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RESEARCH PAPER

DEVELOPING OF AN URBAN ENVIRONMENTAL QUALITY INDICATOR

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ABSTRACT. Human intervention on vegetation cover has always had a negative impact on the environment, directly affecting the quality of life in urban areas. Therefore, this study aimed to develop a methodology for the construction of an urban environmental quality indicator (UEQI) that could reflect the environmental quality of urban areas considering the vegetation conditions to which the resident population is exposed. For this, the method sought to integrate data on demographic density (Dd), leaf area index (LAI), normalized difference vegetation index (NDVI), and surface temperature (St). The Mamdani fuzzy inference system was used to generate a rule base containing 108 variations and a defuzzed output with five condition classes, ranging from very bad to excellent. The results showed that the studied area is characterized by a very bad to good UEQI, with most neighbourhoods having poor conditions (64.51%) and only two with good conditions. It was found that in general the studied area has unsatisfactory environmental quality, showing the need for initiatives aimed at urban afforestation in order to improve the quality of life for the studied population. It can be concluded that UEQI proved to be an efficient tool to identify priority areas for the planning and management of vegetation cover in urbanized areas, enabling the improvement of people's living conditions.

KEYWORDS: vegetation indexes, population dynamics, urban areas, fuzzy logic

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INTRODUCTION

The dynamics of urbanization and its effects, such as high population density and human pressure on natural areas, result in the hindering of the urban environmental balance, which is manifested mainly in the reduction of vegetation cover (Melazo and Nishiyama 2010; Hartig et al. 2014; Duarte et al. 2017), as many cities have a low amount of vegetation. This reflects, above all, the lack of planning during the expansion of cities and the lack of projects aiming to restore degraded areas or encourage conservation, preservation and maintenance of the vegetation cover.

Understanding how transformations take place in the urban environment is essential for proposing strategies to mitigate the negative consequences of the urbanization process. According to Magalhães et al. (2017) and Bargos and Matias (2012), urban vegetation directly influences the population's quality of life and the maintenance of ecological balance. Such claims are essential for its prioritization in urban planning.

Thus, the analysis of urban quality of life can be performed by combining several factors, both social and environmental. Among them, this article addresses the integration of population data that could show spatial distribution patterns of demography, vegetation and heat flow in a densely occupied urban area using geoprocessing techniques (Shimabukuro et al. 2015) and fuzzy inference system, as proposed by Mamdani (1974).

To carry out studies like this it is necessary to use tools such as geographic information systems (GIS), which Magalhães et al. (2017) classified as of great importance due to its reliability, agility in obtaining data and low cost, as even in small areas, without the support of this geotechnology, the costs for conducting a research can be high. Therefore, the use of spatial analysis tools is essential to assist in the identification and analysis of urban environmental conditions, thus helping to support management and planning programs aiming to maintain and conserve vegetation, especially trees or shrubs.

In this sense, this study aims to present a model that, using GIS, integrates data on demographic density (Dd), leaf area index (LAI), normalized difference vegetation index (NDVI) and surface temperature (St) for the creation of an urban environmental quality indicator (UEQI) applied to study an urban area of a municipality with a high population concentration.

MATERIALS AND METHODS

Study area

The study was carried out in the urbanized area of the municipality of Sorocaba, located in the southeastern part of the state of São Paulo, Brazil, with an estimated population of 671,186 inhabitants and a demographic density of approximately 1,304.18 inhabitants/km2 (Figure 1).

The municipality is highly urbanized and marked by the presence of an important commercial and industrial area (Lopes et al. 2019). It has Argisols, Cambisols, Gleysols and Latosols (Rossi 2017). The vegetation is transitional between the Atlantic Forest and the Cerrado biome and is marked by high forest fragmentation (IBGE 2012; Mello et al. 2014). Both biomes are characterized by rich biodiversity of fauna and flora, being considered worldwide hotspots (Myers et al. 2000).

The climate is Cwa, which is characterized by hot summers and dry winters (Dubreuil et al. 2017; Lopes et al. 2019). The average annual temperature ranges from 14.5°C to 27.5°C. The monthly rainfall for the rainiest period (January) reaches 200 mm, while for the driest period (August) it is 35 mm (CIIAGRO, 2019).

Demographic density (Dd)

Demographic density (Dd) was obtained from values found in the urban and rural census sectors (IBGE 2010; IBGE 2011), which were subsequently adjusted for the population by neighborhoods in the study area.

After obtaining the population of the neighborhoods, the total population was divided by the neighborhood area according to Equation 1.

$$Dd = \frac{Pop}{Csa} \tag{1}$$

Where: *Dd* = Demographic density (inhabitants/ha); *Pop* = Number of inhabitants per census sector; *Csa* = Census sector area.

The values of Dd obtained by census sector area were converted into the centroid of the polygon of each neighborhood using the Feature to Point tool and interpolated using inverse distance weighing (IDW) in the ArcGIS 10.6 software (ESRI 2016).

Obtaining vegetation indexes

The study of vegetation indexes was based on the images of the Landsat 8 bands 4, 5, 10 and 11 with orbit 220/point 76 and a spatial resolution of 30 meters, available free of charge on the United States Geological Survey website (USGS 2018a). The images were taken for August 2018 and January 2019 and were redesigned for the southern hemisphere. The reference is the plane coordinate system SIRGAS 2000 and spindle 23S. For the treatment and processing of images as well as for other modeling, Matlab R2010a (Mathworks 2014) and ArcGIS 10.6 (ESRI 2016) software were used.

The indexes NDVI, LAI and St indexes were obtained for January and August using the bands 4, 5, 10 and 11 of the Landsat 8 satellite.

NDVI is one of the most used indexes for studies on the quality of vegetation cover. The higher is the density of vegetation, the greater is the reflectance in the near-infrared part of the spectrum. The values of NDVI usually range from -1 to 1: the closer to 1, the better is the vegetation condition, and the closer to zero, the worse is the vegetation condition (Gandhi et al. 2015; Santos and Aquino 2015).

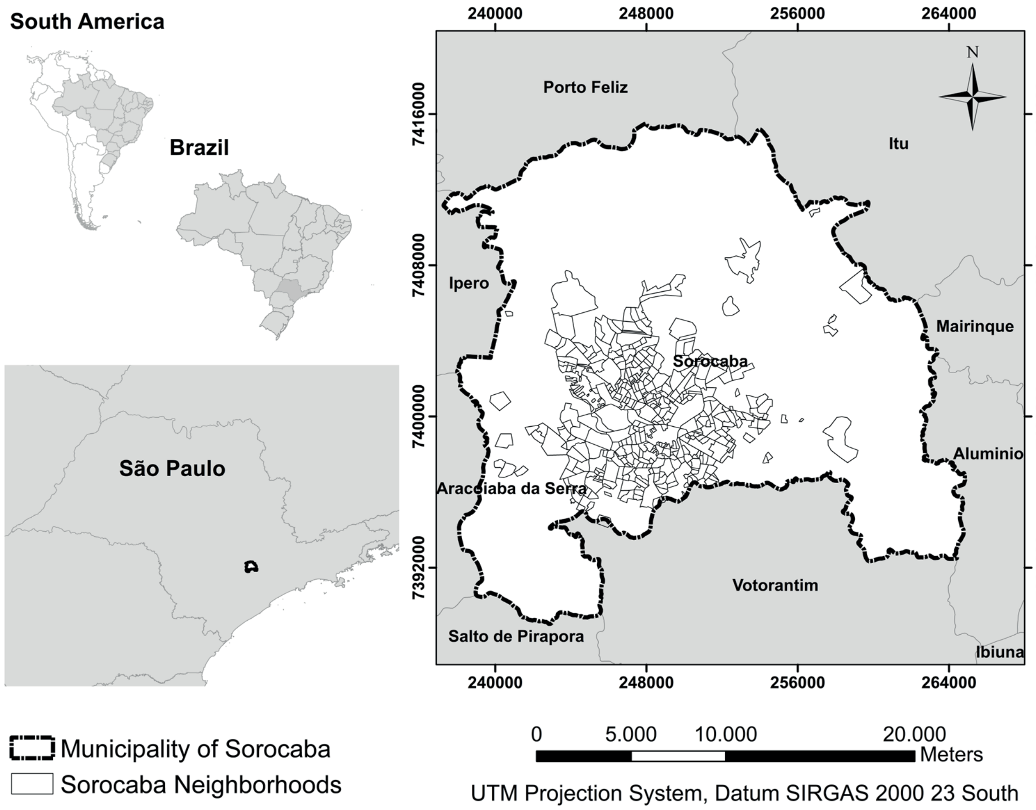

Fig. 1. Location of the Municipality of Sorocaba, São Paulo, Brazil

LAI corresponds to the ratio of leaf area over the land where the vegetation is found. It is an important index to estimate, for example, vegetative development and biomass (Allen et al. 2002; Fernandes et al. 2016).

