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LAND USE AND LAND COVER DYNAMICS: IMPACTS ON LAND SURFACE TEMPERATURE IN SÃO PAULO STATE

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Abstract: Land Surface Temperature (LST) is related to several physical processes and impacts significantly on the environment. It is important to highlight that the increase in LST causes adverse effects on the environment and climate. Changing natural coverage negatively impacts human health, ecosystems, energy efficiency and quality of life. The objective of the study was to evaluate the impacts of variations in land use/cover on variations in Land Surface Temperature in São Paulo state (Brazil) over 10 years. Furthermore, it was also intended to look for correlations with LST and spectral indices (NDVI, NDBI, NDWI). It was possible to observe that areas with natural vegetation formation had lower temperatures than urban and sugar cane areas. On the other hand, three of the four main uses, combined with urban areas, stood out with higher average temperatures than the other uses. We highlight that the most abundant use in the state is also the one with the highest soil surface temperatures. Each index has a distinct correlation with temperature, which may indicate that they can be considered to establish models for prediction, filling gaps and even improving LST resolution.

Keywords: spatial analysis, thermal, reforestation, management strategies, urban planning.

DINÂMICA DO USO E COBERTURA DO SOLO: IMPACTOS NA TEMPERATURA DA SUPERFÍCIE TERRESTRE NO ESTADO DE SÃO PAULO

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Resumo: A temperatura da superfície terrestre (LST, sigla em inglês) está relacionada a diversos processos físicos e impacta significativamente no meio ambiente. É importante destacar que o aumento da LST causa efeitos adversos no ambiente e no clima. A mudança da cobertura natural impacta negativamente a saúde humana, os ecossistemas, a eficiência energética e a qualidade de vida. O objetivo do estudo foi avaliar os impactos das variações no uso e cobertura do solo nas variações na temperatura da superfície terrestre no estado de São Paulo (Brasil) ao longo de 10 anos. Além disso, também buscou-se correlações entre a LST e índices espectrais (NDVI, NDBI, NDWI). Foi possível observar que áreas com formação vegetal natural apresentaram temperaturas mais baixas do que áreas urbanas e de cana-de-açúcar. Por outro lado, três dos quatro principais usos, combinados com áreas urbanas, destacaram-se com médias de temperatura superiores às demais. Destaca-se que o uso mais abundante no estado também é aquele com as maiores temperaturas superficiais do solo. Cada índice apresenta correlação distinta com a temperatura, o que pode indicar que podem ser considerados para estabelecer modelos de predição, preenchimento de lacunas e até aprimoramento da resolução da LST.

Palavras-chave: análise espacial, termal, reflorestamento, estratégias de gestão, planejamento urbano.

DINÁMICA DEL USO Y COBERTURA DEL SUELO: IMPACTOS EN LA TEMPERATURA SUPERFICIAL TERRESTRE EN EL ESTADO DE SÃO PAULO

Resumen: La Temperatura Superficial Terrestre (LST, por sus siglas en inglés) está relacionada con varios procesos físicos y tiene un impacto significativo en el medio ambiente. Es importante destacar que el aumento de la LST provoca efectos adversos en el medio ambiente y el clima. El cambio de la cobertura natural afecta negativamente la salud humana, los ecosistemas, la eficiencia energética y la calidad de vida. El objetivo del estudio fue evaluar los impactos de las variaciones en el uso y cobertura del suelo sobre las variaciones en la Temperatura Superficial Terrestre en el estado de São Paulo (Brasil) a lo largo de 10 años. Además, también se pretendió buscar correlaciones entre la LST y los índices espectrales (NDVI, NDBI, NDWI). Se pudo observar que las áreas con vegetación natural presentaron temperaturas más bajas que las áreas urbanas y las de caña de azúcar. Por otro lado, tres de los cuatro principales usos del suelo, combinados con áreas urbanas, se destacaron por presentar temperaturas medias más

altas que los demás usos. Cabe destacar que el uso más abundante en el estado es también el que presenta las temperaturas superficiales del suelo más elevadas. Cada índice presenta una correlación distinta con la temperatura, lo que puede indicar que pueden ser considerados para establecer modelos de predicción, llenar vacíos e incluso mejorar la resolución de la LST.
Palabras clave: análisis espacial, térmico, reforestación, estrategias de gestión, planificación urbana.

Introduction

In recent years, phenomena such as floods, droughts, and contamination of natural water resources have been observed with increasing frequency and intensity, largely because of human activities. Moreover, there is concern about the consequences of global warming, including water and food scarcity and depletion of finite resources. Therefore, productive activities must be evaluated considering these consequences by analyzing natural phenomena, relevant physical processes, and related indices.

Land Surface Temperature (LST) is related to many physical processes (Hamstead et al., 2016; Khan et al., 2021), therefore significantly impacts the environment. Among these impacts, it is highlighted that the increase in LST causes adverse effects on the environment and climate (Mehmood & Butt, 2019). One of the potentials of LST is to provide estimates of the spatial pattern of temperature over large areas. LST values are significantly impacted by changes in land use/land cover (LULC).

