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1 mensaje

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Para: nandino@unsj-cuim.edu.ar

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Re: "Land surface temperature in an arid city: assessing spatio-temporal changes"

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Land surface temperature in an arid city: assessing spatio-temporal changes

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ABSTRACT

In a city located in a desert environment (Tulum Valley, Argentina) we proposed to assess in the coldest and warmest periods (1) the urban cold/heat island (UCI/UHI) phenomenon; 2) which driving factors currently affect the Land Surface Temperature (LST). In the study area, we selected 50 points for the urban class and 49 points for the rural class. The LST data was obtained from Landsat 5 TM y Landsat 8 OLI/TIRS, for 1988, 2000, 2010, and 2021 years. As driver factors, we assessed the median (med) and standard deviation (sd) of NDVI (Normalized Difference Vegetation Index), NDBI (Normalized Differences Built-up Index), and BI (Brightness Index). The Tulum Valley behaved like a UCI during almost all studied years, except for 2010 and 2021. Probably because the city was undergoing reconstruction after a major earthquake. In the urban class, the LST were affected positively by $NDVI_{med}$ during the cold period, while in the rural class the LST were explained by a negative relationship with $NDVI_{med}$, and positive with $NDBI_{med}$. In the urban class during the warm periods, the LST were affected negatively by BI_{sd}, BI_{med}, $NDVI_{med}$, and $NDVI_{sd}$, which leads to a decrease in LST. Contrarily, an increase of $NDBI_{sd}$ produces an increment of LST. The only driver for LST in the rural class was $NDBI_{med}$, which had a positive effect. Different drivers affected the LST behavior in Tulum Valley, moreover, these drivers explained more variability in rural than in urban class.

Keywords: urban cold island, drivers of temperature, vegetation, built-up areas, bare soil, heterogeneity

1. INTRODUCTION

The emergence, development, and expansion of the city in a geographic area disrupt the natural land surface characteristics. The urban landscape is a complex combination of green vegetation, water surfaces, impervious surface materials and bare soils (Rasul et al. 2017). In last decades, the climate change due to sprawl of the urban areas has gained relevance (Rasul et al. 2017). One of the key climatic effects is increased Land Surface Temperature (LST) in the urban environments compared to their surrounding non-urban areas, i.e. the Urban Heat Island (UHI) phenomenon (Oke 1982) frequently recorded in cities of temperate and subtropical climates (see review Rasul et al. 2015). This phenomenon is due to many common construction materials used in urban areas, which absorb and retain more of the sun's heat than natural materials used in rural areas. Additionally, urban materials are mostly impermeable, i.e. do not have moisture able to dissipate the heat from the sun. Other factors that contribute to heat island formation are the shape of buildings, the pavement, the anthropogenic heat or human-produced heat, slower wind speeds, and air pollution in urban areas (Gartland 2008).

Contrarily, in most arid and semi-arid environments urban areas have been found to exhibit lower surface temperatures compared to non-urbanized dry surroundings, a phenomenon that is known as the Urban Cool Island (UCI) (see review Rasul et al. 2015). Different drivers can be attributed as a cause of UCI, i.e. the amount of soil moisture in the urban area, the cooling caused by urban parks and green spaces with dense vegetation that reduces the solar radiation reaching the surface, the presence of urban rivers (see review Masoodian et al. 2021). Particularly the urban parks and green spaces, i.e. irrigated vegetation of urban areas, cool their surroundings through an increase of evapotranspiration which enhances latent heat exchange. On the other hand, the surrounding area becomes warmer than the urban areas, due to the sun's radiation turning into sensible heat by the presence of bare soil (Masoodian et al. 2021). There is much interest in the study of vegetation in different cover classes, as a measure of heat storage capacity and evaporation (Voogt and Oke 2003).