To calculate NDVI and LAI, the bands 4 and 5 of Landsat 8, previously converted from digital numbers (DN) into reflectance at the top of the atmosphere (TOA), were used according to Equation 2, and later this value was corrected for solar angulation using Equation 3. This conversion was performed using the radiometric coefficients available in the image file metadata. Further details can be found in the LDCM Cal/Val Algorithm Description Document and Landsat 8 Science Users' Handbook available at <http://landsat.usgs.gov/Landsat8_Using_Product.php>.

$$P\lambda' = Mp * Qcal + Ap \tag{2}$$

Where: Pλ'= TOA reflectance without correction of the solar angle; Mρ = Multiplying factor for resizing the band (0.00002); Qcal = Quantified and calibrated pixel value in gray level (DN); Ap = Additive scaling factor specific to the band (-0.1).

$$P\lambda = \frac{P\lambda'}{\operatorname{Cos}(\theta_{SZradian})} \tag{3}$$

Where: Pλ= TOA reflectance with correction of the solar angle; θSZ = Local solar zenith angle, defined as θSZ = 90° – θSE; where θSE = Local solar elevation angle. Its value for August 2018 was 43.36905219 and for January 2019 – 58.8671889; θSZradian = θSZ*(π/180).

After correcting the images, Equation 4 was used to calculate NDVI (Rouse et al. 1973).

$$NDVI = \frac{(NIR - R)}{NIR + R} \tag{4}$$

Where: NDVI = Normalized difference vegetation index; NIR = Planetary reflectance at the top of the atmosphere within the near-infrared range; R = Planetary reflectance at the top of the atmosphere within the red range.

For the calculation of LAI, Equation 5 was used (Allen et al. 2002).

$$LAI = -\frac{Ln\left(\frac{069 - SAVI}{0.59}\right)}{0.91} \tag{5}$$

Where: LAI = leaf area index; SAVI = Soil-adjusted vegetation index.

SAVI is calculated according to Equation 6, proposed by Huete (1988). Its value varies from -1.5 to 1.5. The factor L varies according to the characteristics of the vegetation. However, the value most used in the literature is 0.5, the same as adopted in this study.

$$SAVI = \frac{(1+L)*(NIR - RED)}{(L + NIR + RED)} \tag{6}$$

Surface temperature (St)

Generally, urban climate presents different micro-meteorological conditions, such as increase of temperature and decrease of humidity, and specific climatic conditions such as heat islands may occur. The surface temperature can be determined through the flow of energy that arrives and leaves a given Earth surface creating an interaction with the atmosphere. The range that allows greater transmission of the energy emitted from the Earth that reaches the sensor in the thermal infrared region of the electromagnetic spectrum is the range 8.0-14.0 μm (Steinke et al. 2010). Thus, to perform the St calculation, the quantized and calibrated values (DN) of the bands 10 and 11 of the Landsat 8 OLI sensor system were converted into spectral radiance at the top of the atmosphere using the radiometric coefficients provided in the metadata of the images files (USGS, 2018a) according to Equation 7.

$$L\lambda = ML * Qcal + AL \tag{7}$$

Where: Lλ = Spectral radiance at the top of the atmosphere (Watts/(m^2*srad*μm)); ML = Multiplying factor of band resizing (0.0003342); Qcal = Quantified and calibrated pixel value in gray level (DN); AL = Additive scaling factor specific to the band (0.10000). Then, the spectral radiance at the top of the atmosphere in bands 10 and 11 was converted into brightness temperature at the top of the atmosphere (satellite temperature) according to Equation 8 (USGS, 2019b).

$$T = K2 / \ln\left(\frac{K1}{L\lambda} + 1\right) - K \tag{8}$$

Where: T = Effective temperature on the satellite in Kelvin (K); K1 = Band 10 or 11 calibration constant; K2 = Band 10 or 11 calibration constant; Lλ = Spectral radiance (Watts/(m^2*srad*μm)); and K = Kelvin temperature constant (273.15).

Finally, S_t is obtained by Equation 9 (Artis and Carnahan 1982).

$$T_S = TM / \left[1 + \left(\frac{\lambda * TM}{C2}\right) * \ln(e)\right] \tag{9}$$

Where: TM = Temperature mean (°C) of bands 10 and 11; λ= Radiation emission wavelength equal 10.89 μm (referring to the average wavelength of the Landsat 8 band 10); c2 = h*c/s= $1.4380*10^{-2}$ m.K = 14,380 μm. K, where h = Planck constant = $6{,}626*10^{-34}$ Js and s = Stefan Boltzmann constant = $1.38*10^{-23}$J/K; c = speed of light = $2{,}998*10^{8}$m/s; = Emissivity from the Earth's surface calculated according to Equation 10 (Sobrino et al. 2004).

$$e = 0.004 * Pv + 0.986 \tag{10}$$

The vegetation proportion (Pv) value is calculated by Equation 11, where NDVImax = 0.5 and NDVImin = 0.2 (Carlson and Ripley 1997; Sobrino et al. 2004).

$$Pv = \left[\frac{(NDVI - NDVImin)}{(NDVImax - NDVImin)}\right]^2 \tag{11}$$

After calculating the vegetation indexes and the St, the ArcGIS 10.6 tool Cell Statistics was applied to obtain a matrix image of the means of the two periods, which was used for the preparation of the indicator.

Preparation of the urban environmental quality indicator (UEQI)

The urban environmental quality indicator (UEQI) was quantified from a fuzzy inference system considering the simultaneous treatment of quantitative and qualitative variables.

The indicators used to calculate the UEQI were Dd, NDVI, LAI and St. These indicators were interpreted through linguistic variables, since, when using these linguistic expressions in a fuzzy inference system, it is possible to define sets in which the values are allocated with different degrees of pertinence, this process is called fuzzification. Through this process the main function of the linguistic variables is to provide an approximate way for the characterization of complex phenomena to be analyzed through conventional mathematical models (Lourenço et al. 2015). In this study, these linguistic variables were expressed by ranges of values found in the literature in pertinence functions of the triangular and trapezoidal type.

Demographic density directly affects the environment and, at the same time, has negative impacts and benefits for both regions with a low population density and regions with a high population density (Campoli and Maclean, 2007).

In this context, Haughton and Hunter (1994) and Chakrabarti (2013) stated that regions with a high demographic density can be considered relevant in the process of achieving sustainable development. This is explained by the large concentration of people, which allows to maximize the use of the installed infrastructure, reduce the relative cost of its implementation and reduce the need for its expansion to peripheral areas as well as the need for travel since the concentration of people favors economic activities such as commerce and service at the local level, and, finally, encourage walking and enable the implementation of public transport systems (Haughton and Hunter 1994; Cioly and Davidson 1998; Jacobs 2000; Campoli and Maclean, 2007).

However, in many cases, these environments that do not interact with nature, since there is an absence of tree-lined streets, which directly impacts the thermal sensitivity of these places, maximizing the use of energy, among other impacts. Therefore, there is a need to use indicators or indexes that can reflect the variables affecting such regions, including temperature and the presence of tree vegetation.