Changing natural coverage has a negative impact, for example, on human health, ecosystems, energy efficiency and quality of life (Bektas & Ergene, 2016). Unplanned urbanization and industrialization, through the consequent conversion of vegetated areas into constructions, such as buildings and roads, contribute to the increase in LST values (Ashwini & Sil, 2022; Nongpiur, 2023). This is related to the increase in impervious surfaces such as building roofs and paving (Azizah, 2022; Haldar et al., 2023). Furthermore, emissions from industrial production also interfere, increasing LST values (Lu et al., 2021). Spatial and temporal variations in LST can be influenced by CO_2 concentration levels (Datta et al., 2017). On the other hand, forests, agricultural areas, and water bodies reduce the rate of increase in LST (Ashwini & Sil, 2022) and humidity in neighboring regions (Feng et al., 2018). However, different agricultural crops have different impacts on LST (Chen et al., 2022), which can be explained by biophysical characteristics (Feng et al., 2018). Therefore, identifying and mapping LULC is necessary to provide adequate planning and management (Hamad, 2020). It is noteworthy that LULC patterns in different regions are driven by several factors, including socioeconomic and environmental conditions (Rawat & Kumar, 2015).

While LST can be directly retrieved from thermal infrared remote sensing data, its relationship with spectral indices derived from visible and near-infrared bands offers valuable insights into the surface energy balance and land cover characteristics.

Spectral indices, such as the Normalized Difference Vegetation Index (Tan et al., 2004) and other vegetation indices (Sinha et al., 2015), are sensitive to vegetation properties like biomass, leaf area index, and canopy cover. These vegetation properties influence the surface energy budget by affecting evapotranspiration and shading, which directly impact LST.

Denser vegetation, indicated by higher Normalized Difference Vegetation Index (NDVI) values, tends to have lower LSTs due to increased evaporative cooling and reduced solar radiation absorption. Conversely, sparse vegetation or bare soil areas exhibit higher LSTs due to minimal evaporative cooling and greater solar heating.

Therefore, integrating LST with spectral indices provides a comprehensive understanding of the land surface processes and their interactions. For instance, combining LST with NDVI can help assess drought conditions, monitor crop stress, and analyze urban heat island effects.

Furthermore, advanced thermal vegetation indices (Sinha et al., 2015) can enhance the accuracy of land-use/land-cover classification by incorporating thermal information with spectral data. Indices, calculated through the relationship between different spectral responses, highlight characteristics of interest.

The most used in environmental studies are the Normalized Difference Vegetation Index (NDVI), the Normalized Cumulative Difference Index (NDBI) and the Normalized Difference Water Index (NDWI) (Szabó et al., 2016). Used, respectively, to indicate the condition of vegetation cover, build-up areas, and water bodies (Sun & He, 2021).

Some studies have sought to evaluate the impact of LULC changes on LST and the relationships between spectral indices and LST. Some authors have indicated that LST has a positive relationship with building density and a negative relationship with vegetation density (Guha & Govil, 2021; Hashim et al., 2022).

Nevertheless, other studies found a positive relationship for both indices and the negative relationship only occurs in the presence of water (Sun & He, 2021). However, analyzing changes in the atmosphere or LST and exploring the relationship between spectral indices is challenging due to the scarcity of high-resolution meteorological data (Haldar et al., 2023).

The expectation with the study is to evaluate the impacts of LULC variations on LST in São Paulo state (Brazil) over 10 years. Furthermore, it is also intended to seek correlations with spectral indices (NDVI, NDBI, NDWI).

Material and Methods

The analysis was conducted over the area of São Paulo state (Fig. 1), a region located in southeastern Brazil, through the analysis of a historical series (10 years) of LST, LULC and spectral indices. The state represents the most populous in the country, with the highest Gross domestic product (GDP), with a large concentration of industrial activities. Furthermore, it is also among the main agribusiness producers. In the environmental sphere, São Paulo is contained in two Biomes (Atlantic Forest and Cerrado, which occupy, respectively, 13% and 24% of the national territory). Furthermore, it presents areas of outcrop of the Guarani Aquifer System, which may be related to the recharge of this natural resource. In summary, São Paulo presents economic, social and environmental interests to justify the study.

The area of interest experiences a diverse range of climatic conditions due to its varied topography and latitudinal span. The state's climate is generally classified as subtropical, with distinct wet and dry seasons. São Paulo state experiences a wide range of temperatures, influenced by altitude and proximity to the coast. Coastal areas have higher average temperatures, typically ranging from 17°C to 28°C. Inland regions, particularly those at higher elevations, experience cooler temperatures, with averages ranging from 15°C to 25°C. Diniz et al. (2018) discusses climatological normals for Brazil, including temperature data, for the period 1981-2010. Dantas et al. (2015) analyzes temperature trends in Campina Grande, Paraíba, which, while not in São Paulo state, can offer insights into regional temperature patterns. Marengo et al. (2022) discusses regional warming and drying trends, particularly in Southeastern Amazonia, which may influence the climate of parts of São Paulo state.

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Figure 1 - Study area location.

São Paulo's rainfall patterns are characterized by a distinct wet season from October to March and a dry season from April to September. The coastal regions receive higher annual rainfall, averaging between 1,200 mm and 1,500 mm. Inland areas experience slightly lower rainfall, with averages around 1,000 mm to 1,200 mm. Hofmann et al. (2023) discusses changes in rainfall patterns in the Brazilian Cerrado, which borders São Paulo state and may influence its precipitation regime. Marengo et al. (2022) also mentions the impact of El Niño and La Niña events on rainfall patterns in Brazil, which can affect São Paulo state.

