR bands have a resolution of 30m / pixel (https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LT05_C01_T1_SR#description).

On the GEE platform (https://earthengine.google.org/), all data processing was done using cloud computing technology. To this purpose, a script was created with the goal to acquire the overall value of NDVI and UI for the study area for all images available throughout the study period. Landsat 7 ETM+ images were not used due to the failure of the Scan Line Corrector (SLC) in 2003, resulting in some areas that are imaged twice and others that are not imaged at all.

In addition, only cloudless images are selected through the script, for both satellite catalogues. Finally, the mean was obtained from the images of the entire study area using the ReduceMean feature.

There are different indices obtained from satellite images that allow us to know the state of the vegetation where the Normalized Difference Vegetation Index (NDVI) is the most recognized and used. It is calculated by using the following expression:

$$NDVI = \frac{NIR - R}{NIR + R}$$

where NIR is near-infrared reflectivity (Landast 5 TM band 4) and R is reflectivity in red (Landsat 5 TM band 3). The image value is delimited by the range -1 and 1 and the closer it is to 1 the greater the presence of healthy vegetation in a place.

The UI normalizes the NIR and SWIR 2 band, which makes full use of the inverse relationship between the brightness of the NIR and SWIR in built-up area (Xi et al., 2019).

$$UI = \frac{SWIR2 - NIR}{SWIR2 + NIR}$$

where SWIR2 is Short Wave Infrared 2 (Landast 5 TM band 7) and NIR is near-infrared reflectivity (Landast 5 TM band 4).

The entire data analysis of both indices was conducted using GEE. An imported shapefile of the Central area of Santiago del Estero city was imported into the GEE for extracting the NDVI and UI values over a 19-year timelapse (1992–2011). With the resulting dataset, which provided no data for the year 1991, we computed a mean value of the NDVI and UI from all pixels in the study area for all the 60 images in order to globally know the temporal evolution of both indices. Furthermore, the seasonality patterns of the NDVI and UI were examined using long-term monthly means. Next, we studied the annual performance to examine the fluctuation of the NDVI and UI over time.

Finally, the relationship between both indices was analyzed using the R-squared procedure.

4. Results

4.1. Dataset analysis

The data processing from the GEE platform resulted in a total of 60 images corresponding to Feb 5, 1992 to Sept 25, 2011. An initial visual interpretation of the original dataset allows us to observe a continuous decrease in the NDVI while the UI records show a general increasing trend (Fig. 4). The correlation of both datasets registers a negative slope, with a high R-squared of -0.863 with an NDVI mean of 0.136 and 0.023 for the UI.

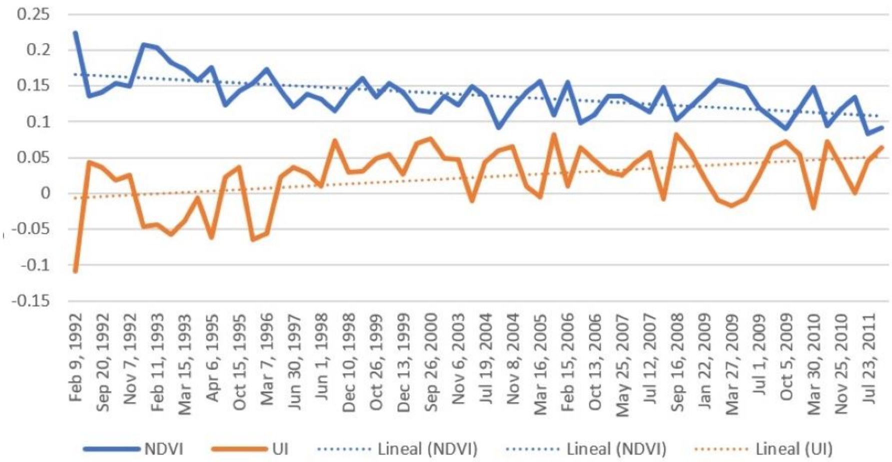

Fig. 4. NDVI-UI evolution (complete dataset)

4.2. Annual and temporal variations of NDVI and UI

The next result models the trend of the NDVI and UI over 19 years in the central area of the city of Santiago del Estero (Fig 5). By averaging the mean NDVI and UI values over all pixels in the study area the linear regression model was adopted to identify the temporal variation of both indices. The mean NDVI values vary from 0.161 in 1992 to 0.103 in 2011, while the mean UI has a score of 0.003 in 1992 and 0.036 in 2011. Consequently, since 1992, there has been an overall constant decaying trend in NDVI while the UI has the opposite output, although with more abrupt fluctuations. In the first years it registers negative values, with the exception of 1992, that quickly rise to positive scores beginning in 1997. From that date on the UI plateaus and even decreases a little. The NDVI has an annual mean for the 19-year period of 0.136, while the UI registers a mean of 0.023. Furthermore, the NDVI has a higher R-squared in the linear regression model with a score of 0.66, while the UI has a 0.38 score. Both have similar Standard Deviation values with 0.021 and 0.029 respectively.

