

Thermal Dynamics of Peri-Urban Landscapes: A Paired Spatial Analysis of Brick Kilns and Bare Soil in León, Guanajuato

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Highlights

- Paired design isolates thermal impacts of peri-urban soil exposure.
- Exposed soil showed higher daytime surface temperatures than kilns.
- LST-NDMI coupling confirms severe water stress in peri-urban zones.
- 3-year Landsat analysis provides a robust baseline for León, Mexico.
- Multi-buffer method reveals thermal dissipation limits at 500 m.

Abstract

Urban expansion and industrial activities in peri-urban environments modify land cover and influence surface thermal patterns. This study examines the thermal behavior of artisanal brick kilns in León, Guanajuato, Mexico, using a paired spatial approach designed to distinguish the contribution of kiln activity from that of the surrounding landscape. Landsat 8 Collection 2 Level-2 imagery acquired during the dry seasons (March–May) of 2024–2026 was processed in Google Earth Engine. Eight active brick kiln polygons were paired with eight bare-soil control sites and evaluated within concentric buffers of 100, 500, and 1000 m. Eight spectral and thermal indices, including Land Surface Temperature (LST), NDVI, and NDMI, were calculated. Wilcoxon signed-rank and Mann–Whitney U tests indicate that bare-soil control sites consistently exhibited higher LST values than active brick kilns, with a mean difference of approximately $\Delta\text{LST} \approx -3.7^\circ\text{C}$. Spearman correlation showed a moderate inverse relationship between LST and NDMI ($\rho \approx -0.49$), indicating that higher surface temperatures are associated with reduced vegetation moisture. The results indicate that, under the analyzed daytime Landsat observations, exposed bare soil exhibited higher surface temperatures than the active brick kiln polygons. This three-year assessment provides a reference for monitoring peri-urban thermal conditions and supports the use of paired multi-buffer analyses to evaluate the effects of land cover on surface temperature.

Resumen

La expansión urbana y las actividades industriales en zonas periurbanas modifican la cobertura del suelo e influyen en los patrones térmicos de la superficie. Este estudio analiza el comportamiento térmico de los hornos ladrilleros artesanales en León, Guanajuato, México, mediante un diseño espacial pareado que permite distinguir la contribución de la actividad ladrillera de la influencia del paisaje circundante. Se procesaron imágenes Landsat 8 Colección 2 Nivel-2 correspondientes a las temporadas secas (marzo–mayo) de 2024–2026 utilizando Google Earth Engine. Ocho polígonos de ladrilleras activas se compararon con ocho sitios de control de suelo desnudo mediante áreas de influencia concéntricas de 100, 500 y 1000 m. Se calcularon ocho índices espectrales y térmicos, entre ellos la Temperatura Superficial Terrestre (LST), el NDVI y el NDMI. Las pruebas de rangos con signo de Wilcoxon y Mann–Whitney U muestran que los sitios de control de suelo desnudo presentaron valores de LST consistentemente superiores a los de las ladrilleras activas, con una diferencia media de aproximadamente $\Delta\text{LST} \approx -3,7^\circ\text{C}$. La correlación de Spearman mostró una relación inversa moderada entre LST y NDMI ($\rho \approx -0,49$), lo que indica que el incremento de la temperatura superficial está asociado con una menor humedad de la vegetación. Los resultados indican que, bajo las observaciones diurnas analizadas de Landsat, el suelo desnudo expuesto mostró temperaturas superficiales más altas que los polígonos de los hornos activos. Este análisis de tres años proporciona una referencia para el monitoreo de las condiciones térmicas periurbanas y respalda el uso de diseños pareados con múltiples áreas de influencia para evaluar el efecto de la cobertura del suelo sobre la temperatura superficial.

Graphical Abstract

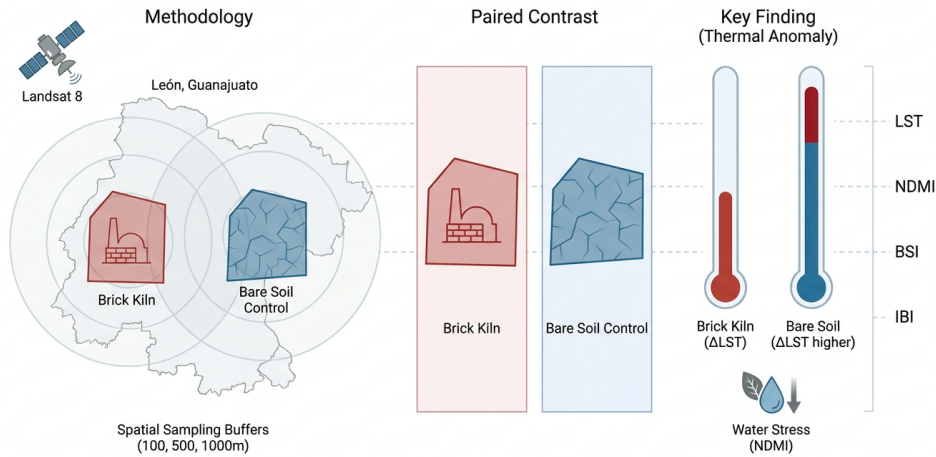


Fig. 1: Summary of the paired multi-buffer spatial methodology and core findings.

1 Introduction

Rapid urbanization and industrial expansion have changed natural landscapes and created environmental problems around the world. One main consequence of these land use changes is the modification of the surface energy balance. This often leads to higher land surface temperatures (LST) and increases the urban heat island (UHI) effect (Estoque et al., 2017; Du et al., 2020). Understanding spatial and temporal variations in LST is important because they affect local climates, increase energy use, and influence human health and thermal comfort (Portela et al., 2020; Kanga et al., 2022). Monitoring surface thermal dynamics and their relationship with landscape features, such as vegetation cover and surface moisture, helps guide sustainable urban planning. It also supports environmental management and climate change mitigation strategies worldwide (Velázquez et al., 2010; Vázquez-Jiménez et al., 2021).

Remote sensing has become the standard approach for environmental monitoring. Many studies use satellite imagery, especially from Landsat sensors, to estimate LST with single-channel algorithms, split-window methods, and radiative transfer equations (García-Santos et al., 2018; Duan et al., 2019; Sekertekin and Bonafoni, 2020). Many studies have also established methods to analyze the relationship between LST and spectral indices such as the Normalized Difference Vegetation Index (NDVI). These methods help evaluate how vegetation reduces thermal stress (Kumar and Shekhar, 2015; García-Santos et al., 2018; Sekertekin and Bonafoni, 2020; Guha and Govil, 2022; Ullah et al., 2023). Seasonal studies in tropical urban areas show that the inverse relationship between LST and NDVI remains stable throughout the year. Areas with healthy vegetation consistently have lower temperatures than bare soil or built-up areas (Guha and Govil, 2020). Recent studies covering large areas and long time periods report

the same negative relationship. They show that vegetation loss during rapid urban expansion increases thermal anomalies (Kliengchuay et al., 2025). A common approach in these studies combines thermal infrared data with multi-temporal land cover maps to measure the cooling effect of green spaces and the warming effect of built environments over large areas (Kumar and Shekhar, 2015; Zhang et al., 2017; Roy and Bari, 2022).

In peri-urban and industrial landscapes, informal and traditional industries such as brick kilns are important point sources of air pollution, soil degradation, and thermal anomalies (Hossain et al., 2019; Khan et al., 2019; Misra et al., 2020). Recent geospatial studies use high-resolution satellite data to detect, map, and monitor these kilns while assessing their environmental compliance in developing countries (Misra et al., 2020; DeWitt et al., 2021). Scalable machine learning pipelines have also improved the processing of large geographic areas. They reduce the limitations of manual image annotation and support systematic monitoring of emission sources (Patel et al., 2025). In Mexico, researchers have examined how land cover changes and urban growth affect LST under different climatic conditions. Their results show that industrial corridors and urban vegetation influence thermal patterns in cities such as Querétaro, Puebla, and the Bajío industrial region (Colunga et al., 2015; Gomez-Martinez et al., 2021; Palafox-Juárez et al., 2021; Medina-Fernández et al., 2023). Studies based on Landsat image time series have also shown that vegetation loss caused by peripheral urban expansion increases the formation of surface heat islands in tropical cities such as Mérida (Carrillo-Niquete et al., 2022). Likewise, multi-temporal Landsat analyses indicate that rapid population growth and agricultural expansion in semi-arid regions produce major land use changes. These changes reduce natural vegetation cover and increase landscape degradation at the regional scale (Valencia-Gaspar et al., 2024).