Image collections were processed in Google Earth Engine (GEE). The remote sensing products used were from the MODIS MOD11A1 (LST – daily scale, spatial resolution 1000 meters) and the Landsat 7 mission (Ls7) (for calculating spectral indices – Equations 1, 2 and 3 – spatial resolution 30 meters), and annual LULC maps from MAPBIOMAS – Collection 8 (with spatial resolution of 30 meters). After processing, the images were downloaded to create thematic maps. The LST, LULC, NDVI, NDBI and NDWI values were sampled, with a resolution of 1000m and exported as a [.csv] file.

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

$$NDBI = \frac{SWIR1-NIR}{SWIR1+NIR}, \quad (2)$$

$$NDWI = \frac{G-NIR}{G+NIR}, \quad (3)$$

where NIR is the near-infrared region (Ls7 Band 4), R is the red region of the visible spectrum (Ls7 Band 3), SWIR is the short-wavelength infrared (Ls7 Band 5), and G is the green region of the visible spectrum (Ls7 Band 2).

Indices vary from -1 to 1. In the case of NDVI, negative values may indicate contamination by clouds or water, values close to zero exposed soil, from 0.1 to 0.5 sparse vegetation and values above of 0.6 dense vegetation (Rouse et al., 1973). Positive NDBI values indicate predominantly urbanized areas, lower values indicate regions without buildings, mixed areas, where it is not possible to accurately determine the condition of the region, tend to receive values close to zero (Zha et al., 2003). NDWI ranges <-3; -3 to 0; 0 to 0.2 and > 0.2 suggests, respectively, drought, moderate water scarcity, presence of moisture and bodies of water (McFeeters, 1996). The use of indices facilitates comparison between observations due to the normalization and attenuation of noise, atmospheric effects, and sensor calibration (Alexander, 2020). Nevertheless, care must be taken when comparing values from different sources due to the variation in the wavelength of each sensor (Ji et al., 2011).

To verify that there are statistically significant differences in LST between groups (year and LULC), Two-way ANOVA has been applied. However, Anova evaluates only if there is a difference between the groups, without indicating where there are differences. To find out which groups are statistically different from others, the honestly significant difference from Tukey (Tukey HSD) difference was used. For all cases, the significance level adopted was 5%.

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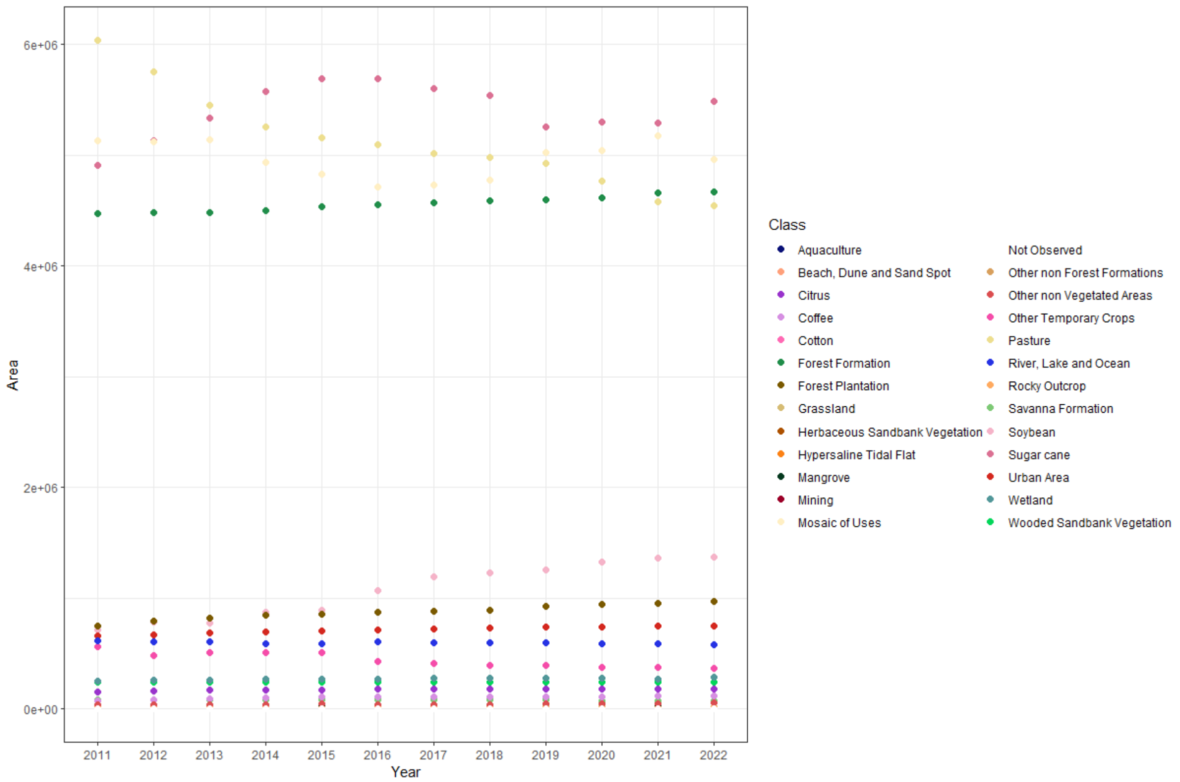
Results