Several studies have examined the effects of the urban landscape on LST using landscape metrics (Madanian et al. 2018). In this regard, these studies assessed the spatial patterns of the landscape components as a significant determinant of the urban LST, i.e the size and complexity of the green spaces, the abundance of each land cover class, their spatial arrangement, and distribution (Jafari et al. 2017; Madanian et al. 2018). Other studies, analyze the relationship between the spatiotemporal variability of LST and driver factors such as vegetation, urban area, and population throughout different indexes calculated from remote sensing data (Rasul et al. 2017). Regardless of the approach used to assess the influencing factors on LST, different studies agree that vegetation, bare soil, and their associated moisture were dominant factors in LST behavior (Rasul et al. 2015; Madanian et al. 2018). Particularly related to vegetation, several studies on many parks showed that LST is lower in larger parks than in smaller ones, in green spaces with trees and shrub cover, and with little paved coverage (see review Rasul et al. 2017). Moreover, other features of urban vegetation arrangement that could affect LST behavior could be the spatial patterns of trees (i.e. individuals, trees along streets, trees cluster in green spaces) (see review Farella et al. 2022), the place where growing (i.e. concrete or grass surface), and the presence of different strata (i.e. trees, shrubs, grass) (see review Bowler et al. 2010). In relation to bare soil as a driver of LST behavior, this variable is especially important in arid and semiarid regions with sparse vegetation in which bare soil represents a significant portion of the soil heat flux. Therefore, in a mixed pixel with vegetation and bare soil, vegetation in the bottom of a canopy can have higher temperatures than top of canopy (see review Farella et al. 2022).

The UHI/UCI phenomenon has been studied in many regions of the world, however, urban areas of South America have been less focused on (Espinoza-Molina et al. 2022). Moreover, the most studied cities are from tropical, Mediterranean, and cold climatic regions, and little attention has been paid to arid regions with extremely high temperatures (Rasul et al. 2017). In Tacna, an arid city of Perú, it was found that the dense vegetation of summer can weaken the UHI effect, due to not allow reach radiation to the surface, and built-up spaces can accelerate its effect (Espinoza-Molina et al. 2022). In Argentina, Casadei and collaborators (2021) quantified the UHI/UCI of various cities on a large scale, using data from MODIS images. They found that urban areas surrounded by desert and xeric vegetation showed a UCI diurnal phenomenon more frequently than urban areas surrounded by forest or jungle.

In this work, we proposed to evaluate the LST behavior and its driving factors in a city placed in the arid lands of Argentina. Therefore we assessed the UHI/UCI phenomenon in the last thirty years. Moreover, since we consider that not only the abundance but also the heterogeneity in the distribution of different drivers affect the behavior of LST, we work with median values and standard deviations of the vegetation, built-up areas, and bare ground indexes. Moreover, considering that UHI/UCI could be a seasonal phenomenon (Rasul et al. 2017), we took into account the effect of drivers on the minimum and maximum values of LST, of the coldest and warmest periods of the year respectively. Thus we addressed the following objectives in the city of San Juan: (1) to assess the behavior of Land Surface Temperature (LST) and the UCI/UHI phenomenon during the coldest and warmest period during the last thirty years; 2) to evaluate which driving factors currently affect the LST in the coldest and warmest periods.

2. METHODS

2.1 Study area

The San Juan province (Argentina) belongs to the South American Arid Diagonal and has two different environments: the oasis and dry lands, defined by the aridity conditions and development urban model (Márquez 2004). In the irrigated oases, human settlements were concentrated together with their main economic activities. The most important oasis, due to the availability of soil and water, is the Tulum Valley, with an approximate area of 1,625 km^2. This Valley is our study area, and is located in the central-southwestern sector of the San Juan province and includes the metropolitan center of San Juan city and its surrounding areas (Fig. 1). Around 73% of the population of this Valley is concentrated in urban areas, while the rest of the population is in surrounding rural areas. During the last decades, the Tulum Valley has experienced remarkable urban growth with a westward orientation (Kurban et al. 2017), with a population of 696,076 in 2010, 789,489 in 2021, and an estimated increase of 926,479 for 2040 (https://www.indec.gob.ar/).

The climate of San Juan is mainly arid (Poblete 2007) with an average temperature of 10.98 °C in the coldest months (i.e. from May to August) and an average of 27.52 °C in the warmest months (i.e. from November to February). Being -5.9 °C the lowest temperature (June 2021), and 45.30 °C the highest temperature (December 2020) recorded in a period of 9 years (2014-2022) (http://siga.inta.gov.ar/#/).