Thus, there is uncertainty about the ideal demographic density, which justifies the process of fuzzification of this variable in the current study. To assist in the process of identifying ranges of values that portray adequate linguistic figures for the construction of the pertinence curve, studies by Del Rio (1990) were used. In their study in the favelas of Rio de Janeiro (RJ), the authors showed that areas with a density equal to or over 1,500 inhabitants/ha have deficiencies in the infrastructure service. Rodrigues (1986) stated that density below 100 inhabitants/ha makes the presence of services unfeasible, while density greater than 1,500 inhabitants/ha generate 'dis-economies'. Mascaró and Yoshinaga (2005) argued that demographic density should be close to 600 inhabitants/ha to sustain infrastructure systems.

In this sense, the value considered ideal for population concentration in this study was Dd equal to 600 inhabitants/ha, while ranges of less than 100 inhabitants/ha and above 1,500 inhabitants/ha were classified as regular Dd, as there are exceptions in regions with densities within these ranges of values that present ideal housing conditions (Figure 2).

The NDVI values found for areas covered by vegetation in tropical regions vary from 0.10 to 0.80 depending on the vegetation architecture, density and humidity, with the highest values associated with a very dense vegetation cover and, normally, around 0.6 for humid forests such as the Atlantic Forest (Parkinson 1997). According to the studies by Chouhan and Rao (2011), NDVI values lower than 0.1 indicate areas where there is no vegetation, values between 0.2 to 0.3 represent pasture areas and shrubs, while values between 0.6 to 0.8 correspond to tropical and temperate forests and indicate the presence of 'living vegetation'. In these studies on NDVI it was noticed that there is uncertainty about the classification of NDVI values, which makes its fuzzification justified.

Given the above, the pertinence curve of NDVI values was plotted (Figure 3), with values lower than 0.1 classified as bad, values between 0.2 and 0.3 classified as regular, values between 0.4 to 0.6 classified as good, and values above 0.6 classified as excellent.

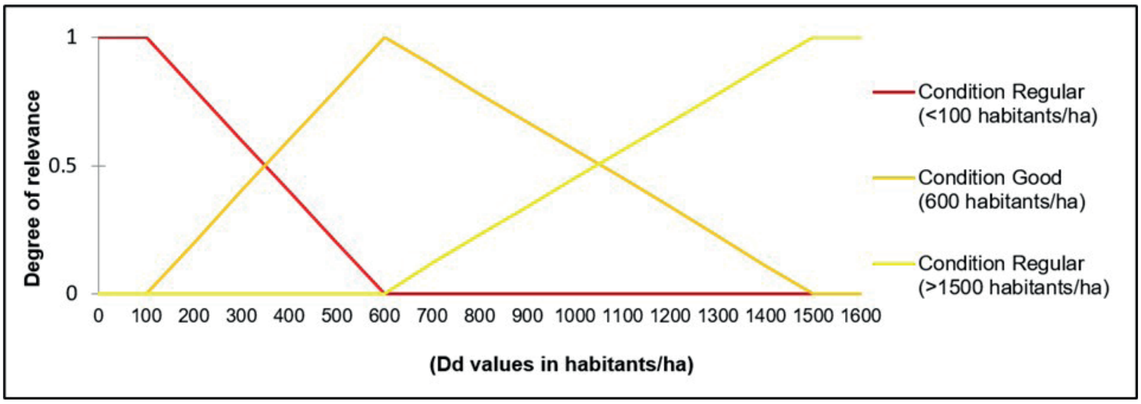

Fig. 2. Relevance function of the input variable Dd

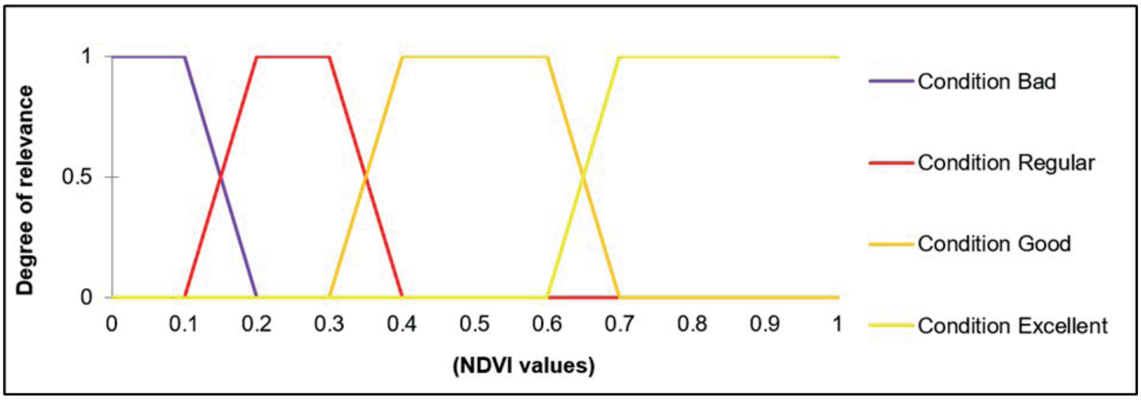

Fig. 3. Relevance function of the input variable NDVI

Regarding the LAI parameter, Garcia et al. (2018) studied the Mata de Santa Genebra in Campinas, SP, Brazil. They studied the interior of the forest and its edges, finding a variation between 0.955 and 3.522 m^2/m^2 in the countryside and 0.741 and 3.120 m^2/m^2 for forest edges. The lower values for forest edges are due to the existence of clearings of different sizes that appear in different periods, resulting from both the extraction and the shallow cut, and also due to the occurrence of specimens decrease due to winds, lightning and fires. Thus, the influence of vegetation density on the LAI values is verified.

For the fuzzification of the values and the construction of the pertinence curve, the following values were adopted: bad = values below 0.5 m^2/m^2, since these values are usually associated with the absence of shrub vegetation at the forest edges; regular = values between 0.7 and 0.9 m^2/m^2, as this interval, in most cases, is associated with border shrub vegetation with greater exposure to anthropic action; and good = values above 1.0 m^2/m^2, which corresponds to the vegetation in the countryside with no clearings and protected from anthropic action (Figure 4).

García (1995) identified in the Madrid region that values close to 25.0°C are considered the ideal comfort temperature for humans, while values below 20.0°C and above 30°C already begin to cause discomfort. Such thermal comfort intervals are consistent with the Brazilian reality, so much so that Gomes and Amorim (2003) used this classification to assess the thermal comfort of public squares in Presidente Prudente (SP). Using the values established by Garcia (1995) the pertinence curve was plotted. Values below 20°C and above 30°C were considered bad and values close to 25°C were considered good (Figure 5).

From the pertinence curves of each variable, a set of rules was established based on the model proposed by Mamdani (1974), which used the knowledge base of linguistic variables (output) for a fuzzy inference system (Table 1).