3.1 Changes in the LULC

Several changes to LULC have been observed over the years, with large areas of sugarcane cultivation, mosaic of uses (where there are changes between crops throughout the year), pasture, and forest formation, mainly in regions close to the coast, some urban clusters. We've noted the reduction of pasture areas and the conversion from other LULC to sugarcane plantations. Although they provide indications, the main uses aren't clear from the maps. The main LULC in the state of São Paulo (Figure. 2) were sugarcane, pasture, Forest Formation and mosaic of uses. Despite still having a considerably smaller area in relation to the main crops, there was a large increase in soybean cultivation areas in the state over the years observed.

Figure. 2 Main uses per year.



Once each LULC interferes with the environmental dynamics and, consequently, changes the local microclimate, it also presents characteristic behaviors, which impacts the temperature variation (Figure. 3). In a similar way, each LULC presents characteristic behaviors

(Fig. 4), where we observed the increasing temperatures of different crops, as if the graph were continually dragged upwards.

Figure. 3 LST variation over the years for each LULC.

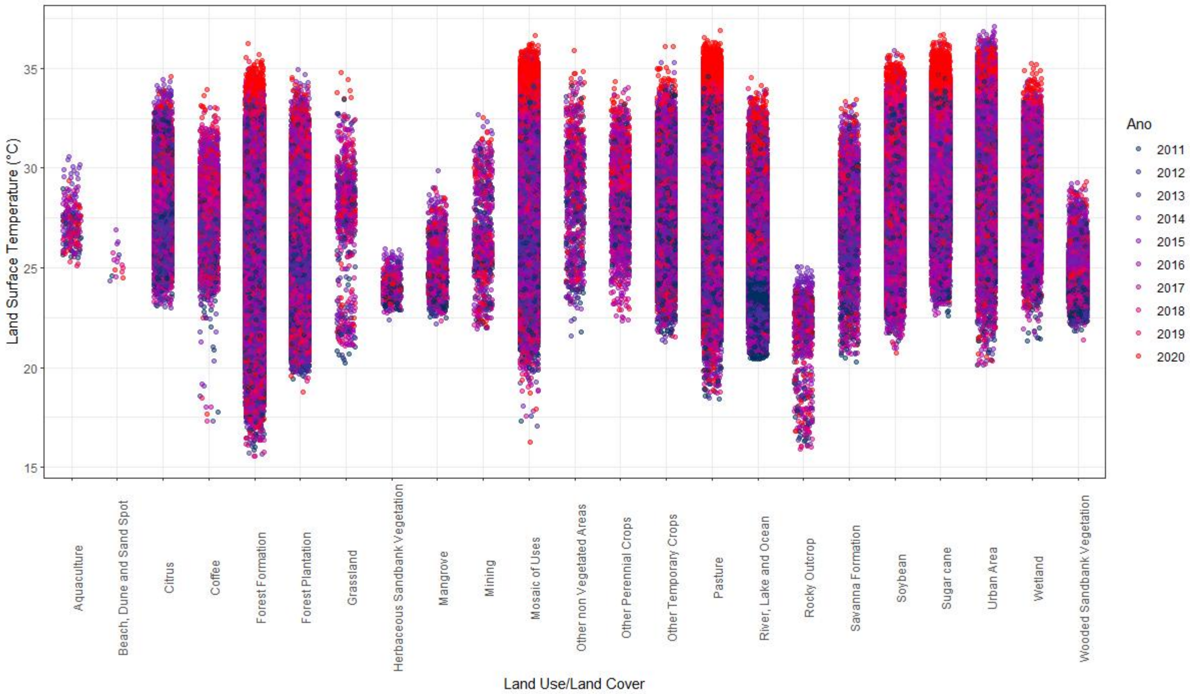
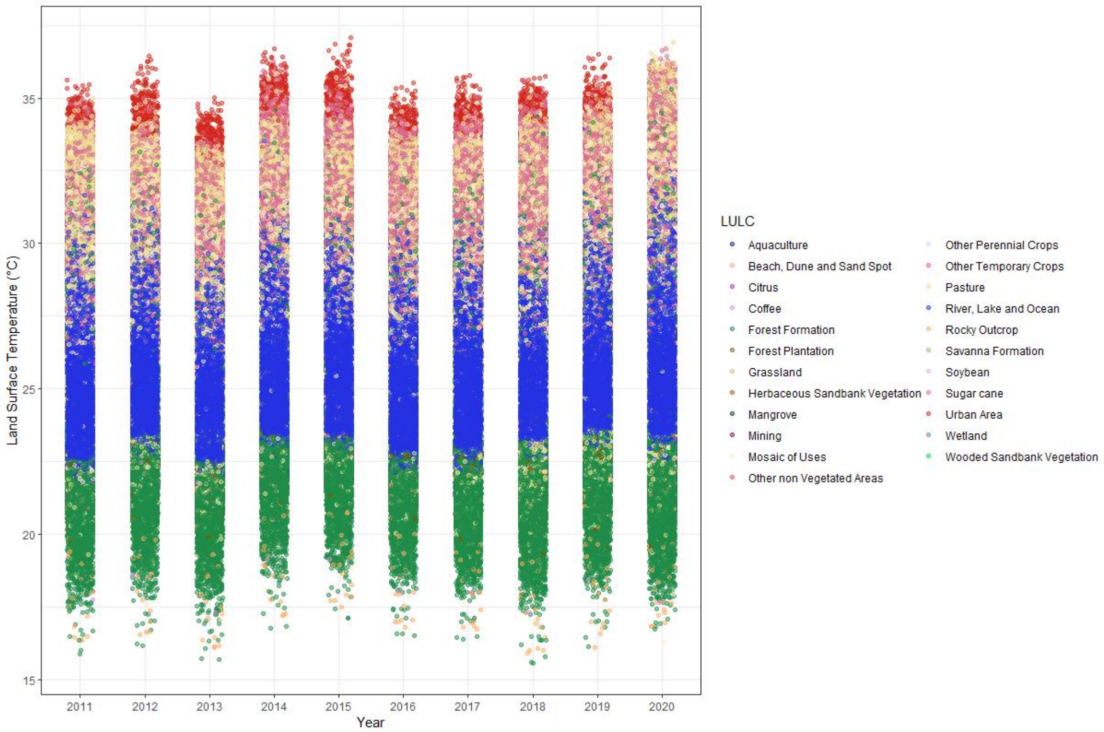


