International Journal of Science and Technology (IJST)
Vol.10:000013 (2026) ISSN 2507-9638 https://ijst.clsu.edu.ph

OPEN ACCESS

Quantifying Land Cover Changes and Urban Temperature Variations in Urdaneta City, Philippines (2000-2025): Implications for Sustainable Development

Jeffrey E. Dela Cruz[1]

[1]School of Advanced Studies, Saint Louis University, Baguio City, Philippines, 2600

Keywords: *Urbanization, Urban Management, Urban Expansion, Urban Landscape, Land Surface Temperature, Land Use Change,*

Type: Research Article

Submitted: August 1, 2025
Accepted: June 22, 2026
Published: June 30, 2026

Corresponding Author:
Jeffrey E. Dela Cruz
(2143079@slu.edu.ph)

Abstract

This study examines land cover changes and their influence on urban temperature trends in Urdaneta City, Pangasinan, from 2000 to 2025, with projections up to 2030. Using time series analysis and linear regression, findings reveal a significant decline in agricultural land and expansion of built-up areas, accompanied by an increase in land surface temperature from 24°C to nearly 30°C. The projected temperature rise underscores the impact of urban expansion on local climate. These results highlight the need for sustainable land management strategies to mitigate heat island effects amid rapid urban growth. Limitations include coarse thermal data resolution and limited temporal data points, which suggest caution in interpreting the projections and emphasize the importance of further detailed research. Understanding these relationships is vital for developing urban planning and environmental management strategies that mitigate heat island effects and promote climate-resilient urban growth.

Citation
Dela Cruz, J.E. (2026). Quantifying Land Cover Changes and Urban Temperature Variations in Urdaneta City, Philippines (2000-2025): Implications for Sustainable Development. *CLSU International Journal of Science and Technology, 10, 000013.* https://doi.org/10.22137/IJST.2026.000013

Introduction

Land is a fundamental resource that supports human societies and ecosystems through agriculture, settlements, industry, and the provision of essential ecosystem services such as carbon storage, water regulation, and biodiversity conservation (FAO, 2021; Daily, 1997). However, as population growth, economic expansion, and urbanization intensify, land resources face increasing pressure, leading to degradation, habitat loss, and declining ecosystem services (Lambin *et al.*, 2003; MEA, 2005). Understanding land use and land cover (LULC) changes is therefore crucial for sustainable development and environmental resilience.

Land use, by definition, encompasses the patterns and purposes of land allocation for various human activities, including residential, commercial, agricultural, and industrial purposes (Digra *et al.*, 2021). These patterns are dynamic and often driven by socio-economic development, policy changes, and population growth, leading to significant environmental impacts. Every change in land use is a critical driver of environmental transformation, affecting climate regulation, biodiversity, and ecosystem health. On the other hand, Land cover, defined as the physical material on the Earth's surface, directly influences ecological processes, local climate, and land productivity (Ellis, 2015).

Land Cover Change—especially conversion of agricultural and vegetated areas into built-up zones—contributes to rising surface temperatures, altered hydrological cycles, and increased greenhouse gas emissions (Foley *et al.*, 2005; Seto *et al.*, 2012). These transformations are particularly critical in the Philippines, where rapid urbanization and agricultural intensification have drastically altered landscapes. For instance, the conversion of mangrove forests into aquaculture ponds and settlements has reduced coastal protection and carbon-sequestering capacities (Primavera, 2000). Similarly, inland cities such as Dagupan, San Fernando, and Urdaneta are experiencing accelerated land conversion driven by urban expansion and economic growth, heightening environmental stress.

Landsat is a vital remote sensing program that provides high-resolution satellite imagery crucial for monitoring land use and land cover changes over time (NASA, 2020). Its multispectral data capabilities enable detailed analysis of environmental and urban development processes, making it an essential tool for land management and research (USGS, 2021). Between 2020 and 2025, Landsat continues to improve its data quality and accessibility, supporting sustainable development initiatives worldwide (NASA, 2024). Numerous studies have utilized Landsat data to analyze urbanization and its environmental impacts, such as the work by Peng and Weng (2020), which conducted a time series analysis of land use change and its effect on land surface temperature. This study aligns with existing research that investigates the relationship between land cover change and urban temperature variations utilizing remote sensing techniques. For example, Landicho & Blanco (2019) employed Landsat data to analyze intra-urban heat island effects in Metro Manila, demonstrating how land use transformations influence surface temperature patterns. Similarly, Landicho and Blanco (2019) analyzed surface temperature trends in Metro Manila over multiple years, emphasizing the impact of urbanization on local climate conditions through multispectral Landsat imagery. These studies share a methodological framework with this research, specifically in the use of Landsat satellite imagery to assess land cover dynamics and their thermal implications in urban environments.