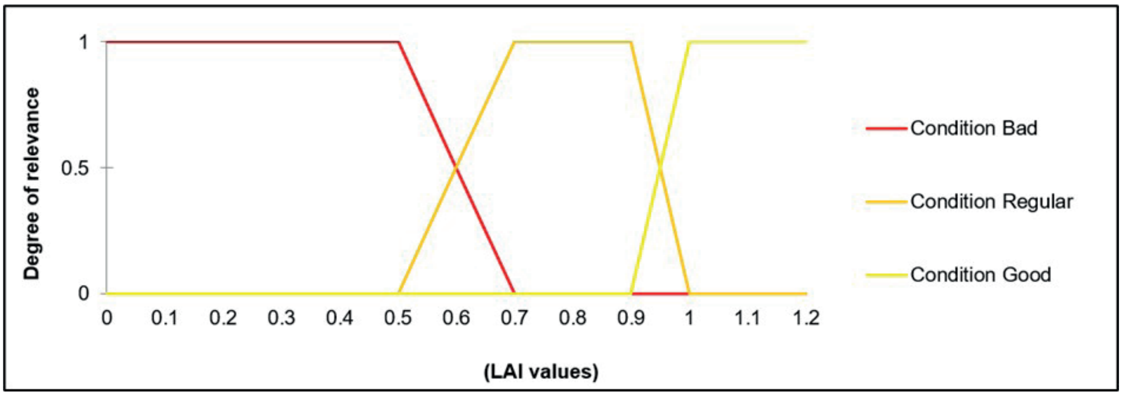

Fig. 4. Relevance function of the input variable LAI

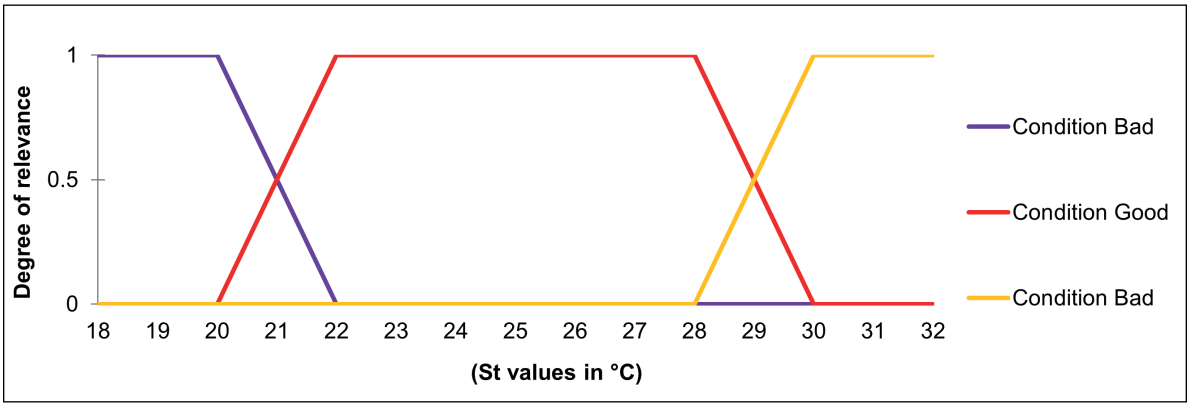

Fig. 5. Relevance function of the input variable St

Table 1. Model rules basis

Rules	Input				Output
	NDVI	LAI	St	Dd	UEQI
1	Condition Bad	Condition Bad	Condition Bad	Condition Regular	Condition Very Bad
2				Condition Good	Condition Bad
3			Condition Good	Condition Regular	Condition Regular
4				Condition Good	Condition Regular
5		Condition Regular	Condition Bad	Condition Regular	Condition Bad
6				Condition Good	Condition Regular

7	Condition Bad	Condition Regular	Condition Good	Condition Regular	Condition Regular
8				Condition Good	Condition Regular
9		Condition Good	Condition Bad	Condition Regular	Condition Regular
10				Condition Good	Condition Regular
11			Condition Good	Condition Regular	Condition Good
12				Condition Good	Condition Good
13	Condition Regular	Condition Bad	Condition Bad	Condition Regular	Condition Very Bad
14				Condition Good	Condition Bad
15			Condition Good	Condition Regular	Condition Regular
16				Condition Good	Condition Regular
17		Condition Regular	Condition Bad	Condition Regular	Condition Bad
18				Condition Good	Condition Regular
19			Condition Good	Condition Regular	Condition Regular
20				Condition Good	Condition Regular
21		Condition Good	Condition Bad	Condition Regular	Condition Regular
22				Condition Good	Condition Regular
23			Condition Good	Condition Regular	Condition Good
24				Condition Good	Condition Good
25	Condition Good	Condition Bad	Condition Bad	Condition Regular	Condition Very Bad
26				Condition Good	Condition Bad
27			Condition Good	Condition Regular	Condition Regular
28				Condition Good	Condition Good
29		Condition Regular	Condition Bad	Condition Regular	Condition Bad
30				Condition Good	Condition Regular
31			Condition Good	Condition Regular	Condition Good
32				Condition Good	Condition Good
33		Condition Good	Condition Bad	Condition Regular	Condition Regular
34				Condition Good	Condition Good
35			Condition Good	Condition Regular	Condition Good
36				Condition Good	Condition Excellent
37	Condition Excellent	Condition Bad	Condition Bad	Condition Regular	Condition Very Bad
38				Condition Good	Condition Bad
39			Condition Good	Condition Regular	Condition Regular
40				Condition Good	Condition Good
41		Condition Regular	Condition Bad	Condition Regular	Condition Bad
42				Condition Good	Condition Regular
43			Condition Good	Condition Regular	Condition Good
44				Condition Good	Condition Good
45		Condition Good	Condition Bad	Condition Regular	Condition Regular
46				Condition Good	Condition Good
47			Condition Good	Condition Regular	Condition Good
48				Condition Good	Condition Excellent

For the output variable (Figure 6), five linguistic variables were used, namely: very bad, bad, regular, good, and excellent (condition). Thus, the UEQI relevance curve was plotted, as shown in Figure 5. UEQI values were classified as very bad (0.0 to 0.2), bad (> 0.2 to 0.4), regular (> 0.4 to 0.5), good (> 0.5 to 0.7), excellent (0.9 to 1.0), giving rise to five output classes from the fuzzy inference system rule basis.

To numerically quantify the UEQI, after establishing the set of rules and the output membership function a conversion method called defuzzification was applied using the center of gravity method (Lourenço et al. 2015). This procedure was carried out using the Matlab R2010a Fuzzy Logic Toolbox module (Mathworks 2014), with output values corresponding to the final numerical values of the UEQI by points (pixels) distributed throughout the study area. Then, the average of the values by neighborhood was extracted, which were geocoded and stored in their respective centroids.

RESULTS

Figure 7 shows Dd (a), NDVI (b), LAI (c) and St (d) for the urban area of the Sorocaba municipality.

Figure 7(a) shows that the highest demographic density is observed in the northernmost, easternmost and westernmost regions of the urbanized area, which may imply a greater impact on wooded areas or an impediment to the creation of these spaces, since the greater concentration of population there

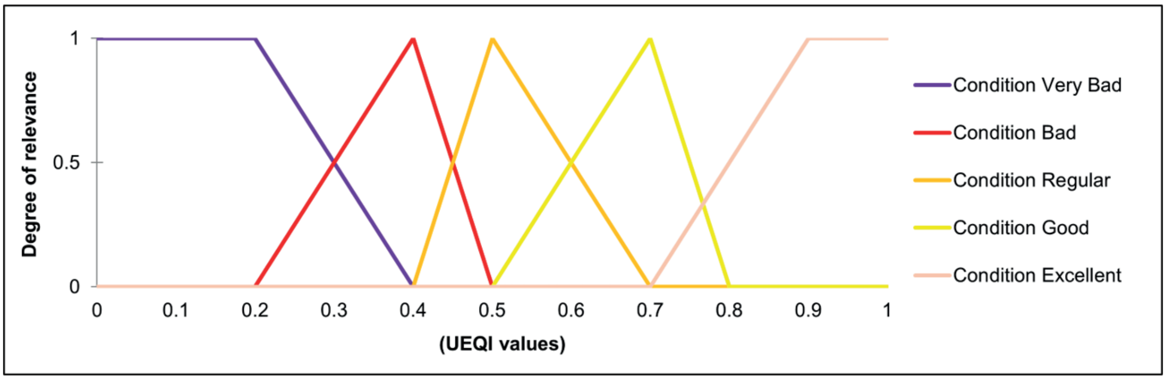

Fig. 6. Output variable membership function (UEQI)