Fig. 4 LULC LST trends over the years.



We checked the temperature variation over the years and for each LULC, also considering the interaction over those variables (Table 1). Once each variable was statistically significant, there is evidence that part of the variation is driven by the year, the LULC and the interaction between them both.

Table 1 Results of Two-Way ANOVA

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Year	9	494711	54968	11154	<2e-16 ***
LULC	22	12289084	558595	113347	<2e-16 ***
Year:LULC	198	102156	516	105.5	<2e-16 ***
Residuals	2691410	13162563	5		
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					
Residual standard error: 2.21995					

According to all 45 comparisons of the variable Year in the Anova considering the interaction between the variables, we observed statistically significant differences in LST in 43. Likewise, for the 253 comparisons of LULC, we found statistically significant differences in 234, except for only 19. The largest differences found between years (Table 2) and between LULC (Table 3) were filtered according to the 5% and 95% percentiles due to the sample size.

Table 2 Tukey's Honestly Significant Difference Test - Year

Year	diff	lwr	upr	p.adj
2016-2014	-1.02	-1.04	-1.01	0.00E+00
2017-2014	-1.01	-1.03	-0.99	0.00E+00
2015-2014	-0.89	-0.91	-0.87	0.00E+00
2019-2013	1.03	1.01	1.05	0.00E+00
2020-2013	1.37	1.35	1.39	0.00E+00
2014-2013	1.47	1.46	1.49	0.00E+00

The temperature in 2015, 2016 and 2017 was, on average, approximately one degree Celsius lower than in 2014. On the other hand, the temperature in 2014, 2019 and 2020 was higher, on average, than the temperatures recorded for the year 2013. The year 2014 is highlighted, appearing four times. This may have occurred due to the water crisis that affected the Brazilian Southeast in 2014. The lower water availability may have interfered with the estimated values of LST. Except for 2014, it is observed that the years at the end of the period appeared with higher averages, indicating an increase in temperature.

Table 3 Tukey's Honestly Significant Difference Test - LULC

LULC	diff	lwr	upr	p.adj
Herbaceous Sandbank Vegetation-Sugar cane	-6.54	-6.93	-6.15	0.00E+00
Herbaceous Sandbank Vegetation-Urban Area	-6.12	-6.51	-5.73	0.00E+00
Wooded Sandbank Vegetation-Sugar cane	-5.94	-5.99	-5.89	0.00E+00
Forest Formation-Sugar cane	-5.78	-5.80	-5.77	0.00E+00
Mangrove-Sugar cane	-5.66	-5.88	-5.45	0.00E+00
Wooded Sandbank Vegetation-Urban Area	-5.52	-5.58	-5.46	0.00E+00
Herbaceous Sandbank Vegetation-Pasture	-5.44	-5.83	-5.05	0.00E+00
Beach, Dune and Sand Spot-Sugar cane	-5.40	-7.41	-3.40	2.62E-13
Forest Plantation-Sugar cane	-5.39	-5.41	-5.36	0.00E+00
Forest Formation-Urban Area	-5.36	-5.39	-5.33	0.00E+00
Mangrove-Urban Area	-5.24	-5.45	-5.02	0.00E+00
Beach, Dune and Sand Spot-Urban Area	-4.98	-6.99	-2.97	1.55E-13
Grassland-Rocky Outcrop	5.80	5.41	6.19	0.00E+00
Other Temporary Crops-Rocky Outcrop	5.95	5.68	6.22	0.00E+00
Coffee-Rocky Outcrop	6.19	5.91	6.47	0.00E+00
Citrus-Rocky Outcrop	6.59	6.32	6.86	0.00E+00
Other non-Vegetated Areas-Rocky Outcrop	6.88	6.51	7.26	0.00E+00
Forest-Rocky Outcrop	6.90	6.60	7.21	0.00E+00
Soybean-Rocky Outcrop	6.94	6.68	7.21	0.00E+00
Wetland-Rocky Outcrop	7.02	6.74	7.29	0.00E+00
Mosaic of Uses-Rocky Outcrop	7.24	6.97	7.50	0.00E+00
Pasture-Rocky Outcrop	7.76	7.49	8.02	0.00E+00
Urban Area-Rocky Outcrop	8.44	8.17	8.70	0.00E+00
Sugar cane-Rocky Outcrop	8.86	8.60	9.12	0.00E+00