Despite advances in LST retrieval and brick kiln mapping, there is still a gap in understanding microscale thermal interactions between industrial point sources and their surrounding environment. Previous spatiotemporal studies show that the high heterogeneity of urban and peri-urban landscapes weakens thermal-spectral relationships, making it difficult to identify the main drivers of surface heat (Guha and Govil, 2021). Most published studies evaluate LST at the city scale or focus mainly on the effects of brick kilns on air quality. As a result, they do not clearly separate the thermal contribution of the kilns from the influence of nearby land cover, which can act as a confounding factor. In arid and semi-arid peri-urban environments, there is still limited evidence about whether the observed thermal stress is driven by industrial activity itself or by the large areas of bare soil created by clay extraction and dry landscapes. There are also few localized paired approaches that evaluate both spatial thermal gradients and vegetation water stress around these sites. Fine-scale comparative spatial methods are still needed to separate the overlapping thermal signatures of industrial kilns and surrounding bare soil.

To address this knowledge gap, this study evaluates the thermal dynamics associated with brick kilns and compares them with the surrounding land cover in the peri-urban area of León, Guanajuato, Mexico. A satellite-based methodology using a paired multi-buffer analysis was

applied to isolate localized land surface temperature (LST) gradients around active brick kilns and compare them with reference areas that have similar environmental conditions. This approach reduces the influence of surrounding landscape characteristics and allows a more accurate evaluation of the thermal effect associated with each site. The findings indicate that, during the analyzed daytime satellite passes, bare soil consistently exhibited higher surface temperatures than the brick kiln polygons within the study area. The relationship between these thermal patterns and vegetation water stress is also evaluated, helping to improve the understanding of the environmental degradation processes that characterize peri-urban landscapes.

2 Methodology

2.1 Study area and datasets

This study was conducted in the municipality of León de los Aldama, Guanajuato, in central-northern Mexico (approximately 21°07' N, 101°40' W). The municipality is located at an average elevation of 1,798 m above sea level within the Bajío region. According to the Köppen climate classification, León has a semi-arid temperate climate (BS1h), with a mean annual temperature of 18–20 °C and an average annual rainfall of about 670 mm. Most rainfall occurs during summer, while the dry season is characterized by exposed soil and limited vegetation cover. León is the largest urban center in Guanajuato, with more than 1.7 million inhabitants according to the 2020 Population and Housing Census. The population has a median age of 27 years and an almost equal distribution of men and women. Rapid urban growth has expanded the city toward its outskirts, where residential areas are increasingly located next to clay extraction sites and traditional brick kilns. Most of these kilns operate under informal and artisanal conditions. Their production depends on continuous clay extraction, which removes natural vegetation and leaves large areas of bare soil exposed to solar radiation. These landscape changes favor the development of surface thermal anomalies and vegetation water stress. The figure 2 shows the study area and the spatial distribution of the selected brick kilns. It also presents the 100 m, 500 m, and 1 km buffer zones used in the spatial analysis.

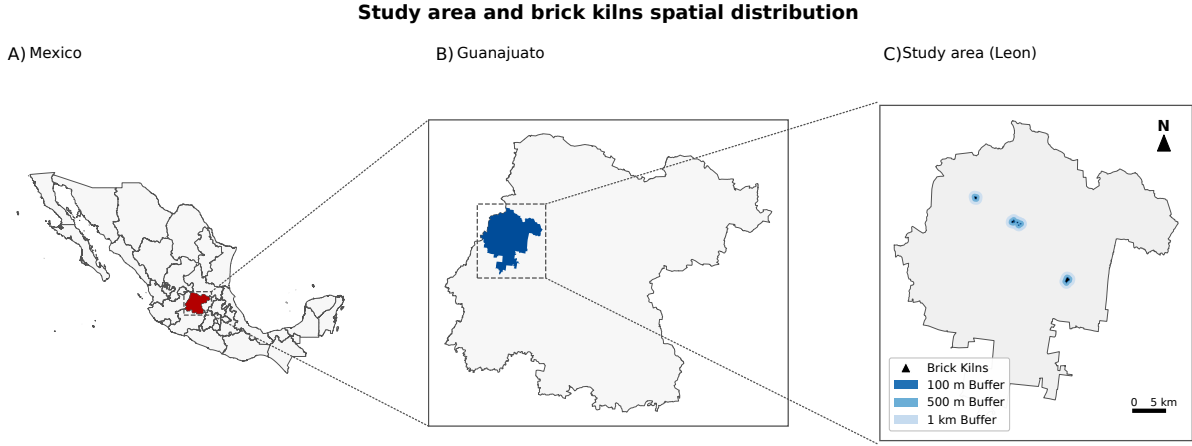


Fig. 2: Location of the study area. (A) Guanajuato within Mexico, (B) León within Guanajuato, and (C) the study area showing brick kilns and the 100 m, 500 m, and 1 km buffer zones used for the spatial analysis.

2.2 Data acquisition

Satellite data for this study were processed using the Google Earth Engine (GEE) cloud platform. Landsat 8 Collection 2 Level-2 imagery was selected because it provides consistent processing and validated accuracy for land surface temperature (LST) retrieval under different land cover conditions (Duan et al., 2021). To keep similar surface conditions, reduce the influence of rainfall, and allow comparison between years, only images from the dry season (March to May) of 2024, 2025, and 2026 were used. Eight spectral variables were extracted to evaluate the peri-urban thermal environment: Land Surface Temperature (LST), NDVI, NDBI, NDMI, BSI, UI, MNDWI, and IBI.

The municipal boundary of León was obtained from the official database of the National Institute of Statistics and Geography (INEGI). Sample selection was based on detailed visual interpretation using Google Earth Pro to verify the documented locations. The selection criteria included geometric structures corresponding to traditional and MK2 ecological brick kilns, bare soil patterns related to clay extraction, and brick storage areas. Based on these criteria, eight active brick kiln polygons and eight bare soil polygons were selected as control sites, located between 1 and 3 km from the source. The polygons were exported as KML files, topologically corrected in QGIS, and packaged as a ZIP file. Finally, the vector data were imported into GEE as *Assets* and used as the geometric basis for extracting spectral information within concentric buffer zones of 100, 500, and 1000 m.

2.3 Data preprocessing

To ensure data quality, clouds and cloud shadows were masked using the *QA_PIXEL* band from the Landsat 8 Collection 2 Level-2 product. Median composites were then generated from all available scenes during the dry season (March–May) of 2024, 2025, and 2026. This reduced the influence of contaminated pixels and remaining outliers. Land Surface Temperature (LST),

NDVI, NDBI, NDMI, BSI, UI, MNDWI, and IBI were calculated from the corresponding Landsat 8 bands at a spatial resolution of 30 m. Recent studies support the use of the Landsat 8 OLI and TIRS sensors for this purpose because they provide accurate LST estimates when appropriate atmospheric corrections are applied (Vanhellemont, 2020). The use of these datasets in cloud computing platforms also supports the development of geospatial industrial inventories for environmental compliance and monitoring of technological changes (Rauf et al., 2022).

A paired spatial design was then applied by matching each of the eight active brick kilns with one bare soil control polygon using a unique identifier (*par_id*). Concentric buffers of 100, 500, and 1000 m were created around each spatial unit to evaluate the spatial variation of the selected variables at different distances. Finally, the *sampleRegions* and *reduceRegions* algorithms in Google Earth Engine (GEE) were used to extract pixel values and summary statistics (mean and standard deviation) for each polygon and buffer. These datasets were used for the following statistical analyses, including descriptive statistics, non-parametric tests, and the evaluation of spatial and temporal relationships between brick kilns and their corresponding control sites.

2.4 Computational pipeline and algorithm

The methodology follows a spatially paired quasi-experimental design to separate the thermal and spectral effects of brick kiln activity from those of natural control areas. The workflow consists of three sequential stages: site identification and paired design, remote sensing analysis, and statistical analysis. The main idea of the method is to compare each active brick kiln polygon with one control polygon (bare soil without industrial activity) located within a validation distance of 1 to 3 km. This distance keeps similar macroclimatic and topographic conditions between paired sites and reduces the effect of environmental confounding factors. To evaluate how the thermal response changes with distance, concentric buffer zones of 100, 500, and 1000 m were created around each site. As shown in figure 3, the computational workflow combines automated satellite data extraction with non-parametric statistical tests. Spectral processing was carried out using Landsat 8 OLI/TIRS imagery. Cloud and cloud shadow masking was applied at the pixel level with the *QA_PIXEL* band, followed by seasonal median composites to reduce atmospheric noise.