The seasonal variability of NDVI and UI illustrates the NDVI and UI seasonal patterns for the study area (Fig. 6). The seasonal peaks of the NDVI are observed during spring and summer seasons, while the lowest NDVI mean scores are observed in the winter. On the contrary, the UI presents negative values in the summer months and from mid-autumn it increases considerably reaching its peak in late winter (August-September).

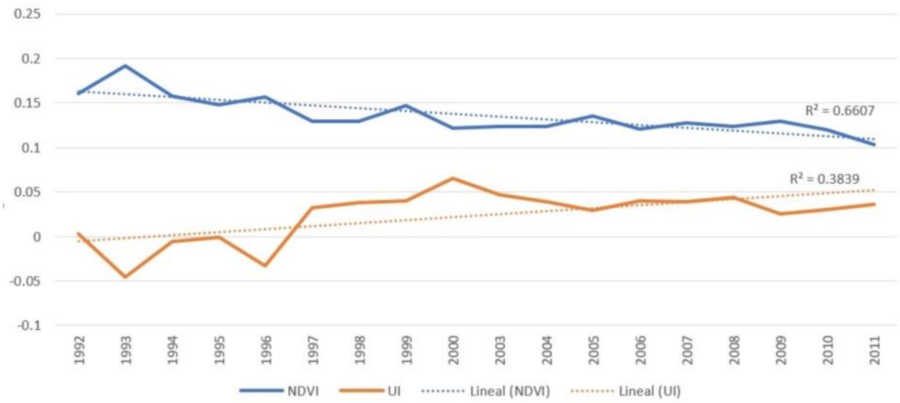

Fig. 5. Annual performance of NDVI and UI

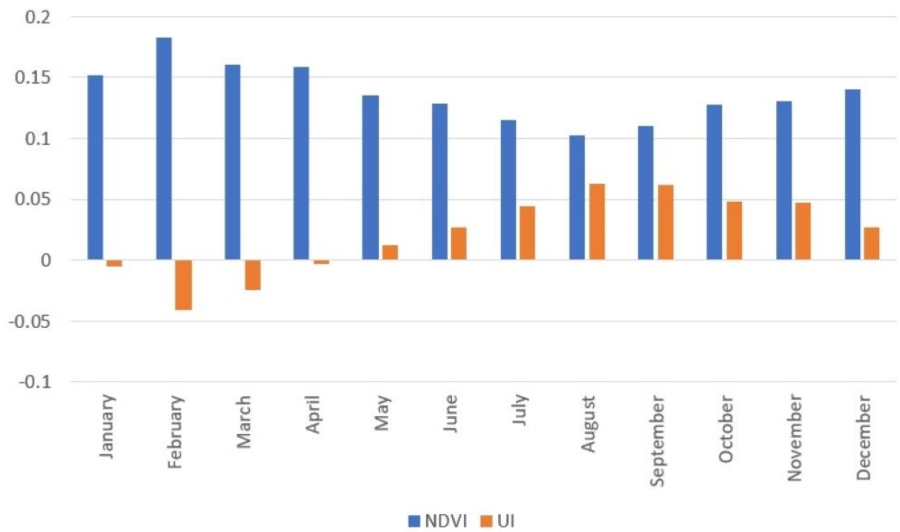

Fig. 6. Seasonal variability of NDVI and UI

5. Discussion

The impact of urbanization on natural ecosystems and on habitat quality is a topic of current study as the relationship between urban dynamics and plant communities involves processes with complex characteristics. Population growth is decisive in the decline of NDVI, with strong negative correlations in urban sites, especially in Latin America (ARBOIT & MAGLIONE, 2018). A global scale study focused on urban vegetation cover (RICHARDS & BELCHER, 2019) shows how it had decreased in most urban areas between 2000 and 2015, mainly in less developed countries; however, vegetation cover slightly increased in some urban areas in eastern North America and parts of Europe. Urbanization that does not take care of its own natural landscape poses a threat to the quality of the urban environment and, thus, the quality of life of the inhabitants (YEPEZ ET AL., 2014). Remote sensing techniques can be used to analyze the increase of impervious surfaces and vegetation status to gain a better understanding of urban areas. Spectral indices have the advantages of being easy to build, parameter-free, and useful in land surface information extraction applications and provide geographical and temporal data that are utilized to assist urban populations and decision-makers in maintaining, or improving, their cities' quality of living in the future (HIDAYATI ET AL., 2021). The loss of vegetation in a context of coexistence of new urban peripheries and densification in Latin American cities urges urban planning to enact strategies that not only facilitate the creation of new green spaces, but also to form an urban framework sustained by regulations that favour the planting and maintenance of vegetation in private spaces (DE LA BARRERA & HENRÍQUEZ, 2017).