Areas with natural vegetation (Wooded Sandbank Vegetation, Herbaceous Sandbank Vegetation, Forest Formation, Mangrove) and tree cultivation (Forest Plantation) presented temperatures lower by at least 5 °C compared to temperatures in urbanized and sugarcane areas. All cultures had average temperatures at least 6 °C higher than those of the Rock Outcrops. This may be related to the fact that the Rocky Outcrop areas are surrounded by forest areas, the emissivity and reflection characteristics of the material and the altitude of the region of occurrence. The biggest differences recorded include almost all the main uses in the state of São Paulo (sugar cane, urbanized area, pasture, mosaic of uses and soy).

The comparisons that didn't present statistical significance difference was, in most, between natural areas and areas with a predominance of water. It can be observed that soy, one of the uses that became popular in the period evaluated, showed no difference between forested areas and non-vegetated areas, such as exposed soil.

Focusing on the main LULC, the main crops/urbanized areas presented similar behavior (quartile position, median) (Figure. 5). On the other hand, the most abundant type of natural use in the state (Forest Formation) showed temperatures concentrated at lower values. This distinction can also be observed in the annual averages for the period (Figure. 6).

Figure. 5 LST for the main LULC.

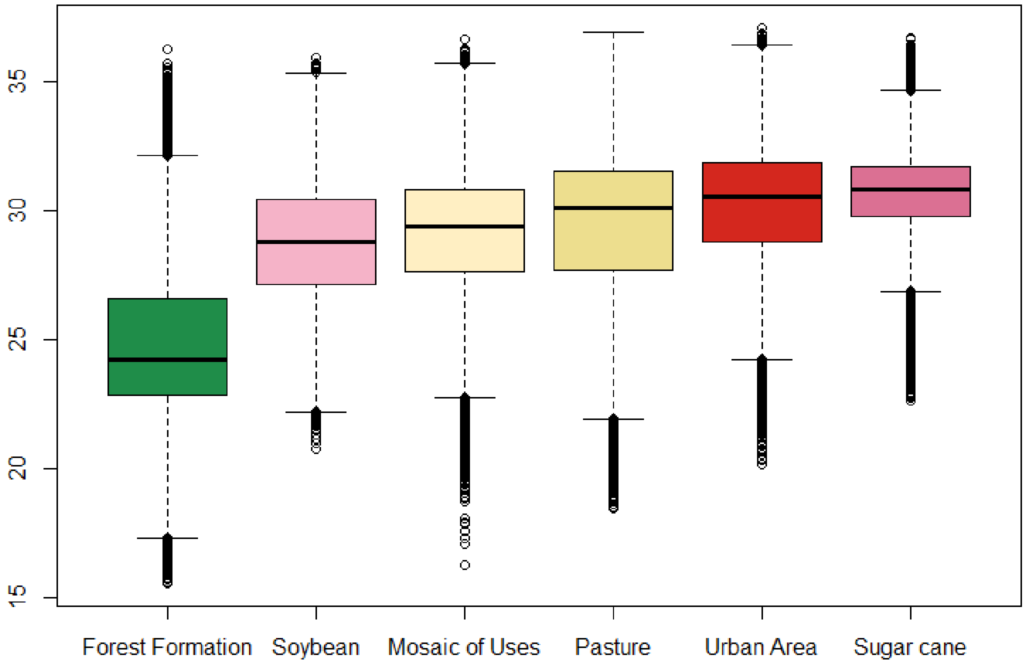
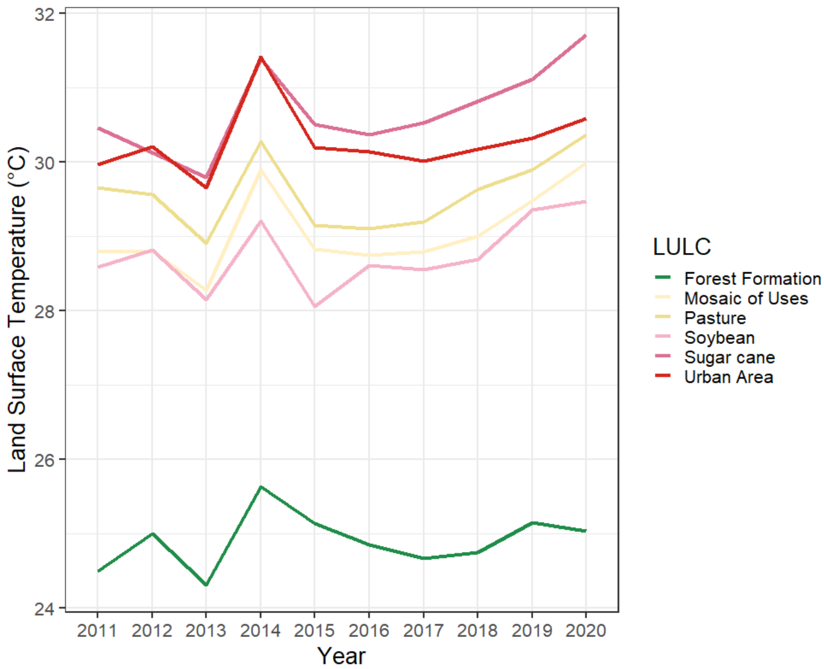


Figure. 6 Mean annual LST for the main LULC.