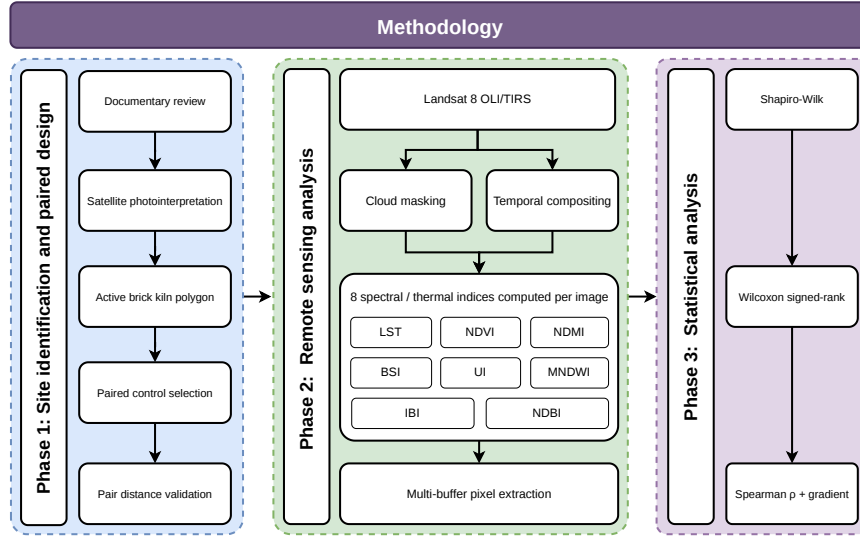


Fig. 3: Workflow of the computational pipeline. Phase 1 includes the literature review, satellite photo interpretation, and distance validation used to define the paired design. Phase 2 describes the remote sensing analysis with Landsat 8 OLI/TIRS imagery, including cloud masking, seasonal image compositing, calculation of eight spectral and thermal indices (LST, NDVI, NDMI, BSI, UI, MNDWI, IBI, and NDBI), and multi-buffer pixel extraction. Phase 3 summarizes the statistical analysis, from the Shapiro–Wilk normality test to the Wilcoxon signed-rank test and the spatial gradient analysis based on Spearman’s correlation coefficient.

For each image, the algorithm calculated eight spectral and thermal indices. Their mathematical formulas, Landsat bands, and ecological interpretation are summarized in Table I. These indices include Land Surface Temperature (LST) as the main response variable, vegetation and water stress indicators (NDVI and NDMI), indices related to impervious surfaces and bare soil (NDBI, BSI, and IBI), and spatial control variables (UI and MNDWI).

After the multi-buffer pixel extraction, the statistical analysis was performed in three steps. First, data distribution was evaluated with the Shapiro–Wilk test. Since the data did not follow a normal distribution, paired differences between each brick kiln and its control were analyzed with the Wilcoxon signed-rank test at the polygon level and the Mann–Whitney U test at the buffer level. Finally, the thermal change with distance was evaluated using Spearman’s correlation coefficient (ρ) together with a spatial gradient analysis.

2.5 Experimental and computational configuration

Image acquisition and preprocessing were performed in the Google Earth Engine (GEE) cloud platform, while the statistical analysis and figure generation were carried out locally using Python 3.10. The workflow used the *pandas*, *NumPy*, *SciPy* (v1.10), *Matplotlib*, and *Seaborn* libraries for data processing, statistical analysis, and visualization. Landsat 8 Collection 2 Level-2 products were used because they include atmospheric and surface reflectance corrections with a native spatial resolution of 30 m. To reduce the influence of soil moisture and cloud cover, only images acquired during the dry season (March to May) of 2024, 2025, and 2026 were included

Table I: Spectral and thermal indices computed from Landsat 8 OLI/TIRS Collection 2 Level-2 imagery. Band designations correspond to the OLI sensor (SR_Bn) and the TIRS sensor (ST_B10). SWIR1 = shortwave infrared band 1; NIR = near infrared; DN = digital number of the ST_B10 thermal product.

Index	Formula	Bands (L8)	Ref.	Role in this study
LST	$DN \times 0.003418 + 149.0 - 273.15$	ST_B10	United States Geological Survey (2024)	Core variable for assessing surface thermal response and urban heat island intensity.
NDVI	$\frac{B5 - B4}{B5 + B4}$	B5, B4	Roy and Bari (2022)	Proxy for green cover and its capacity for thermal mitigation.
NDBI	$\frac{B6 - B5}{B6 + B5}$	B6, B5	Roy and Bari (2022)	Indicator of urban surface impermeability and spatial heat retention.
NDMI	$\frac{B5 - B6}{B5 + B6}$	B5, B6	Roy and Bari (2022)	Assesses vegetation water stress and foliar moisture in peri-urban environments.
BSI	$\frac{(B6 + B4) - (B5 + B2)}{B6 + B4 + B5 + B2}$	B6, B4, B5, B2	Rikimaru et al. (2002)	Quantifies the fraction of exposed soil, critical for distinguishing brick kilns from vegetated areas.
UI	$\frac{B7 - B5}{B7 + B5}$	B7, B5	Bouhennache et al. (2018)	Distinguishes consolidated urban zones to control for urbanization levels between paired sites.
MNDWI	$\frac{B3 - B6}{B3 + B6}$	B3, B6	Xu (2006)	Detects surface water bodies, utilized as an exclusion control variable to prevent thermal bias.
IBI	$\frac{\frac{2B6}{B6+B5} - \left[\frac{B5}{B5+B4} + \frac{B3}{B3+B6} \right]}{\frac{2B6}{B6+B5} + \left[\frac{B5}{B5+B4} + \frac{B3}{B3+B6} \right]}$	B3, B4, B5, B6	Xu (2008)	Robust composite index to separate built environments from bare soil, measuring impermeable surface contribution.

in the analysis. The paired design was validated before the statistical analysis. Each active brick kiln was matched with one bare soil control site (1:1), and the Urban Index (UI) and the Modified Normalized Difference Water Index (MNDWI) were compared between paired sites. No statistically significant differences were found before applying the main statistical tests.

2.6 Evaluation metrics

This study used an observational statistical framework instead of a predictive machine learning model. For this reason, the results were evaluated with statistical measures that describe significance, differences between groups, and the strength of the observed relationships. A significance level of $p < 0.05$ (two-tailed test) was adopted for all hypothesis tests, including the Shapiro–Wilk, paired Wilcoxon signed-rank, and Mann–Whitney U tests. The difference between groups was calculated as the mean difference ($\Delta = \mu_{\text{brick kiln}} - \mu_{\text{control}}$) and reported together with the corresponding standard deviation ($\pm\sigma$) to describe the thermal difference in land surface temperature ($^{\circ}\text{C}$). The Spearman correlation coefficient (ρ) was used to measure the strength and direction of the monotonic relationship between the distance from each site (100, 500, and 1000 m) and the spectral variables, mainly LST and NDMI. The coefficient of determination (R^2), obtained from simple linear regression models, was also calculated to evaluate the interannual temperature trend during the 2024–2026 period.

3 Results

3.1 Descriptive statistics

A total of 327,012 pixels were extracted from the buffer zones, representing 48 paired sites during the 2024–2026 period. The control polygons had a slightly larger average area than the brick kiln polygons, which resulted in a higher number of sampled pixels in each buffer (e.g., 2,305 versus 1,697 pixels at the 100 m buffer in 2024).

The figure 4 shows the overall distribution of Land Surface Temperature (LST) values. When all buffer zones are combined, both classes have very similar thermal distributions, with a large overlap between them. Their median values were also very close across the three years. For example, in 2025 both classes had the same median temperature (43.22 °C). This overall similarity supports the use of a spatially stratified analysis to identify local thermal differences.