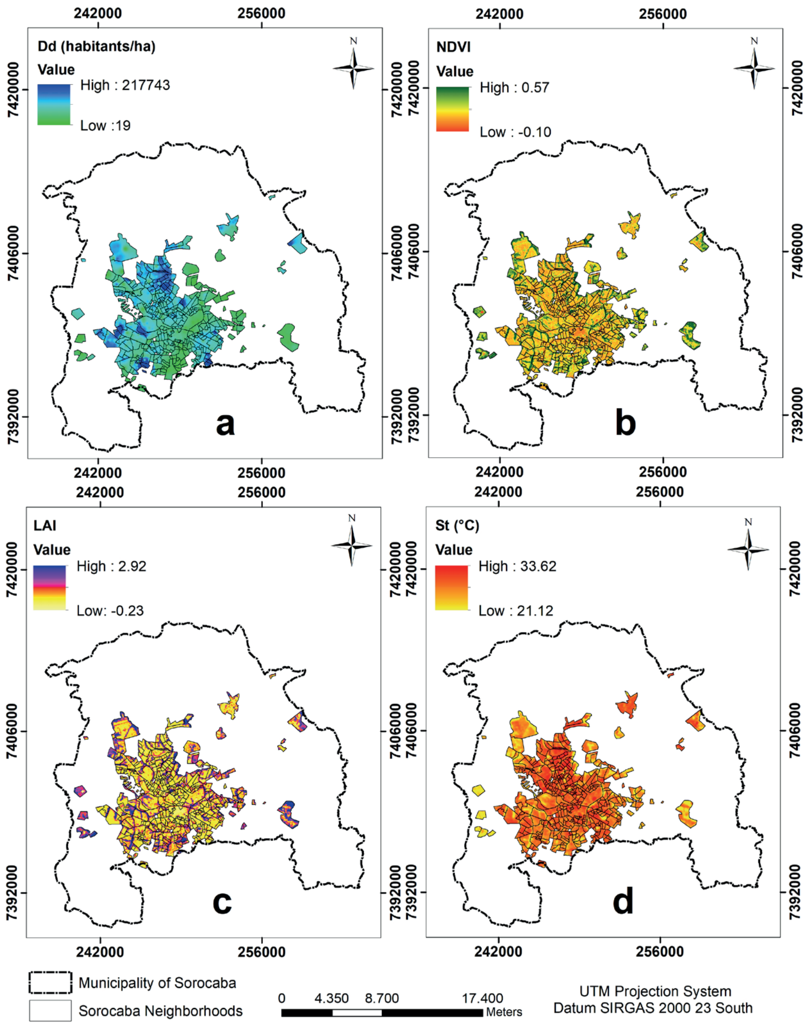

Fig. 7. Dd (a), NDVI (b), LAI (c) and St (d)

demands more services, which has a negative impact the environment, for example, through an increase in impermeable areas.

NDVI for the studied area showed values varying from -0.10 to 0.57 (Figure 7b), with only a few places with values approaching 0.57, since most areas do not have vegetation or, when they have it, vegetation is at a stage of low vegetative vigor. This NDVI analysis made it possible to confirm how compromised the quality of the municipality's vegetation is, especially in the areas of greater urban concentration.

LAI ranged from -0.23 to 2.92 (Figure 7c) with a predominance of negative values, which was expected since it is an urbanized area. In general, this index reflects what has already been verified by NDVI, i.e., vegetation with low health characteristics indicating areas that tend to have higher temperatures, contributing to thermal discomfort. In addition, these indexes make it possible to observe that vegetation in most neighborhoods is isolated as there are no long stretches formed by dense vegetation cover.

For the surface temperature (Figure 7d), it can be seen that the minimum was approximately 21.12°C and the maximum was 33.62°C with higher temperatures corresponding to the urban perimeter. This is justified by the dense urbanization and low vegetation coverage, which lead to differences in atmospheric pressure and retention of particulate material on the surface, contributing to heating and thermal discomfort. This is extremely harmful to the health of the population as it may cause more respiratory problems and allergies in these areas.

Figure 8 shows the UEQI maps, in which the conditions, classified as very bad, bad, regular and good, are presented per pixel and as the average value per neighborhood, respectively. It is important to note that excellent conditions were not found. Table 2 shows the number of neighborhoods for each condition class.

The bad condition of UEQI was prevalent in more than 64% of Sorocaba neighborhoods, almost double the regular condition, which ranked second (34.05%). The very bad condition was present in only four neighborhoods, namely, Jardim Maria do Carmo, Jardim Henrique, Vila Franco, and Vila Porcel. The good condition, on the other hand, had the lowest number (Vivenda do Lago and Portal da Raposo) (Table 2).

Figure 9(b) shows a neighborhood with a very bad condition, Jardim Maria do Carmo, which does not have areas with a representative tree or shrub cover, vegetation is only present alongside roads or in some homes. Moreover, it is marked by the predominance of built areas with a high population density.

DISCUSSION

It can be stated that the isolation of vegetation cover makes it difficult to form an environmental balance and create ecological corridors. According to Bryant (2006), Haaren and Reich (2006) and Hong et al. (2017), corridors are essential to provide ecosystem services such as dispersion and biological migration, buffer zones, and conservation of water resources, in addition to mitigating the effects of high temperatures.

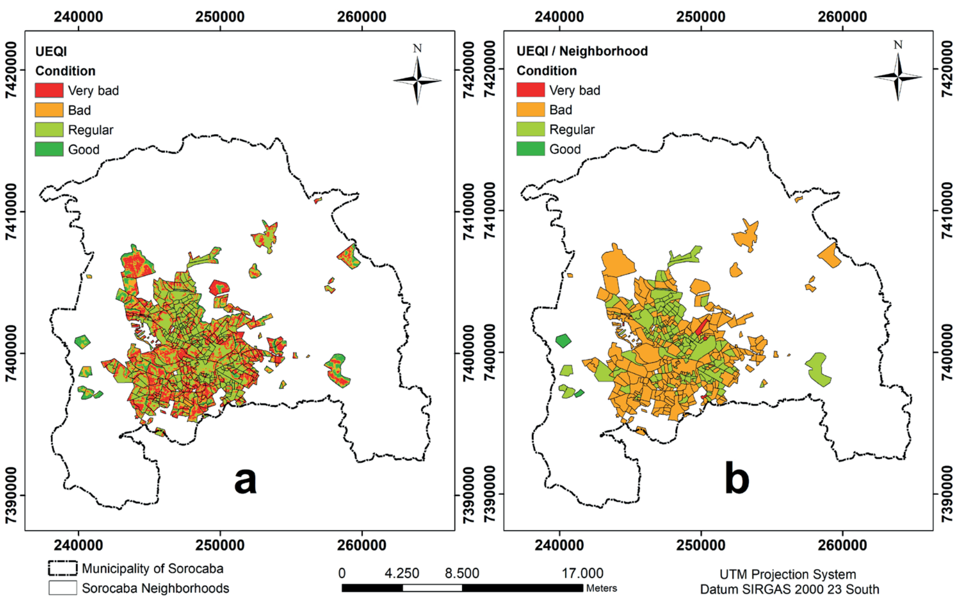

Fig. 8. Distribution of UEQI condition classes

Table 2. Distribution of neighborhoods according to UEQI condition

Condition of UEQI	Total Neighbourhoods	Neighborhoods (%)
Very bad	4	0.96
Bad	269	64.51
Regular	142	34.05
Good	2	0.48
Total	417	100.00