In all LULC, it was possible to observe an LST increase in 2014. The 2014 water crisis may have influenced LSD values. The most adopted land use (sugar cane) stands out with values extremely high, even exceeding the average temperatures of urbanized areas. The Forest Formation maintains average values while other land uses have increased.

3.2 LST and Spectral Indices Correlations

We've correlated LST with the spectral indices NDVI, NDWI and NDBI (Figure. 7). The correlation between LST and NDVI presents a medium negative relationship, with NDWI the relationship is low positive and NDBI has a high positive relationship, all of which are statistically significant. It was possible to observe the maintenance of these values throughout the study period (Figure. 8). The correlation between the values of the spectral indices (and their respective correlations with the LST) indicates that the indices reflect different behaviors. Therefore, the application of these indices together should be considered to propose models that aim to improve the spatial and temporal resolution of the LST.

Figure. 7 LST, NDVI, NDWI and NDBI correlations, histogram and relation graph.

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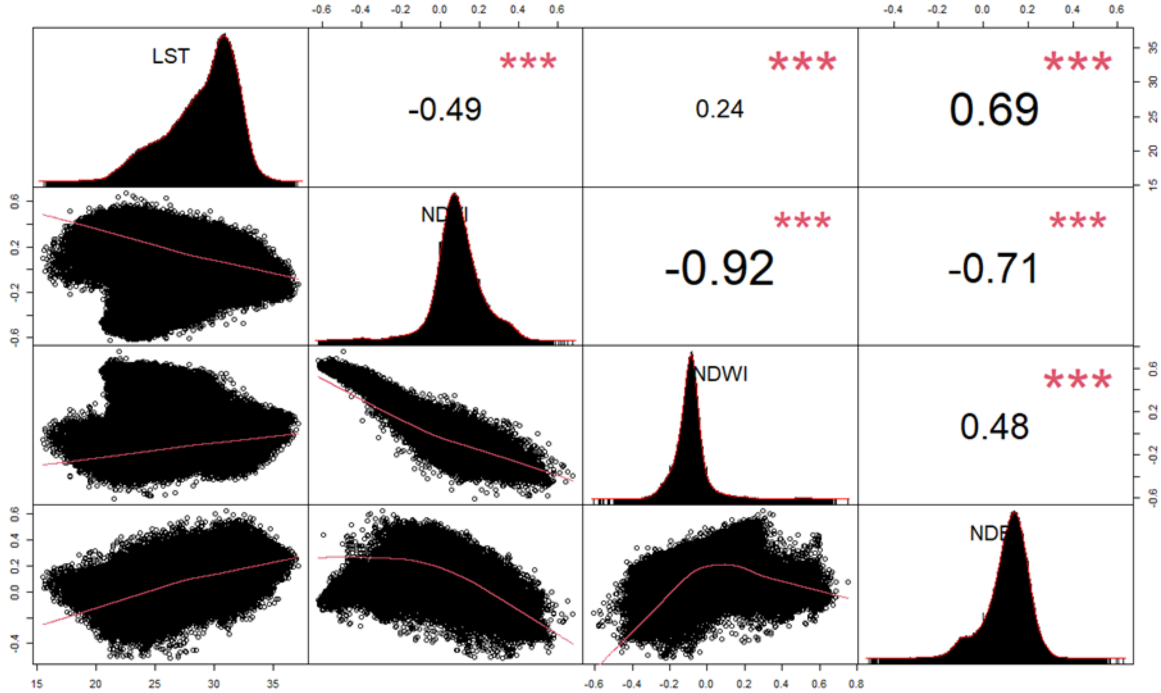
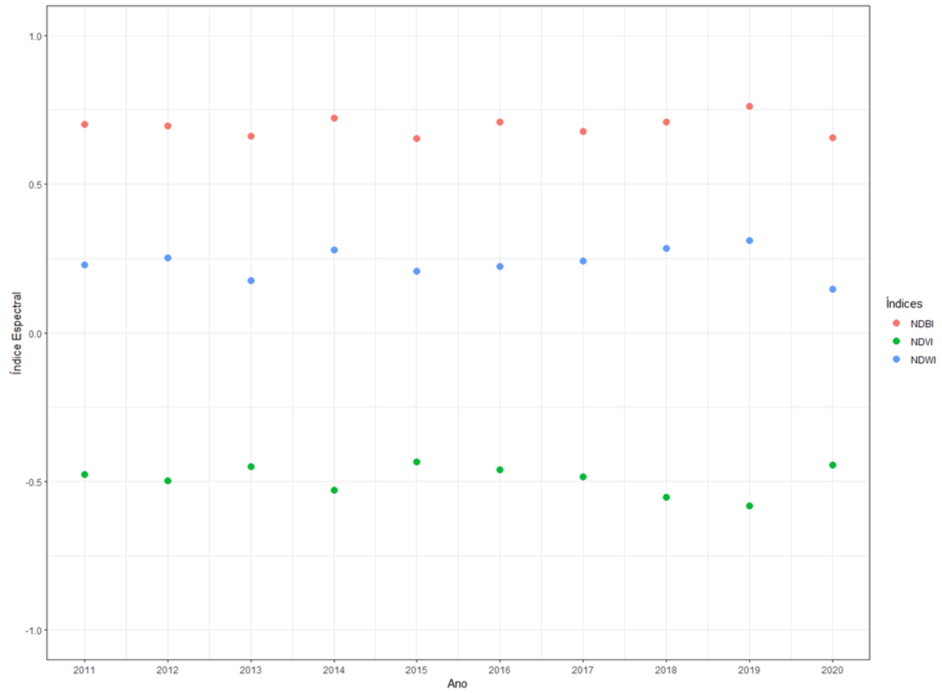