2.2 Image data

To obtain land surface reflectance and land surface temperature data, we used Landsat 8 OLI/TIRS Collection 2 Level 2 products (https://www.usgs.gov/) corresponding to the study area (path 232 row 82) at 30-meter spatial resolution. The collections of Landsat ensure consistent data quality through time and across all the Landsat sensors, with sensor-specific geometric and radiometric adjustments. These collections improve substantially in the absolute geolocation accuracy of the global ground reference dataset, which improves the interoperability of the Landsat archive through time. Moreover, includes updated global digital elevation modeling sources and calibration and validation updates.

We worked with images of the coldest months (i.e. from November to February) and images of the warmest months (i.e. from May to August) from 1988, 2000, 2010, and 2021 years.

To evaluate the LST behavior and its drivers, we considered urban and rural land-cover classes. The urban class included impervious surfaces such as asphalt and pavement (i.e. parking lots, roads, highways), built-up areas (i.e. with houses, and buildings), and green irrigated spaces. Instead, the rural class included croplands, land for cultivating, and sparsely vegetated or barren soil areas. Using Google Earth Pro (versión 7.3.1) high-resolution images we selected 50 points for the urban class and 49 points for the rural class.

2.3 Land surface temperature

To obtain LST data, we composed an image with median values for each period, i.e. coldest and warmest periods, taking into account the images of different months included in each period. Moreover, to consider the temporal variability of LST values, each image were normalized for the study area with the following equation (1):

$NLST = (LST_i - LST_{min}) / (LST_{max} - LST_{min})$ (Equation 1)

Where NLST is the normalized LST, LST_i is the initial LST of pixel i, LST_{min} and LST_{max} are the minimum and maximum LST's value of a given scene; respectively.

For each study year (i.e. 1980, 2000, 2010, and 2021), the median (annual), minimum (of cold period), and maximum (of warm period) values of LST (hereafter LST_{med}, LST_{min}, and LST_{max}) were calculated in window sizes of 3x3 pixels (equivalent to 90x90 m, area 0.81 ha) where each value was assigned to the central pixel of the window.

2.4 Identification of UHI/UCI phenomenon

We determined UHI/UCI phenomenon as the difference between surface temperature of an urban area and its rural surroundings (Stathopoulou and Cartalis 2007). Therefore, the UHI/UCI intensity were defined using following equations (2 y 3 respectively):

$UHII = LST_{urban} - LST_{rural}$ (Equation 2)

$UCII = LST_{rural} - LST_{urban}$ (Equation 3)

where UHII is Urban Heat Island Intensity and UCII is Urban Cool Island Intensity. LST_{urban} is the median of LST for points of urban land cover class (n=50), and LST_{rural} is the median of LST for points of rural land cover class (n=49).

2.5 Drivers of LST

Different indexes were calculated to assessed the effect of drivers on LST behavior, i.e. vegetation, constructions and bare soil. These indexes were estimated for the 2021 year.

2.5.1 *Vegetation index*

The NDVI (Normalized Difference Vegetation Index; Townshend and Justice 1986) is a good estimator of green and vigorous vegetation. This index was obtained by using the following equation (Equation 4):

NDVI = (NIR band– Red band) / (NIR band + Red band) (Equation 4)

Where NIR is the near infrared band. NDVI is used to indicate the green space of an area. The value of NDVI varies from - 1 to +1. Values closes to +1 indicate high vegetation cover.

2.5.2 *Built-up index*

The NDBI (Normalized Differences Built-up Index) is an indicator of built-up areas (Zha et al. 2003) and was obtained by using the following equation (5):

NDBI = (MIR band – NIR band) / (MIR band + NIR band) (Equation 5)

Where MIR is the middle infrared band and NIR is the near infrared band. The value of NDBI varies from -1 to +1. Values close to 1 indicate high density of built-up areas.