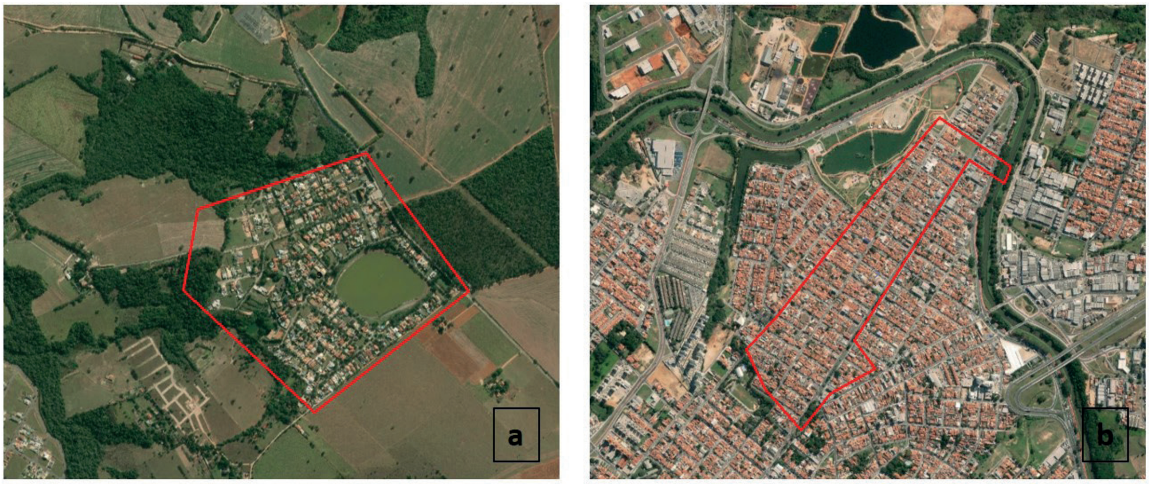

Fig. 9. Neighborhood Vivenda do Lago (a) and Neighborhood Jardim Maria do Carmo (b). Source: Google Earth Pro images, year 2019

The low vegetation cover can also contribute to the formation of heat islands, which are areas with higher temperature than in their surroundings. They are considered as one of the factors responsible for the increase in thermal discomfort, thus contributing to the reduction of the population quality of life and impairment of ecosystem functions (Amorim et al. 2009; Amorim 2017). Barros and Lombardo (2016) suggested detailing the existing relationship between heat islands and problems such as concentration of pollutants and gases in the atmosphere and pointed it out as a factor responsible for morbidity and mortality due to problems in respiratory functions.

According to Amorim et al. (2009) and Amorim (2017), the development of such heat islands is driven by multiple processes including suppression of vegetation, waterproofing of soils, and increase in built area. Amorim (2017) reported that areas covered by vegetation have a greater thermal capacity, that is, they need a greater amount of solar incidence to raise their temperature by 1°C. This is different from urban areas, which are formed by other materials that make that thermal capacity smaller.

In cities, there are areas with little afforestation. In the central region this is due to the urban expansion process and in the peripheral areas – due to the absence of public policies aiming at the implementation and maintenance of this vegetation. However, it should be noted that urban planning must be done seeking to reconcile the demands of urbanization with demands of the environment to reduce the impacts that may be caused (Cruz 2009; Teixeira and Amorim 2011).

Barros and Lombardo (2016), also using NDVI, LAI and St, found that in the city of São Paulo the highest concentration of vegetation were marked by a decrease in the intensity of heat island, therefore making vegetation responsible for mitigating heat in urban areas. These results are similar to the conclusions of this study as areas with the highest concentration of vegetation present a more pleasant temperature. It is worth highlighting places furthest from areas with high urban density, where temperature around 21.12-25°C was observed, which is within the ideal thermal comfort interval.

The resulting UEQI classification is consistent with the reality of the neighborhoods. Figure 9 shows the representation of two neighborhoods, one with conditions characterized as good, which refers to the neighborhood Vivenda do Lago (Figure 9a). This neighborhood is further away from the urban center and is surrounded by tree or shrub vegetation, which contribute to its environmental quality, especially in terms of thermal comfort.

Figure 8 shows that the neighborhoods that presented the worst indicators of urban environmental quality are those characterized by a set of factors that determine this result, such as the absence of dense vegetation cover, high ratio of urbanized areas and presence of areas that may cause some type of soil degradation.

Duarte et al. (2017) stated that the urbanization process enlarges the distance between society and nature as artificial spaces are increasingly created. Often the lack of knowledge of the benefits provided by the vegetation cover restricts its use to only the beautification of cities. However, its benefits go beyond the aesthetic factor, as they present social, ecological and educational functions.

The ecological function of vegetation is in providing well-being to the local population, thus mitigating the negative impacts of the urbanization process, such as thermal discomfort and soil waterproofing. The social function is to provide leisure. Therefore, it is essential that these locations are properly maintained so that they can properly perform their functions (Porto-Gonçalvez 2006; Bargos and Matias, 2011; Bargos and Matias 2012).

As mentioned, there are several factors that contribute to urban quality of life, but the main one is the presence of plant cover given its association with improving the quality of life of the population. Therefore, Souza and Amorim (2016) emphasized the need to allocate areas and financial resources aiming to implement afforestation. However, according to Bargos and Matias (2012), there is a neglect of vegetation, which is not given due importance in the urban planning of cities.

Many studies have reported the positive impacts of urban vegetation, which go beyond improving the microclimate, such as its relationship with the physical and mental health of the population. Among these studies, Lin et al. (2019) focused on a survey conducted in different green spaces and Juan et al. (2017) studied the role of public squares in offering psychological benefits. These authors define them as potential restorer of natural landscapes.

The UEQI analysis has shown that none of the neighborhoods in the municipality of Sorocaba demonstrates ideal conditions that could guarantee a good environmental harmonization. It confirmed that vegetation cover is not sufficient to provide a pleasant environment to the population, as neighborhoods lack spaces with vegetation, which can contribute to the residents' quality of life. However, it is not just a question of planting flowerbeds and roads but of creating well-wooded squares, restoring degraded areas and creating campaigns encouraging the population to contribute to the maintenance of these areas.

Degraded areas may be subject to ecological restoration, but a feasibility study must be carried out so that appropriate management techniques are adopted to restore the environmental quality of these places, thus providing well-being for the population, scenic beauty and proper environment for fauna and flora, in addition to helping to maintain the quality of water resources.

Therefore, given the results, urban planning for the expansion of urban vegetation is recommended in different neighbourhoods of the municipality of Sorocaba, especially in those where UEQI was very bad or bad, as it indicates conditions that can compromise the quality of life of the population.

Studies on environmental quality are essential to understand the problems resulting from the expansion of urbanization since they serve as subsidies for decision-making aiming to mitigate the environmental impacts resulting from anthropic interventions on the urban environment (Estêvez and Nucci 2015). Duarte et al. (2017) reported that it is possible to reconcile urban space with environmental quality as long as there is adequate urban planning and the population is willing to contribute to the insertion of vegetation cover.

There are several methodologies to assess urban environmental quality, such as the ones presented in Ávila and Pancher (2014), Minaki and Amorim (2012), Dias, Gomes and Alkmim (2011) and Nucci (2008). However, most of them aim to characterize factors, different from the point of view proposed in this study, which, in addition to using special analysis tools, adopts a fuzzy inference system to encompass environmental quality.

The methodology applied to elaborate UEQI becomes relevant as it can cover the resident population and small spatial variations disregarding local homogeneity, that is, any changes that occur in the studied variables are included in the modeling of the reproduced scenario, thus enabling results consistent with reality.

Given the above, UEQI becomes an important public management tool since the support of geospatial technology tools for spatial analysis can assist in obtaining data and allow to identify the places where the most urgent interventions are needed, thus improving the conditions in these locations in order to guarantee environmental quality.

The use of population data referring to the last demographic census (2010) was a limiting factor in this research, since such a census is carried out every ten years and, due to the pandemic, it was not carried out in 2020. And these data are particularly important because they provide a population overview of the municipality, serving as the basis for several studies carried out in Brazil.

Temporal analysis of UEQI using data on the demographic density and other variables (St, NDVI and LAI) referring to the year of publication of the demographic census is suggested for future research. In this way, a future projection will be obtained, which can help to identify neighbourhoods that are more conducive to a scenario of suppression of urban vegetation cover or intensification of the heat island phenomenon. This will help to outline more effective urban planning strategies and, consequently, positively affect the quality of urban life.

CONCLUSIONS

The variables used in this research are adequate for the assessment of UEQI, which is evident from the coherence of the information presented since areas without vegetation cover and with the highest demographic density presented the worst conditions and the highest temperatures.