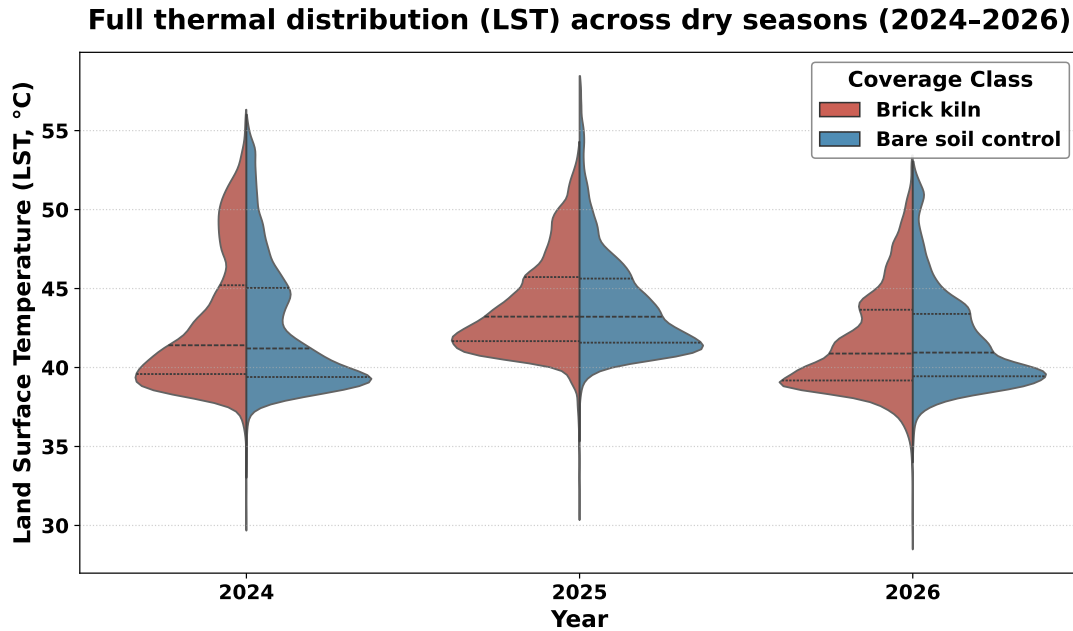


Fig. 4: Split violin plots showing the distribution of Land Surface Temperature (LST) for all sampled pixels ($N = 327,012$) during the 2024–2026 dry seasons. The left side (red) represents brick kiln sites and the right side (blue) represents paired bare-soil controls. Dashed lines indicate the 25th percentile, median, and 75th percentile. The strong overlap between both distributions supports the later analysis by buffer distance.

The descriptive statistics showed that the differences between both classes depended on the buffer distance rather than remaining constant across the study area. Table II summarizes the mean and standard deviation of the main thermal and vegetation variables for the three buffer distances. The largest differences were observed in the immediate surroundings of the brick kilns (100 m). During the three study years, the control sites (bare soil) consistently presented higher land surface temperatures than the brick kiln areas. Mean LST reached 46.53 ± 4.96 °C versus 44.36 ± 4.12 °C in 2024, 47.69 ± 4.25 °C versus 44.78 ± 2.92 °C in 2025, and 45.30 ± 4.13 °C versus 42.52 ± 3.14 °C in 2026.

The same pattern was observed for NDMI, where the control areas showed more negative values at 100 m, while NDVI values remained similar between both classes in all years. At 500 m, the differences between both classes became much smaller, and at 1000 m the average values were very similar for most variables.

Table II: Descriptive statistics (Mean $\pm$ Standard Deviation) of the main thermal and vegetation variables by class and buffer distance.

Buffer	Year	Class	LST ($^{\circ}\text{C}$)	NDVI	NDMI
100 m	2024	Brick kiln	44.36 $\pm$ 4.12	0.10 $\pm$ 0.03	-0.05 $\pm$ 0.03
		Bare soil	46.53 $\pm$ 4.96	0.08 $\pm$ 0.03	-0.07 $\pm$ 0.04
	2025	Brick kiln	44.78 $\pm$ 2.92	0.10 $\pm$ 0.03	-0.05 $\pm$ 0.02
		Bare soil	47.69 $\pm$ 4.25	0.08 $\pm$ 0.03	-0.06 $\pm$ 0.03
	2026	Brick kiln	42.52 $\pm$ 3.14	0.11 $\pm$ 0.03	-0.05 $\pm$ 0.03
		Bare soil	45.30 $\pm$ 4.13	0.10 $\pm$ 0.03	-0.06 $\pm$ 0.03
500 m	2024	Brick kiln	43.03 $\pm$ 4.43	0.10 $\pm$ 0.03	-0.05 $\pm$ 0.04
		Bare soil	42.90 $\pm$ 4.35	0.09 $\pm$ 0.04	-0.04 $\pm$ 0.04
	2025	Brick kiln	44.10 $\pm$ 3.20	0.09 $\pm$ 0.03	-0.05 $\pm$ 0.03
		Bare soil	44.24 $\pm$ 3.54	0.09 $\pm$ 0.04	-0.04 $\pm$ 0.04
	2026	Brick kiln	41.86 $\pm$ 3.40	0.11 $\pm$ 0.04	-0.04 $\pm$ 0.03
		Bare soil	41.97 $\pm$ 3.37	0.10 $\pm$ 0.05	-0.04 $\pm$ 0.04
1000 m	2024	Brick kiln	42.65 $\pm$ 4.02	0.10 $\pm$ 0.04	-0.05 $\pm$ 0.04
		Bare soil	42.31 $\pm$ 3.77	0.09 $\pm$ 0.05	-0.03 $\pm$ 0.04
	2025	Brick kiln	43.86 $\pm$ 2.97	0.10 $\pm$ 0.04	-0.04 $\pm$ 0.03
		Bare soil	43.72 $\pm$ 2.94	0.09 $\pm$ 0.05	-0.03 $\pm$ 0.04
	2026	Brick kiln	41.53 $\pm$ 3.16	0.11 $\pm$ 0.04	-0.04 $\pm$ 0.04
		Bare soil	41.46 $\pm$ 2.82	0.10 $\pm$ 0.05	-0.03 $\pm$ 0.04

Note: LST = Land Surface Temperature; NDVI = Normalized Difference Vegetation Index; NDMI = Normalized Difference Moisture Index.

3.2 Central test of the paired design

The Shapiro–Wilk test indicated that all groups departed from normality ($p < 0.05$). Therefore, paired comparisons were performed using the Wilcoxon signed-rank test. The figure 5 summarizes the polygon-level comparisons for the eight paired sites during 2024–2026. Land Surface Temperature (LST) was significantly different in all three years ($p = 0.0078$), with brick kilns showing lower temperatures than their paired control areas. The mean difference (ΔLST) ranged from -3.64 to -3.84 $^{\circ}\text{C}$.

Interannual variation and paired Wilcoxon signed-rank test distributions for key spectral and thermal indices (2024–2026)

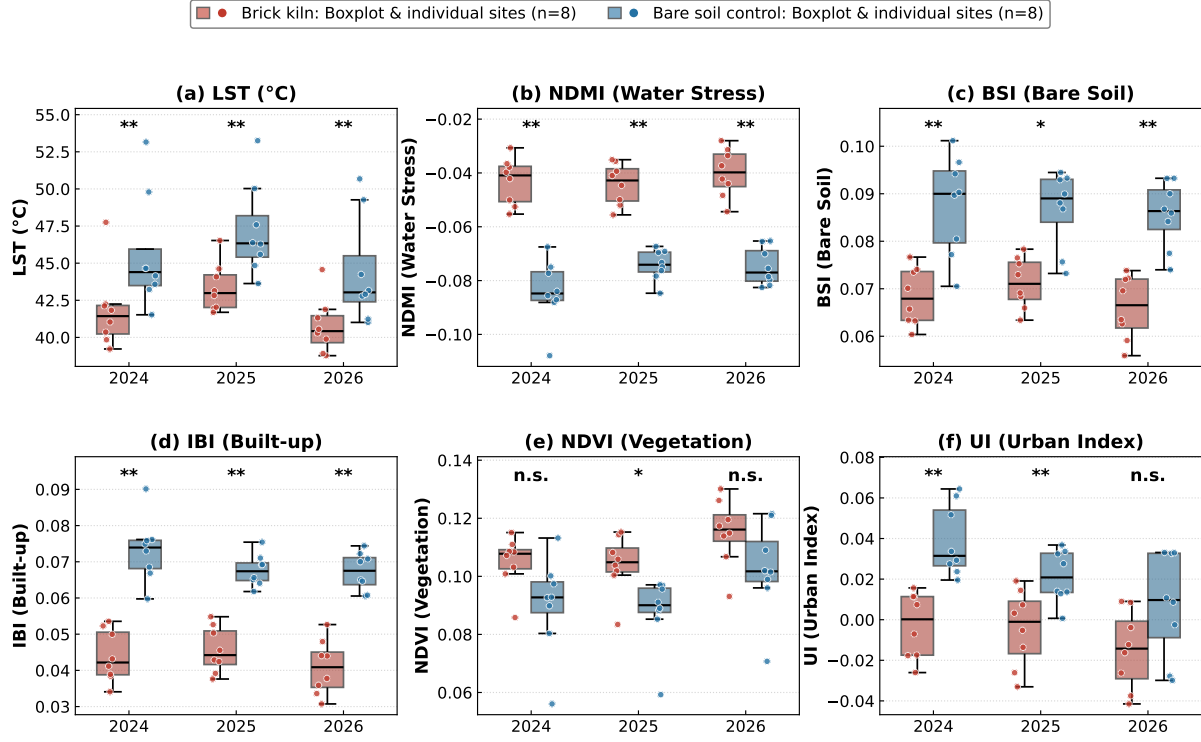


Fig. 5: Polygon-level paired comparison between brick kilns and control sites for the three study years ($n = 8$ pairs). Boxplots show the median and interquartile range, while points represent individual polygon values. Statistical significance was evaluated using the Wilcoxon signed-rank test (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, n.s. = not significant).