2.5.3 *Bare soil index*

The Tasseled Cap transformation (Kauth and Thomas 1976; Crist and Cicone 1984) results in new bands by combining the original bands of the image, in order to enhance some features of interest. The first Tasseled Cap index (Brightness Index, BI) (Crist and Kauth 1986) provides information about reflectivity particularly generated by the soil. This BI was obtained by using the following equation (6):

BI = 0.3029 * Red band + 0.2786 * Blue band + 0.4733 * Green band + 0.5599* NIR band + 0.5080 * $SWIR_1$ band + 0.1872 * $SWIR_2$ band (Equation 6)

Where NIR is the near infrared band, $SWIR_1$ and $SWIR_2$ are short-waves infrared. This index values increase with high percentage of bare soil.

2.5.4 *Abundance and heterogeneity of drivers*

To taking into account the abundance and heterogeneity of each driver, we considered windows sizes of 3x3 (i.e. 90x90 m, area 0.81 ha), where the median and standard deviation values of each indexes were assigned to the central pixel. Henceforth, $NDVI_{med}$ and $NDVI_{sd}$ for median and standard deviation of vegetation, $NDBI_{med}$ and $NDBI_{sd}$ for median and standard deviation of built-up areas, BI_{med} and BI_{sd} for median and standard deviation of bare soil. Moreover, each driver was calculated by period (i.e. coldest and warmest months) and land-cover class (i.e. urban and rural).

2.6 Statistical Analysis

We parameterized generalized linear models (GLMs) with remotely sensed independent variables as drivers of LST: vegetation ($NDVI_{med}$ and $NDVI_{sd}$); built-up areas ($NDBI_{med}$ and $NDBI_{sd}$) and bare soil (BI_{med} and BI_{sd}). We build different models using as response variables to LST_{med}, LST_{min} and LST_{max} (all variables with Gaussian error distribution). The models were performed on data of the coldest and warmest periods, and considering the land-cover class (i.e urban and rural).

The information-theoretic approach described by Burnham and Anderson (2002) was used to model the data, based on the second-order Akaike Information Criterion (AIC). Akaike's information criterion corrected for small sample size (AICc) was calculated for each model. Models were compared with ΔAICc, which is the difference between the lowest AICc value (i.e., the best of suitable models) and AICc from all the other models. We considered an Akaike weight of a model (w_i), which determines the relative likelihood that the specific model is the best of the suite of all models. The *wi* for a model is just exp (−0.5×ΔAICc score for that model) divided by the sum of these values across all models. We evaluated the parameter likelihood of each predictor variable as a measure of important effects in the models (Burnham and Anderson 2002). Moreover, to supplement parameter-likelihood we calculated 95 % confidence interval limits (CL) of parameter estimates. We calculated a pseudo R^2 (Zuur et al. 2009), with deviance values of the best models following equation (7):

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To identify collinearity between independent variables we used Pearson rank correlation, a parametric measure of statistical dependence (Zar 1999). It is important to identify the high collinearity because this can result in coefficient estimates that are difficult to interpret as independent effects and/or have high SE (see review of Zuur et al. 2009). We excluded variables when the coefficient r was >|0.8|. Then, we assessed the variance inflation factor (VIFs) for any remaining collinearity on the full models from different sets and excluded variables with VIFs >5, which indicate collinearity between predictors (Heiberger 2022).

All statistical analyses were performed using R version 4.2.1 (R Core Team 2022). We assessed the VIFs using 'HH' package (Heiberger 2022). The models were selected with 'MuMIn' package (Barton 2022). The relative importance of predictors were calculated using 'relaimpo' package (Grömping 2006). The graphs of each best model were performed using 'effects' package (Fox 2003).

3. RESULTS

During cold periods of all years and warm periods of 1988 and 2000, the Tulum Valley behaved like a UCI, being LST_{rural} higher than LST_{urban} (Table 1, Fig. 2 and 3). However, this Valley behaved as a UHI in the warm periods of 1988 and 2000, with more intensity in 1988 (Table 1).

Our model selection approach showed that in the cold period the $NDVI_{med}$ was the dominant driver of the spatial variations in LST_{min} y LST_{med} due to the fact that it was retained in the best models in both rural and urban systems (Table 2). We found that LST_{min} and LST_{med} increased with increasing $NDVI_{med}$ in urban areas (Table 3, Fig. 4); while the opposite pattern was founded in rural area (Table 3, Fig. 5). In addition, another important driver of the LST_{med} in the rural class was the abundance of built-up area ($NDBI_{med}$), which increased the LST_{med} (Table 3, Fig. 5). These drivers explained more than 61% of LST (Table 2).