Figure. 8 Average values of spectral indices over the years.



Besides there's significantly changes in LULC over time, certain land cover types can exhibit relatively stable spectral characteristics despite these changes. This stability can be attributed to several factors, including the resilience of specific vegetation communities, consistent management practices, or the inherent spectral properties of certain land cover types.

For instance, in forested areas undergoing selective logging or experiencing minor disturbances, the overall spectral signature might remain relatively consistent if the dominant tree species and canopy structure are preserved. Imbernon e Branthomme (2001) discusses the characterization of landscape patterns of deforestation in tropical rainforests, which can provide insights into how spectral indices might change or remain stable under different disturbance regimes. Similarly, agricultural lands under consistent management practices, such as regular irrigation and fertilization, can maintain stable spectral indices even with crop rotation or changes in planting schedules.

Furthermore, spectrally homogenous land cover types, such as bare soil or water bodies, tend to exhibit stable spectral indices over time, as their inherent spectral properties are less susceptible to LULC changes. Szabó et al. (2016) discusses the specific features of NDVI, NDWI, and MNDWI as reflected in different land cover categories, which can shed light on the stability of these indices in various land cover types.

Discussion

The impact of land use on surface temperature is a critical area of research as it has significant implications for urban planning, climate change mitigation and environmental management.

Particular focus on the high surface temperatures observed in urban and agricultural areas, as well as the cooler temperatures in forested regions (Beg, 2018; Das & Angadi, 2020; Abdalkadhum et al., 2021).

The results indicate that urban and agricultural areas, particularly sugarcane plantations, have notably higher surface temperatures compared to forested regions (Anandababu et al., 2018; Zhi et al., 2020). Furthermore, the study highlights the usefulness of spectral indices, such as the Normalized Difference Vegetation Index (NDVI), in providing a stable and reliable proxy for understanding the relationship between land surface characteristics and LST (Wang et al., 2020).

Research demonstrates that spectral indices have a strong correlation with observed ground surface temperatures, suggesting their potential for incorporation into predictive models to improve the scale and understanding of underlying phenomena (Wu et al., 2019; Abdalkadhum et al., 2021). The heterogeneity and complexity of the urban landscape, as well as the use of different spatial analysis units, may introduce additional uncertainties in quantifying the relationship between urban heat island effects and underlying variables (Zhang et al., 2022).

The findings of this study have important implications for land use planning and management strategies, as they highlight the need to prioritize the preservation and expansion of forest areas, which can serve as natural heat sinks, and to carefully consider thermal impacts in urban and agricultural areas (Wu et al., 2019; Kikon et al., 2023). By incorporating this knowledge into urban development and landscape design, policymakers and urban planners can work to mitigate the adverse effects of urban pollution on the urban heat islands and promote more sustainable and resilient communities (Zhang et al., 2022).

Conclusions

- Throughout the evaluated period, five types of land use and cover stood out, presenting a much larger area than the other destinations. Sugarcane, Mosaic of uses, Pasture, Forest Formation. It was also possible to observe a significant increase in areas destined for soybean planting – in addition to the conversion of pasture areas into sugarcane planting areas. The series of maximums, minimums, and averages, when analyzed separately, did not show a clear trend of increase, or decrease, but rather an alternation between behaviors, which must be conditioned by other meteorological and/or environmental variables.
- Areas with natural vegetation formation had lower temperatures than urbanized areas and sugar cane areas. On the other hand, three of the four main uses stood out, combined with urban areas, presenting higher average temperatures than the other uses (6 °C, when compared to areas of Rocky Outcrops). It is worth mentioning that the most abundant use in the state is also the one with the highest surface soil temperatures. It was also possible to observe differences between years, related to area conversion. Increased soil surface temperature can impact water availability and flora and fauna diversity, therefore, further research considering these impacts and application of remedial/corrective measures are highly desired/needed.
- To improve understanding of the phenomenon and increase data availability and quality, a correlation was established between the values of the spectral indices NDVI, NDWI

and NDBI with the LST values. Each index has a distinct correlation with temperature, which may indicate that the indices can be considered together to establish LST prediction/gap filling/resolution improvement models.

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