The same pattern was observed for most spectral indices. Bare Soil Index (BSI), Impervious Built-up Index (IBI), NDMI, NDBI, BSI, and MNDWI showed significant paired differences in almost all comparisons. In contrast, NDVI was not significant in 2024 ($p = 0.078$) or 2026 ($p = 0.195$), and the Urban Index (UI) was also not significant in 2026 ($p = 0.109$). These results indicate that the paired sites had similar background vegetation and urban characteristics, while the strongest differences were related to exposed soil and surface thermal conditions. The figure 6 shows the spatial consistency of these differences across the eight geographic pairs. Most pairs presented negative Δ LST values during the three study years, meaning that brick kilns remained cooler than their corresponding control sites. A similar spatial pattern was observed for BSI and IBI, while NDMI showed the opposite direction. The average panel confirms that these differences were consistent through time for most paired locations.

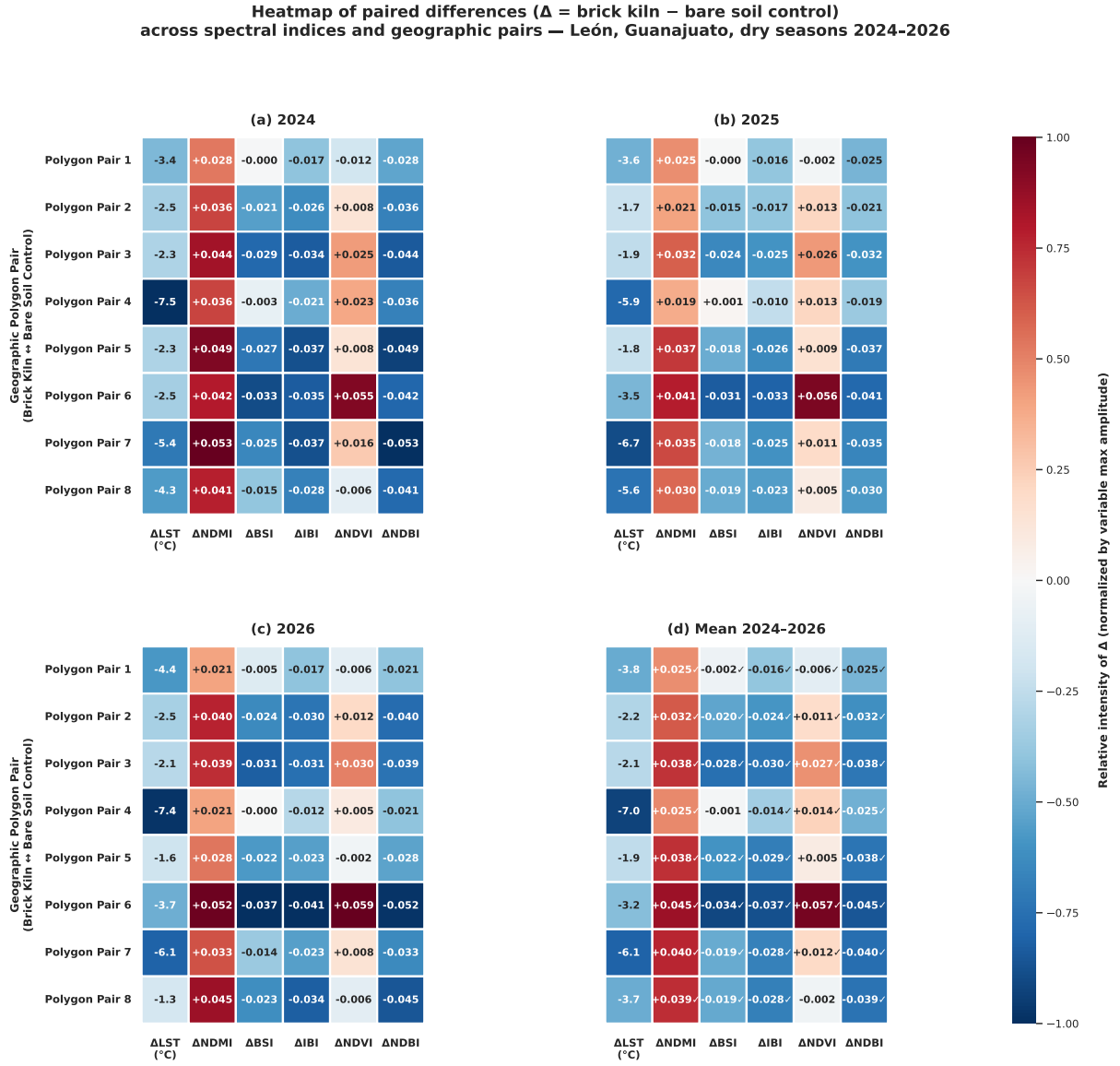


Fig. 6: Heatmap of paired differences (Δ = brick kiln – control) for LST and the main spectral indices across the eight geographic pairs. Panels show results for 2024, 2025, 2026, and the three-year average. Blue colors indicate lower values in brick kilns, while red colors indicate higher values. Check marks identify pairs with the same direction of change during the three study years.

3.3 Spatial gradient analysis

The spatial gradient analysis (Fig. 7) evaluated how the differences between brick kilns and paired control sites changed with distance. The strongest thermal contrast was observed within the 100 m buffer, where control sites consistently showed higher Land Surface Temperature (LST) than brick kilns in all three years ($p < 0.0001$). At 500 m, LST differences became very small and were not significant in 2024 and 2025, while a small difference remained in 2026 (Δ LST = -0.11 °C, $p < 0.001$). At 1000 m, the thermal contrast disappeared and even changed direction in 2024 and 2025, although the differences were small ($+0.34$ °C and $+0.14$ °C, respectively). Overall, the thermal contrast was strongest near the paired sites and decreased with

283 increasing distance.