During warm periods in the urban class, the best model explaining spatial variations in LST_{med} and LST_{max} was the additive effect among heterogeneity and abundance of vegetation (i.e. $NDVI_{sd}$, $NDVI_{med}$), heterogeneity of built-up areas ($NDBI_{sd}$), heterogeneity and abundance of bare soil (i.e. BI_{sd}, BI_{med}) (Table 2), which explained 42.3% of variance in LST_{med} and 38.72% of that in LST_{max}. Almost all drivers had a negative effect on LST_{max} and LST_{med} with the exception of built-up areas ($NDBI_{sd}$) that had a positive effect (Table 3, Fig. 6). For the rural class, the main driver was $NDBI_{med}$, with a positive effect that explained more than 67% of the variance in LST_{max} and LST_{med} (Table 2 and 3, Fig. 7).

The drivers related to vegetation and built-up areas explained more variance of the spatial variations in LST in rural class (> 61% for cold periods and > 67% for warm periods) than in urban class (> 19% for cold periods and > 40% for warm periods) (Table 2).

4. DISCUSSION

Our results indicated that Tulum Valley showed a consistent pattern with UCI characteristics during cold periods of all studied years, and during warm periods of 2010 and 2021. However, in the warm periods of 1988 and 2000, this Valley behaved as a UHI, being more intense in 1988. Related to possible causes of LST behavior, the LST_{min} and LST_{med} were affected by different drivers in urban and rural classes during the cold period. The vegetation affected positively the LST_{med} and LST_{min} in the urban class, meanwhile, the relationship was negative for both LSTs in the rural class. Another important variable for the LST_{med} behavior of the rural class was $NDBI_{med}$ since an increase in built-up areas leads to an increase in $LST_{med.}$ The spatial heterogeneity of drivers did not affect LST_{min} or LST_{med} in cold months in any classes. In warm months, the LST_{max} and LST_{med} had the same spatial pattern, in the urban class. An increase in the BI_{med}, BI_{sd}, $NDVI_{med}$, $NDVI_{sd}$, leads to a decrease in LST. However, the increase in heterogeneity of built-up areas (i.e. $NDBI_{sd}$), induced an increment in LST. On the other hand, the only driver for LSTs in the rural class was $NDBI_{med}$, since an increase in built-up areas produces an increment in LSTs.

Regardless if there is a UHI or a UCI, there is a general consensus on their causes. These islands are produced because the expansion of the city and constructions change the characteristics of the earth's surface (Masoodian et al. 2021). Our results showed that taking into account the differences between LST_{urban} and LST_{rural}, the Tulum Valley of San Juan is a UCI mainly in the cold period, with increasing intensity through the years. The same UCI phenomenon was reported for other cities in arid, semi-arid, arctic, and subarctic environments, where the urban areas showed lower surface temperatures than non-urbanized or rural areas (Rasul et al. 2017). In the years1988 and 2000, the Tulum Valley behaved as a UHI during the warm periods. This UHI phenomenon probably happen because the city was undergoing reconstruction after a major earthquake in 1977 with a 7.4 Ritcher magnitude. An earthquake of this magnitude produces partial or complete damage to most buildings and could affect great distances, such as 250 km from the epicenter, with major damage.