5.1. Densification and loss of vegetation cover

The current study employed Landsat 5 TM images to examine the NDVI and UI evolution for the downtown neighbourhood of Santiago del Estero from 1992 to 2011. In the context of densification in the research area, the results suggest a decreasing presence of vegetation. Densification is an urbanization approach that entails increasing the amount of built space and creating compact cities rather than expanding cities in order to make better use of limited space (EGGIMANN ET AL., 2021). In Argentina, the analysis of several cities in the Region of Cuyo (Argentina) carried out by ARBOIT & MAGLIONE (2018) highlights population growth as a factor in the decline of NDVI. Other studies on the spatial and temporal analysis of NDVI for the town of Monte Hermoso in the province of Buenos Aires, Argentina, in the period 2008-2012 (FERRELLI ET AL., 2018) and for the city of Bahía Blanca also shows a loss of NDVI values (FERRELLI ET AL., 2015). More specifically related to densification in cities of Argentina, we can mention the work of MERLOTTO ET AL., (2012) who carried out a study on land cover between 1967-1984 for the towns of Quequén and Necochea, with results showing that the process of densification of urban occupation is significantly higher than that of the expansion. On the other hand, a study focused on twelve cities in northern Argentina (the poorest region of the country) (PAOLINI ET AL., 2016) found that the dynamics of urban growth in this area were dominated by patterns of expansion rather than homogeneous densification, although both processes coexist to some extent, and which seems to be the case for the city of Santiago del Estero. For Latin America, the work of VEGA ET AL. (2019) records a considerable loss of vegetation cover by estimating

NDVI for urban areas of the city of Iquitos (Peru) between the years 1999-2009. Another recent case is in the city of Medellín, for the 1986-2016 timelapse shows a greater loss of vegetation in the densest area of the town (SOTO-ESTRADA, 2019). Similar results are presented by DE CARVALHO & SZLAFSZTEIN (2018) in a case study of the city of Belém (Brazil) for the period 1986-2009 using Landsat 5 TM images.

A limitation to appropriately measure densification in Argentina (either due to an increase in population and/or buildings) is the way in which the censuses in Argentina record the information. Moreover, in most cases, the total population can be only approximately known since the unit of measurement of the censuses (census blocks) rarely coincides with the limits of a neighborhood. For example, in the interior of the downtown neighborhood of the city of Santiago del Estero, there are 18 census blocks, but 7 partially occupy the surface of the neighborhood.

Built-up indices are sensitive to construction and are frequently used to represent the degree of development and density of a built-up area. Different indices have been developed to determine built-up areas from satellite images, however, none have obtained a much higher precision than the rest, resulting in a proliferation of indices. They all have potential and limitations, while the NDBI and the UI stand out for their ease of implementation. Previous research revealed that built-up indices were better than NDVI for quantitatively detecting land changes over time (XIE ET AL., 2021; KUMARI ET AL., 2020). However, this is not the case in this study since the interpretation of the graphs and the data indicates a slightly greater variability of the UI than that of the vegetation index. In addition, the results arise new interrogations that will be addressed in future works. For example, it is interesting to observe how the UI index plateaus since the late nineties. This could suggest that the area has reached some degree of building saturation, although this does not explain the decrease of NDVI values since that date.

5.1. Potentialities and limitations of the use of GEE

Long-term satellite imaging is critical for understanding dynamic land cover, and it is especially good for detecting vegetation changes. A variety of sensors produce images with varying resolutions with the goal of detecting specific types of land cover. GEE is a cloud-based geospatial processing platform that provides a vast collection of data for analyzing free satellite imagery, producing statistics and maps, and graphical representations (MUGIRANEZA ET AL., 2020). The Landsat library in GEE comprises more than three decades of Earth observation photos, giving researchers a unique chance to track land cover changes through time with high temporal and spatial resolution. Because of their great spatiotemporal resolution, Landsat-based time series data are ideal for detecting vegetation change (HUANG ET AL., 2018). This study demonstrated that a simple analysis of NDVI and UI trends in a local context can be easily replicated in other areas. The scripts are stored in the GEE platform and by replacing the polygons corresponding to a study area with another area of interest, the information for a new set of data is generated. Finally, the importance of obtaining temporally continuous data is highlighted, unlike the census information that is available on specific dates, separated by many years.

6. Conclusions

Latin American cities experience simultaneous processes of urban growth and densification. Both are complementary but each has its own dynamics. The study of densification, which can be observed in greater detail in the central areas of cities, is not as advanced as that of urban growth, even more so it is linked with elements of the local landscape, such as vegetation. The development of artificial spaces and the replacement of natural features are known to function as the main drivers of change in the local space. In this context we found that the NDVI showed a decreasing trend in the timelapse under consideration, while the UI performance registered the opposite trend in a 19-year period in the central area of the city of Santiago del Estero (Argentina) which has rapidly increased its population and housing units in the last decades. Both indices also presented a high negative correlation. Because the results were valuable and consistent, the approach can be used in other cities. The loss of vegetation and the increase in built area are common characteristics of Latin American cities that require more attention, particularly in the context of climate change. The findings of this study can help to implement local policies aimed at improving and increasing the area of green space in the study area.

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