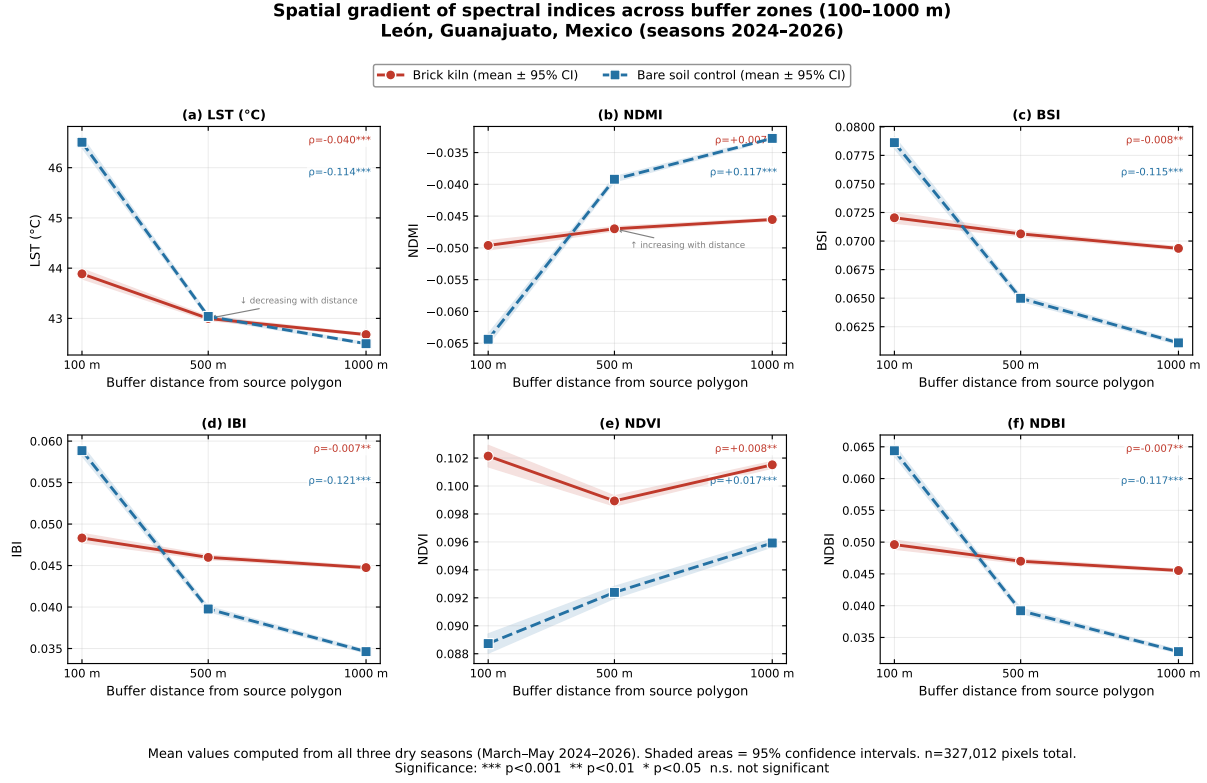


Fig. 7: Spatial gradient of the main spectral and thermal indices across the 100, 500, and 1000 m buffers around brick kilns and paired control sites. Symbols represent mean values, and shaded areas indicate the 95% confidence intervals.

284 The continuous gradient analysis using Spearman's correlation (Table III) showed signifi-
285 cant but weak correlations between buffer distance and the evaluated variables. Around brick
286 kilns, LST changed only slightly with distance ($\rho = -0.040$, $p < 0.001$), while the strongest
287 correlations were found in the control sites. The highest coefficients were observed for IBI
288 ($\rho = -0.121$), NDBI ($\rho = -0.117$), NDMI ($\rho = 0.117$), and LST ($\rho = -0.114$). NDVI
289 showed only weak positive correlations in both classes.

Table III: Spearman correlation between buffer distance and the main variables (2024–2026 combined).

Variable	Brick kiln		Control	
	ρ	Sig.	ρ	Sig.
LST (°C)	-0.040	***	-0.114	***
NDMI	0.007	**	0.117	***
BSI	-0.008	**	-0.115	***
IBI	-0.007	**	-0.121	***
NDVI	0.008	**	0.017	***
NDBI	-0.007	**	-0.117	***

*** $p < 0.001$, ** $p < 0.01$.

3.4 LST-NDMI correlation and multivariate relationships

The figure 8 shows the relationship between Land Surface Temperature (LST) and the Normalized Difference Moisture Index (NDMI). Considering all sampled pixels, LST was negatively correlated with NDMI ($\rho = -0.490$, $p < 0.001$). This pattern remained similar during the three study years, with comparable trends for both brick kiln and control sites.

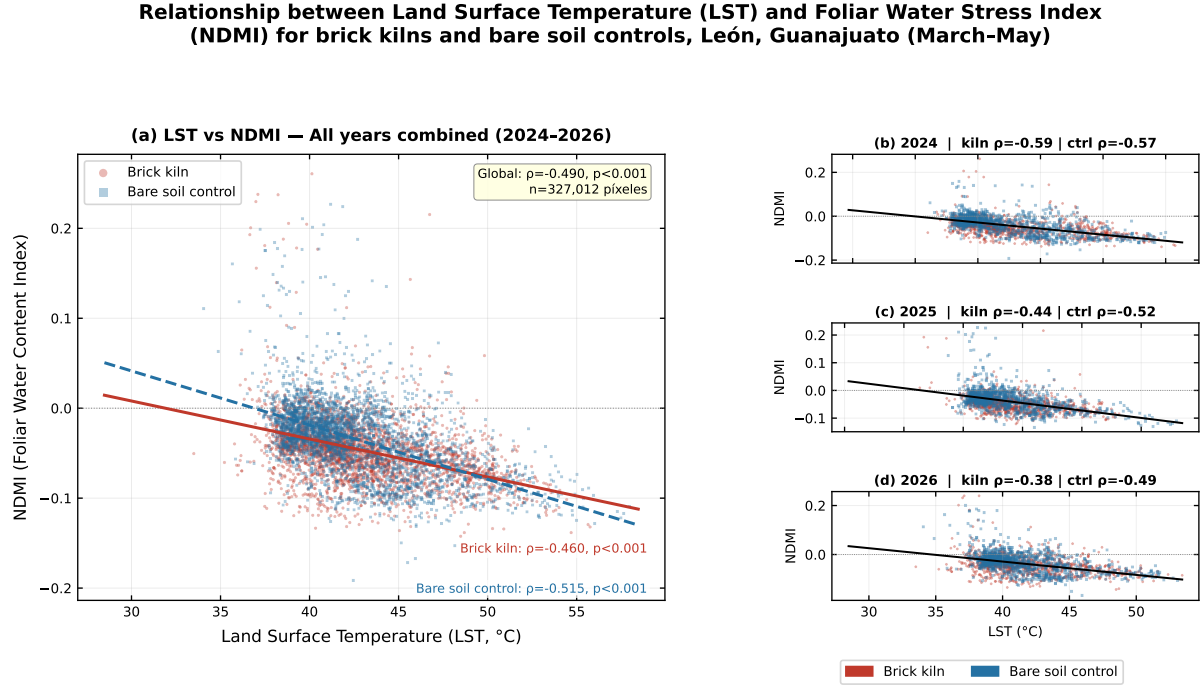


Fig. 8: Relationship between LST and NDMI for brick kiln (red) and control (blue) sites. Panel (a) shows all data combined, while panels (b)–(d) present the results for each study year. Lines represent linear regression fits.

Additional pairwise relationships are shown in figure 9 and summarized in Table IV. LST was positively correlated with BSI ($\rho = 0.464$ – 0.488) and IBI ($\rho = 0.477$ – 0.519) in both classes. NDMI showed strong negative correlations with BSI ($\rho = -0.912$ to -0.936) and an almost perfect negative correlation with IBI ($\rho = -0.993$). Likewise, BSI and IBI were strongly positively correlated ($\rho = 0.940$ – 0.956). All reported correlations were statistically significant ($p < 0.001$).

**Pairwise relationships among key spectral indices
for brick kilns and bare soil controls — León, Guanajuato (2024–2026)**