The vegetation cover is able to mitigate negative impacts on the local climate and environment because it reduces the solar radiation reaching the surface (Mildrexler et al. 2011). Moreover, vegetation causes the cooling of the surrounding air through evapotranspiration, a process that releases moisture (Kaiser 2014). Our results showed that vegetation affected positively the LST_{med} and LST_{min} during cold periods in the urban class, meanwhile, the relationship was negative for both LST in the rural class. The most abundant species of tree, i.e. *Morera blanca* and *Platanus occidentalis*, in urban areas of Tulum Valley lose their leaves in cold periods.The LST maximum values occur after canopy senescence thereby losing transpirational cooling by leaves (Mildrexler et al. 2011). Moreover, the main urban green cover during the cold periods is grass. The grass is a low and homogeneous stratum of vegetation, with shallow and fibrous root systems unable to sustain transpiration (Mildrexler et al. 2011). Meanwhile, in the rural class, the LST_{min} and LST_{med} were negatively affected by $NDVI_{med}$. In the study area, one of the main economic activities together with the vid, is the olive crop (*Olea europaea*), an evergreen tree species, that can reach 8 m. The olive crop occupies 18,000 ha in the province of San Juan and is mainly concentrated in the Tulum Valley (San Juan 2019). Probably their presence leads to a decrease in LST in rural areas in cold periods. Another important variable was $NDBI_{med}$, which produces an increase in LST_{med} during the cold period and in the LST_{max} and LST_{med} during the warm periods. As a part of the olive and vid industry, there are big constructions in crop areas for the extraction and production of olive oil and wine. Probably these built-up zones affected the LST behavior in rural areas, leading to an increase both in cold and warm periods.

The LST_{max} and LST_{med} in the urban class during warm periods was mainly affected by heterogeneity (i.e. BI_{sd}) and abundance (i.e. BI_{med}) of bare soil, producing a decrease in LST_{max} and LST_{med}. Our results disagree with Rasul and collaborate (2015) who found that an increase in wetness and bareness are the main factors leading to an increase in the LST of UCI in the semi-arid environment of Erbil. In the presence of bare soils, the sun's radiation turns into sensible heat, and as a result, the LST increase (see review Mildrexler et al. 2011). However, during warm periods, the climate of San Juan is characterized by strong winds, which could promote the cooling of bare soil through a turbulent exchange. Anyway, future research could assess climate variables that would affect the LST, for a better understanding of drivers' effects.

The spatial heterogeneity in built-up areas leads to an increase in LST_{max} and LST_{med} during warm periods. These results agree with those found by Rasul and collaborators (2017), which report an increase in LST in the city's periphery and in modern neighborhoods with spaced construction of houses. The main urban sprawl in San Juan city was in the Tulum Valley, in the eastern and southern directions, and through the main avenues, replacing rural areas with residential and private neighborhoods (Sánchez and Tejada 2014). These urban areas have large lots that allow separate house constructions and green spaces with grass and trees, where moreover, the spatial heterogeneity and abundance in vegetation (i.e. $NDVI_{sd}$ and $NDVI_{med}$ respectively) during warm periods, would produce a negative effect on LST_{max} and LST_{med}. With vegetation growth, there is an increase in transpiration and evaporation, therefore, the LST decrease in the urban area. This process results because a greater proportion of incoming solar radiation is partitioned to latent heat flux as a result of transpiration, thereby cooling the canopy surface. Moreover, the complex of canopy trees promotes cooling through wind exchange (Mildrexler et al. 2011).

To date, there is much research on UHI and its main drivers but only a few investigate the UCI phenomenon in desert environments and its possible causes. This is the first work that assesses the abundance and heterogeneity of drivers in the LST of a city surrounded by desert. Probably, homogeneous vegetation of crops and the big establishments of the olive oil and vineyard industries, are better captured by the satellite sensors compared with a great diversity of components in the urban landscape (i.e. impervious surfaces, houses, buildings, green spaces). However, the LST behavior in UCI needs to develop more research to understand this phenomenon, considering for example different scales, other possible drivers, and even interactions between them. Based on our results, we encourage urban planners, decision-makers, and city managers to include vegetation, such as trees, shrubs, and grass when planning new construction both in residential areas, and commercial or industrial development.

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8. STATEMENTS & DECLARATIONS

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9. AUTHOR CONTRIBUTIONS

CVE and GGM: conceptualization; CVE, GGM, FMVN and AN: data curation; AN: formal analysis; CVE and GGM: funding acquisition, project administration, resources; CVE and GGM: investigation and methodology; CVE: supervision; AN, FMVN and CA: visualization, CVE: writing original draft; GGM, AN, FMVN and CA: writing-review & editing. All authors read and approved the final manuscript.