The municipality needs measures that prioritize urban afforestation, such as greater incentives for the recovery of degraded areas and creation of green spaces for leisure. Such measures can be carried out in conjunction with an environmental education project for the population focused on the importance of green areas, as they are essential for improving environmental conditions and, consequently, people's quality of life. It should be noted that the urban center of Sorocaba is old and there has been no urban planning that considers factors that were presented in this study.

It is important to highlight the use of geospatial technology for data analysis as these tools enable using environmental and social variables that are not considered in traditional methods. This contributes significantly to the detailing of certain conditions not usually mapped in traditional models and provides the assessment UEQI which can easily be replicated since all variables can be represented spatially making UEQI an important tool that can be used by the public agencies.

REFERENCES

Allen R., Bastiaanssen W., Wartes R., Tasumi M. and Trezza R. (2002). Surface energy balance algorithms for land (SEBAL), Idaho implementation – Advanced training and user manual, version 1.0. Available at: http://www.posmet.ufv.br/wp-content/uploads/2016/09/MET-479-Waters-et-al-SEBAL.pdf [Accessed 20 Mar. 2019].

Amorim M., Quenol V. and Sant'ana Neto, J. (2009). Características das ilhas de calor em cidades de porte médio: exemplos de Presidente Prudente (Brasil) e Rennes (França), Confins, 7, 116, DOI: 10.4000/confins.6070.

Amorim M. (2017). Detecção Remota de Ilhas de Calor Superficiais: Exemplos de Cidades de Porte Médio e Pequeno do Ambiente Tropical, Brasil. Finisterra, 105, 111-133, DOI: 10.18055/Finis6888.

Artis D.A. and Carnahan W. H. (1982). Survey of emissivity variability in thermography of urban areas. Remote Sensing of Environment, 12, 313-329, DOI: 10.1016/0034-4257(82)90043-8.

Ávila M. and Pancher A. (2015). Estudo das Áreas Verdes Urbanas como Indicador de Qualidade Ambiental no Município de Americana – SP. Rev. Bras. Cartogr., 67(3), 527-544. Available at: http://www.seer.ufu.br/index.php/revistabrasileiracartografia/article/view/44648 [Accessed 2 May 2019].

Bargos D., Matias L. (2011). Áreas Verdes Urbanas: Um Estudo de Revisão e Proposta Conceitual. REVSBAU, 6, 3, 172-188, DOI: 10.5380/revsbau.v6i3.66481.

Bargos D. and Matias L. (2012). Mapeamento e Análise de Áreas Verdes Urbanas em Paulínia (SP): Estudo com a Aplicação de Geotecnologias. Sociedade & Natureza, 1, 143-156, DOI: 10.1590/S1982-45132012000100012.

Barros H. and Lombardo M. (2016). A ilha de calor urbana e o uso e cobertura do solo em São Paulo – SP. GEOUSP (Online), 20(1), 160-177, DOI: 10.11606/issn.2179-0892.geousp.2016.97783.

Bryant M.M. (2006). Urban landscape conservation and the role of ecological greenways at local and metropolitan scales. Landscape and Urban Planning, 76, 23-44, DOI: 10.1016/j.landurbplan.2004.09.029.

Campoli J. and Maclean A. (2007). Visualizing density. Cambridge: Lincoln Institute of Land Policy. Available at: www.lincolninst.edu/publications/books/visualizing-density. [Accessed 16 Mar. 2019].

Carlson T. and Ripley D. (1997). On the relation between NDVI, fractional vegetation cover, and leaf area index. Remote Sensing of Environment, 62, 241-252, DOI: 10.1016/S0034-4257(97)00104-1.

CIIAGRO (2019). Valores mensais de temperatura do município de Sorocaba. São Paulo. Available at: www.ciiagro.sp.gov.br/climasp.html. [Accessed 2 Aug. 2018].

Chakrabarti V. (2013). A coutry of cities: A manifesto for an urban America. New York: Metropolis Books.

Chouhan R. and Rao N. (2011). Vegetation Detection in Multispectral Remote Sensing images: Protective Role-Analysis of Vegetation in 2004 Indian Ocean Tsunami. Geo-Information for disaster management, Turkey. Available at: http://www.isprs.org/proceedings/2011/Gi4DM/PDF/OP37.pdf. [Accessed 13 Mar. 2019].

Cioly C. and Davidson F. (1998). Densidade urbana: um instrumento de planejamento e gestão urbana. Rio de Janeiro: Mauad.

Cruz G. (2009). Clima urbano de Ponta Grossa – PR: uma abordagem da dinâmica climática em cidade média subtropical brasileira. Tese de doutorado, Faculdade de Filosofia, Letras e Ciências Humanas, Universidade de São Paulo, São Paulo.

Del Rio V. (1990). Introdução ao Desenho Urbano no Processo de Planejamento. São Paulo: Pini.

Dias F., Gomes L. and Alkmim J. (2011). Avaliação da Qualidade Ambiental Urbana da Bacia do Ribeirão do Lipa Através de Indicadores, Cuiabá/MT. Sociedade & Natureza, 23(1), 127-147. Available at: http://www.seer.ufu.br/index.php/sociedadenatureza/article/view/11389. [Accessed 12 Oct. 2018

Duarte T., Angeoletto F., Santos J., Leandro D, Bohrer J., Vacchiano M. and Leite L. Papel da Cobertura Vegetal nos Ambientes Urbanos e Sua Influência na Qualidade de Vida nas Cidades. Desenvolvimento em Questão, 40, 175-203, DOI: 10.21527/2237-6453.2017.40.175-203.

Dubreuil V., Fante K., Planchon O. and Sant'anna Neto J. (2017). Les types de climats annuels au Brésil: une application de la classification de Köppen de 1961 à 2015. EchoGéo, 41, 01-27, DOI: 10.4000/echogeo.15017.

ESRI (2016). Environmental Systems Research Institute. ArcGis 10.6.

Estêvez L. and Nucci J. (2015). Questão Ecológica Urbana e a Qualidade Ambiental Urbana the Urban Ecological Issue and the Urban Environmental Quality. Revista Geografar, 10(1), 26-49, DOI: 10.5380/geografar.v10i1.37677.

Fernandes A., Coutinho M., Santos V. and Nascimento C. (2016). Utilização de intervalos de índices de vegetação e temperatura da superfície para detecção de queimadas, Cad. Ciênc. Agrá., 8(2), 30-40. Available at: https://periodicos.ufmg.br/index.php/ccaufmg/article/view/2845 [Accessed 4 May 2018].

Gandhi G., Parthiban S., Thummalu N. and Christy A. (2015). NDVI: Vegetation change detection using remote sensing and GIS–A case study of Vellore district. Procedia Computer Science, 57, 1199-1210, DOI: 10.1016/j.procs.2015.07.415

García F. (1995). Manual de climatologia aplicada: clima, medio ambiente y planificación. Madrid: Editorial síntesis S. A.

Garcia J., Longo R., Penereiro J., Mendes D. and Mantovani P. (2018). Uso de fotografias hemisféricas para avaliação da qualidade ambiental na mata de Santa Genebra, Campinas-SP, Brasil. Ciência Florestal, 28(1), 175-190, DOI: 10.5902/1980509831651

Gomes M. and Amorim M. (2003). Arborização e conforto térmico no espaço urbano: estudo de caso nas praças públicas de Presidente Prudente (SP). Caminhos de Geografia, 7(10), 94-106. Available at: http://www.seer.ufu.br/index.php/caminhosdegeografia [Accessed 22 Sep. 2018].

Haaren C.V. and Reich M. (2006). The German way to greenways and habitat networks. Landscape and Urban Planning, 76, 7-22, DOI: 10.1016/j.landurbplan.2004.09.041

Hartig T., Mitchell R., Vries S. and Frumkin H. (2014). Nature and Health. Annu. Rev. Public Health, 35, 207-228, DOI: 10.1146/annurev-publhealth-032013-182443.

Haughton G. and Hunter C. (1994). Sustainable cities. Regional Policy & Development Series, 7, Londres: Jessica Kingsley Publishers LTDA.