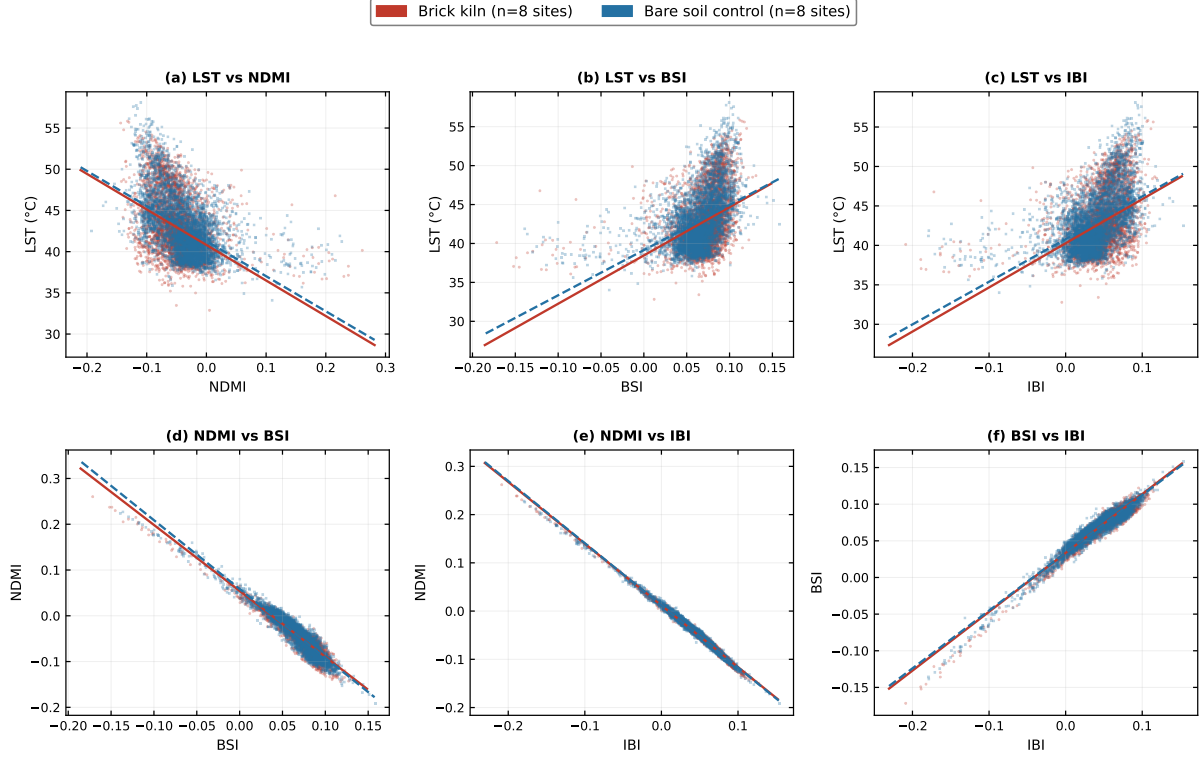


Fig. 9: Pairwise relationships among LST, NDMI, BSI, and IBI for brick kiln and control sites. A stratified subsample ($N = 8,000$ pixels) was used for visualization, while correlation coefficients were calculated using the complete dataset.

Table IV: Spearman correlation coefficients (ρ) between the main spectral indices (2024–2026).

Variable pair	Brick kiln	Control
LST – NDMI	−0.460	−0.515
LST – BSI	0.464	0.488
LST – IBI	0.477	0.519
NDMI – BSI	−0.912	−0.936
NDMI – IBI	−0.993	−0.993
BSI – IBI	0.940	0.956

All correlations were significant ($p < 0.001$).

3.5 Interannual trend and temporal baseline

To evaluate the temporal consistency of the observed patterns, the interannual trend (2024–2026) was analyzed using the 500 m buffer as the baseline. This distance was selected because the LST differences between brick kilns and control sites were small or not significant in most years. The figure 10 shows similar temporal trends for both classes across all variables. Mean

LST increased from 2024 to 2025 and decreased in 2026 for both brick kilns (43.03, 44.10 and 41.86 °C) and control sites (42.90, 44.24 and 41.97 °C). NDMI, BSI, and IBI followed the same temporal pattern in both groups. NDVI and UI remained almost stable during the three study years, with only small year-to-year changes. Overall, the temporal trajectories of the two classes were very similar across the study period.

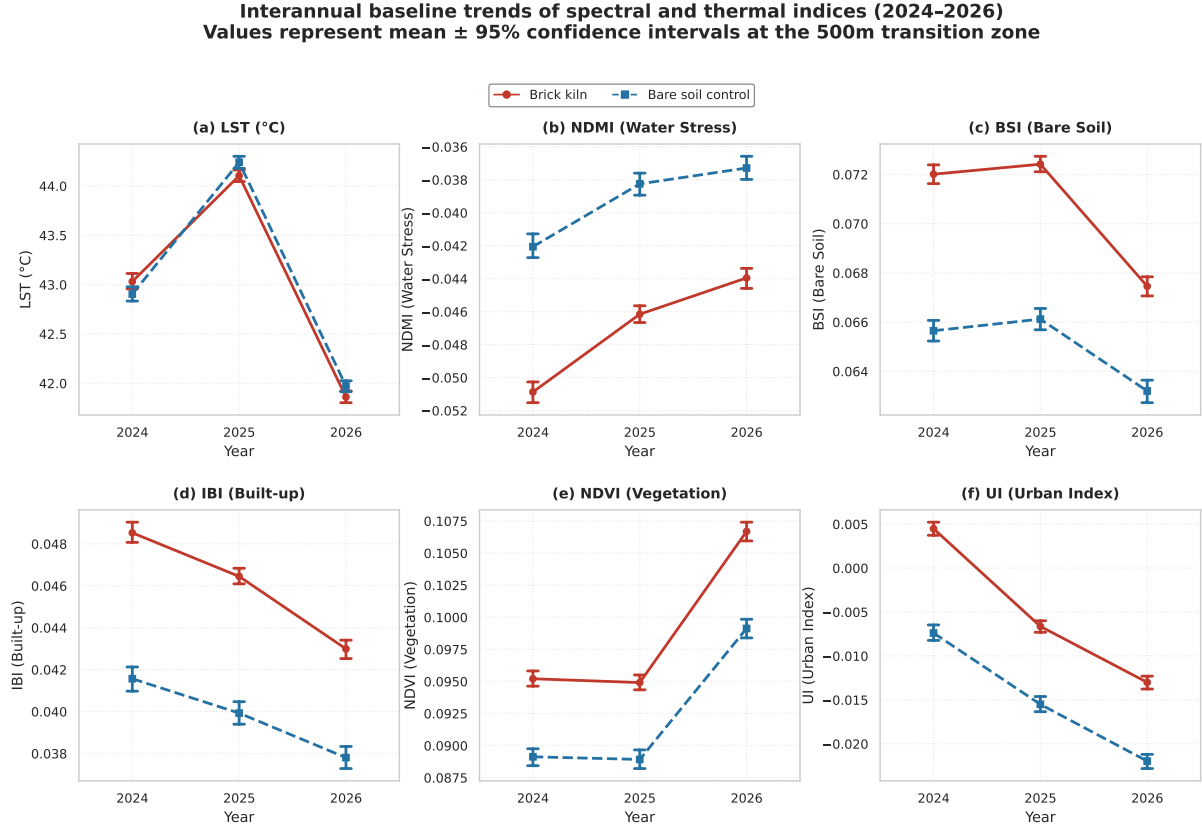


Fig. 10: Interannual trends (2024–2026) of LST and spectral indices at the 500 m buffer. Red circles represent brick kilns and blue squares represent paired bare-soil controls. Error bars indicate 95% confidence intervals.

3.6 Spatial distribution and thermal hotspots

The LST maps showed the spatial distribution of the thermal patterns observed in the statistical analyses (Fig. 11). During the three dry seasons (2024–2026), the highest temperatures were concentrated in different peri-urban areas of León. The paired control sites were commonly located inside these warmer zones, while most brick kiln sites were found in areas with lower LST values.

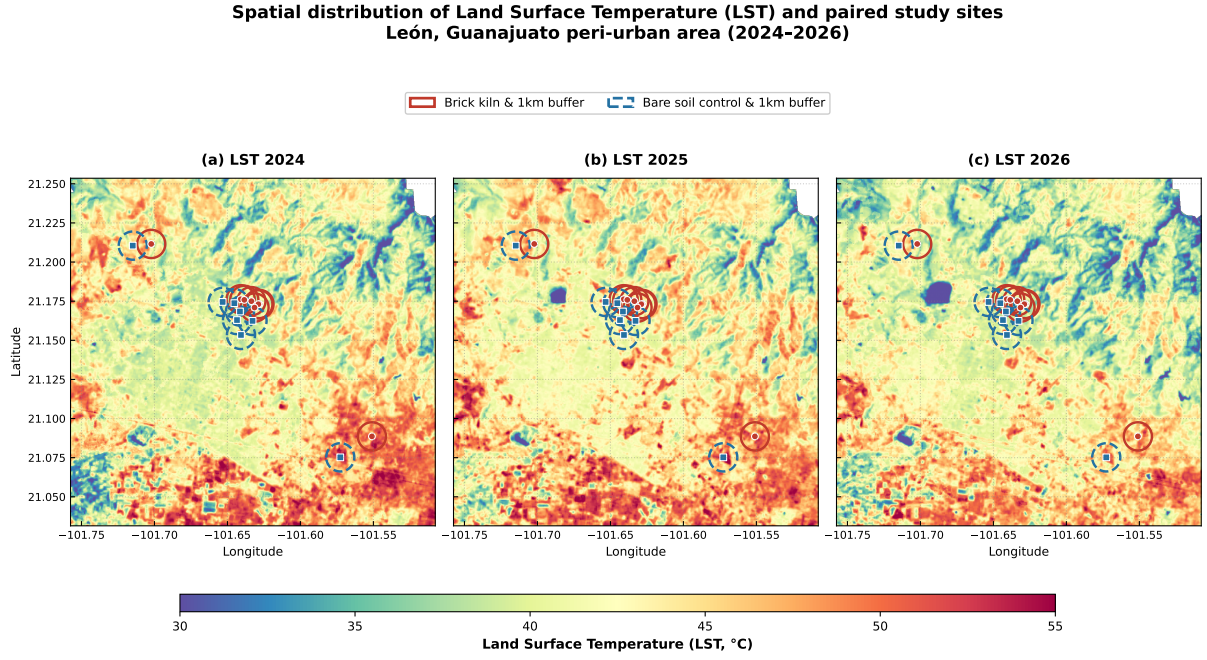


Fig. 11: Spatial distribution of LST during the dry seasons of 2024–2026. Red circles indicate brick kilns and blue squares indicate paired bare-soil control sites. The color scale represents surface temperature.