Hong W., Guoa R., Sua M., Tang H., Chenb L. and Hua W. (2017). Sensitivity evaluation and land-use control of urban ecological corridors: A case study of Shenzhen, China. Land use Policy, 62, 316-32, DOI: 10.1016/j.landusepol.2017.01.010.

Huete A. (1988). A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment, 25, 295-309, DOI: 10.1016/0034-4257(88)90106-X.

IBGE (2010). Censo demográfico – 2010. Rio de janeiro. Available at: https://mapas.ibge.gov.br/bases-e-referenciais/bases-cartograficas/malhas-digitais. [Accessed 2 Mar. 2018].

IBGE (2011). Base de informações do Censo Demográfico 2010: Resultados do Universo por setor censitário. Rio de janeiro. Available at: http://www.ibge.gov.br/estatisticas/downloads-estatisticas.html. [Accessed 2 Mar. 2018].

IBGE (2012). Manual técnico da vegetação brasileira. Rio de Janeiro: IBGE. Available at: http://www.ibge.gov.br/busca.html?searchword=manual+t%C3%A9cnico. [Accessed 4 Mar. 2018].

IBGE (2019). IBGE Cidades. Available at: https://cidades.ibge.gov.br/brasil/sp/sorocaba/panorama >. [Accessed 4 Mar. 2018].

Jacobs J. (2000). Morte e Vida das Grandes Cidades. 1ª ed. São Paulo: Martins Fontes.

Juan C., Subiza-Pérez M. and Vozmediano L. (2017). Restoration and the City: The Role of Public Urban Squares. Frontiers in Psychology, 8, 1-13, DOI: 10.3389/fpsyg.2017.02093.

Lin W., Chen Q., Jiang M., Zhang X., Liu Z., Tao J., Wu L., Xu S., Kang Y. and Zeng Q. (2019). The effect of green space behaviour and per capita area in small urban green spaces on psychophysiological responses. Landscape and Urban Planning. 192, 1-15, DOI: 10.1016/j.landurbplan.2019.103637.

Lopes E., Sales J., Souza J., Sousa J., Matias M., and Lourenço R. (2019). Evaluation of flood risk in Sorocaba – Brazil, using fuzzy logic and geotechnology. Braz. J. of Develop., 5(2), 1422-1434. Available at: http://www.brjd.com.br/index.php/BRJD/article/view/1119 [Acessed 20 Jun. 2018].

Lourenço R., Silva D., Martins A., Sales J., Roveda S., and Roveda J. (2015). Use of fuzzy systems in the elaboration of an anthropic pressure indicator to evaluate the remaining forest fragments. Environmental Earth Sciences, 73, 1-8, DOI: 10.1007/s12665-015-4253-6.

Magalhães I., Carvalho Junior O. and Santos A. (2017). Análise Comparativa entre Técnicas de Sensoriamento Remoto para Mensuração da Vegetação Urbana no Município de Alegre, ES. Revista Cerrados, 15(1), 156-177, DOI: 10.22238/rc24482692v15n12017p156a177.

Mamdani E. (1974). Application of Fuzzy Algorithms for Control of Simple Dynamic Plant. Proceedings of the IEE Control and Science, 121, 298-316, DOI: 10.1049/piee.1974.0328.

Mascaró J. and Yoshinaga M. (2005). Infraestrutura Urbana. (1° ed.) Porto Alegre: Masquatro Editora.

MathWorks (2014). O MathWorks, Fuzzy Logic Toolbox ™ Guia do usuário. © Copyright 1995–2014 de The MathWorks Inc.

Melazo G., and Nishiyama L. (2010). Mapeamento da Cobertura Arbóreo-Arbustiva em Quatro Bairros da Cidade de Uberlândia- MG. REVSBAU, 5(2), 52-66, DOI: 10.5380/revsbau.v5i2.66272.

Mello K., Petri L., Leite E. and Toppa R. (2014). Cenários Ambientais para o Ordenamento Territorial de Áreas de Preservação Permanente no Município de Sorocaba, SP. Revista Árvore, 38(2), 309-317, DOI: 10.1590/S0100-67622014000200011.

Minaki C. and Amorim M. (2012). Análise da Qualidade Ambiental Urbana. Mercator, 11(24), 229-251. Available at: http://www.mercator.ufc.br/mercator/article/view/648. [Accessed 12 Jan. 2019].

Myers N., Mittermeier R., Mittermeier C, Fonseca G. and Kent J. (2000). Biodiversity hotspots for conservation priorities. Nature, 403, 853-858, DOI: 10.1038/35002501.

Nucci J. (2008). Qualidade ambiental e adensamento urbano: um estudo de ecologia e planejamento da paisagem aplicado ao distrito de Santa Cecília (MSP). 2 ed. Curitiba: O Autor.

Parkinson C. (1997). Earth from above; Using Color-Coded Satellite Images to Examine the Global Environment. California: University Sciences Books.

Porto-Gonçalvez C. (2006). A globalização da natureza e a natureza da globalização. Rio de Janeiro, Civilização Brasileira.

Rodrigues F. (1986). Desenho Urbano, cabeça, campo e prancheta. São Paulo: Projeto Editores.

Rossi M. (2017). Mapa pedológico do Estado de São Paulo: revisado e ampliado. 1 mapa em graus. Escala: 1: 250000. Available at: http://datageo.ambiente.sp.gov.br/. [Accessed 14 Dec. 2018].

Rouse J., Haas R., Schell J., and Deering D. (1973). Monitoring vegetation systems in the Great Plains with ERT. In: NASA Earth Resources Techonology Satellite, I Symposium Proceedings. Washington: NASA, 309-317.

Santos F., and Aquino C. (2015). Análise da Dinâmica do Índice de Vegetação por Diferença Normalizada (NDVI), dos Aspectos Econômicos e suas Relações com a Desertificação/Degradação Ambiental em Castelo do Piauí, Piauí, Brasil. Revista Electrónica de Investigação e Desenvolvimento, 4, 1-17. Available at: https://revistas.uece.br/index.php/CCiT/. [Accessed 5 Mar. 2019].

Shimabukuro Y., Maeda E. and Formaggio A. (2009). Sensoriamento Remoto e Sistemas de Informações Geográficas aplicados ao estudo dos recursos agronômicos e florestais. Revista Ceres, 56 (4), 399-409. Available at: http://www.ceres.ufv.br/ojs/index.php/ceres/article/view/3443/1344. [Accessed 3 Jun. 2019].

Sobrino J., Jiménez-Muñoz J. and Paolini L. (2004). Land surface temperature retrieval from LANDSAT TM 5. Remote Sensing of Environment, 90, 434-440, DOI: 10.1016/j.rse.2004.02.003.

Souza M. and Amorim M. (2016). Qualidade Ambiental em Áreas Verdes Públicas na Periferia de Presidente Prudente (SP): Os Exemplos dos Bairros Humberto Salvador e Morada do Sol. Caminhos de Geografia, 17(57), 59-73, DOI: 10.14393/RCG175704.

Steinke V., Steinke E. and Saito C. (2010). Estimativa da temperatura de superfície em áreas urbanas em processo de consolidação: reflexões e experimento em Planaltina-DF. Revista Brasileira de Climatologia, 6, 37-56, DOI: 10.5380/abclima.v6i0.25604.

Teixeira D. and Amorim M. (2011). Estudo do Clima Urbano a Partir da Análise da Temperatura da Superfície em Piracicaba-SP. Geografia Ambiental e da Saúde. Available at: www2.fct.unesp.br/semanas/geografia/2011/2011-urbana/Danielle%20Frasca.pdf. [Accessed 22 Mar. 2019].

USGS (2019a). Earth explorer. Available at: https://earthexplorer.usgs.gov/. [Accessed 8 Feb. 2019].

USGS (2019b). Data and Tools. Available at: https://landsat.usgs.gov/using-usgs-landsat-8-product. [Accessed 8 Feb. 2019].