The figure 12 compares the three-year mean maps of LST and NDMI. Areas with higher LST generally matched areas with lower NDMI values. This spatial pattern was observed across the study area, and the paired control sites were mostly located in regions with both higher surface temperature and lower vegetation moisture. This pattern was similar in all study area.

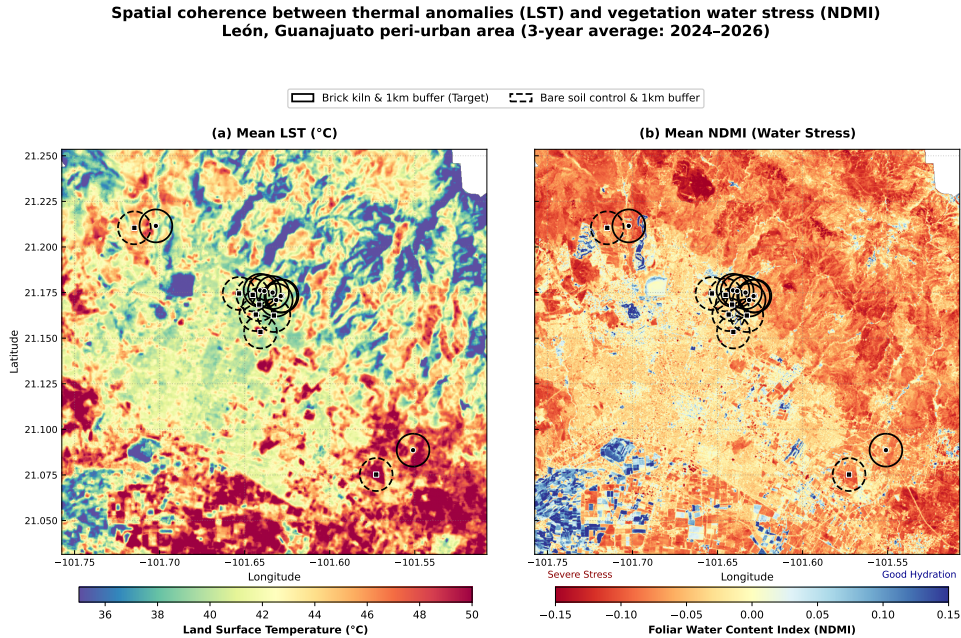


Fig. 12: Three-year mean maps (2024–2026) of (a) LST and (b) NDMI. Black solid outlines represent brick kilns and dashed outlines represent paired bare-soil control sites.

4 Discussion

The results reveal a surprising thermal dynamic in the peri-urban area of León: large areas of bare soil exhibit significantly higher land surface temperatures (LST) than the active brick kilns within the first 100 meters. This happens because the landscape is severely altered. The extraction of clay for artisanal brickmaking removes the natural cover, which increases the bare soil index (BSI) and the impermeable surface index (IBI). Unlike the kilns, which cast shadows and possess varying structures, the flat bare soil absorbs and retains solar radiation directly. This exacerbates water stress (NDMI) in the remaining vegetation.

The spatial gradient analysis shows that the human thermal footprint dissipates at a strict limit of 500 meters from the source. This distance marks a transition zone where the peri-urban microclimate buffers the thermal impact. While urban heat islands in large cities can span several kilometers, in this semi-arid environment, the temperature drops rapidly. This confirms that the surface heat is a localized consequence of soil degradation, rather than a broader atmospheric effect from kiln emissions. Furthermore, the thermal trends between 2024 and 2026 are highly consistent. Since the Urban Index (UI) and NDVI remained stable over these three years, it proves that the extreme temperatures at 100 m are a persistent condition of the bare soil, rather than a result of sudden climatic anomalies.

The ecological implications of these findings require a significant shift in how informal industrial zones are managed. Traditionally, environmental regulations have focused solely on reducing air pollution from the kilns. However, the strong negative correlation between LST and NDMI demonstrates that the most severe environmental impact is the profound desiccation of the landscape. The continuous loss of plant moisture and high surface temperatures accelerate peri-urban desertification, posing a major threat to the future of cities in semi-arid regions.

The primary limitation of this study is the satellite's temporal resolution, as Landsat only captures daytime thermal conditions during the dry season. To address this limitation and observe the complete thermodynamic cycle, the next critical step is the deployment of open-source environmental monitoring stations. Continuous, ground-based sensors will provide high-frequency microclimate data to validate satellite models, enabling real-time evaluation of environmental stress and supporting better-informed urban planning.

5 Conclusions

This study presents a paired multi-buffer satellite analysis of eight active brick kilns and eight bare soil controls in the peri-urban area of León, Mexico. We used Google Earth Engine to process Landsat 8 images from three consecutive dry seasons (2024 to 2026) and evaluated different distances (100, 500, and 1000 m).

The Wilcoxon signed-rank test shows that bare soil controls have much higher land surface temperatures than the kilns in the 100 m buffer, with a difference of -3.6 to -3.8 °C. Also, the Spearman correlation ($\rho = -0.490$) confirms a constant inverse relation between surface heat (LST) and foliar moisture (NDMI). This happens because the bare soil has more impermeable surface (IBI) and soil exposure (BSI) than the kiln sites.

Together, these results show that under the daytime Landsat observations, peri-urban bare soil exhibited significantly higher surface temperatures than the local kiln sites. This gives a quantitative baseline to understand how physical landscape degradation creates severe water stress, which is important to guide environmental management in the Bajío region.

For the next phase of this research program, we will install a network of low-cost environmental sensors in the 100 m thermal hotspots. These sensors will record air temperature, humidity, and particulate matter (PM_{2.5} and PM₁₀) every hour, closing the temporal gap left by the satellite. We will also add biological studies to evaluate the physiological stress in local plants, creating a continuous and accessible monitoring system for the community.

Author Contributions

José Javier Gutiérrez-Ramírez: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization, Project administration, Funding acquisition.

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Carlos Josue González Silva: Formal analysis, Investigation, Visualization, Writing – review & editing.

Mónica Aidee Ortiz Márquez: Investigation, Writing – original draft, Writing – review & editing.

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Gabriela Infante Oliva: Data curation, Investigation, Writing – original draft, Writing – review & editing.

Data availability

The satellite images used in this study were obtained from the Landsat 8 Collection 2 Level-2 product, freely available through the United States Geological Survey (USGS) Earth Explorer platform (<https://earthexplorer.usgs.gov>) and accessed through the Google Earth Engine (GEE) public data catalog (LANDSAT/LC08/C02/T1_L2).

All processing steps, including spectral and thermal index calculation, cloud masking, median seasonal compositing, multi-buffer extraction, and CSV export, were performed using the Google Earth Engine JavaScript API. The complete processing script is available at <https://github.com/Singularity-MX/BareSoil-Thermal-Dynamics-Leon> and can be executed in an authenticated GEE account with minor or no modifications.

The twelve CSV files generated by GEE, including pixel-level data, polygon statistics, buffer statistics, and paired tables for 2024, 2025, and 2026, together with the Python statistical analysis script used to generate the results and figures, are publicly available at <https://doi.org/10.5281/zenodo.21330162>.

The geographic assets, including the León municipal boundary, eight active brick kiln polygons, and eight paired bare-soil control polygons, are also available in the Zenodo repository. These files can be imported into Google Earth Engine as compressed (.zip) files or visualized in standard GIS software. The documentary sources used for brick kiln identification are cited in the References section.

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Gemini Pro version 1.5 was used as a support tool to format the references according to the Journal's style and to improve English grammar and language clarity. Figure Labs was used as a support tool for the design and composition of the Graphical Abstract.

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