Urdaneta City, located in eastern Pangasinan, has emerged as a major commercial and transportation hub in Northern Luzon. Its strategic location along major trade routes and its growing population—approximately 150,000 as of the 2020 Census (PSA, 2021)—have intensified land-use pressures and urban development. Increased impervious surfaces and reduced vegetative cover contribute to higher land surface temperatures, leading to the Urban Heat Island (UHI) effect (Oke, 1982; Voogt & Oke, 2003). This phenomenon poses growing challenges for energy efficiency, public health, and urban livability, especially in tropical climates.

Given these concerns, this study focuses on analyzing land cover change and its relationship with land surface temperature in Urdaneta City from 2000 to 2025, with projections to 2030 using linear regression modeling. The rationale for selecting Urdaneta City lies in its rapid urban expansion, economic significance in Pangasinan, and its representative character as a mid-sized Philippine city undergoing urban transformation. Understanding these spatial and thermal dynamics is vital for crafting evidence-based urban planning and environmental management strategies that mitigate heat stress, promote climate resilience, and support sustainable urban growth.

Materials and Methods

This study is descriptive research using time series data, spatial analysis, and a simulation tool to assess the extent of land cover change and land temperature variation in Urdaneta City, Pangasinan. A quantitative approach was used to answer the given research questions through quantitative data analytics.

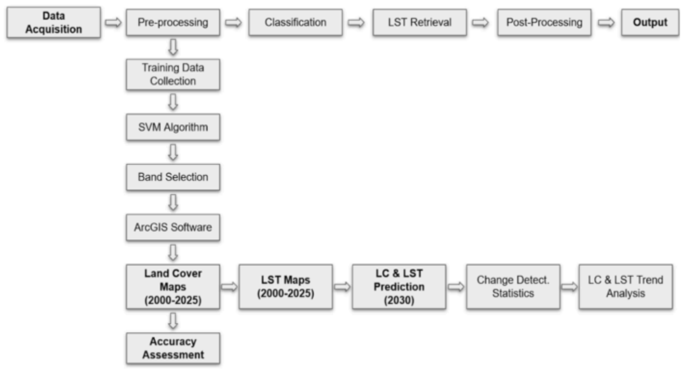

Figure 1. Methodological framework for LC and LST (2000-2030)

The methodological framework describes how Landsat images were used to analyze Land Cover (LC) change and calculate Land Surface Temperature (LST) in Urdaneta City, Pangasinan, Philippines, between 2000 and 2030 (Figure 1). Standard image processing techniques were applied, such as mosaicking, projection, and geometric correction. The applied coordinate system used in this study is World Geodetic System 1984 Zone 51N (WGS1984-Z51N).

Satellite images were acquired using the EarthExplorer website from NASA to generate land cover and land surface temperature. The technique includes supervised image classification using a Support Vector Machine (SVM) algorithm, a powerful tool for classification and regression tasks. Its ability to find optimal separating hyperplanes and handle non-linearly separable data makes it a popular choice in various machine learning applications, systematic band selection for better sampling of the land cover and LST, software image processing, and accuracy assessment. Landsat TM, ETM+, and OLI/TIRS data were collected, pre-processed (atmospheric and geometric correction, picture clipping), and categorized.

Furthermore, the classification is aided through basemaps from the land cover of the National Mapping and Resource Information Authority (NAMRIA) to lessen the possible errors in the classification. For this study, land cover was categorized into eight distinct types. Annual crop land comprised areas assigned for the cultivation of crops within one growing season, represented by rice, corn, and other vegetables. Built-up areas were characterized as those with high human-induced development, represented by constructed structures and infrastructure, including residential, commercial, industrial, and transport sectors. Perennial crop land refers to areas utilized for the cultivation of crops with a life cycle exceeding two years, yielding multiple harvests, including fruit trees, coffee, and cacao. Brush/shrubs denoted areas dominated by low-statured woody vegetation, including shrubs, bushes, and thickets, representing both natural and successional flora. Fishponds represented artificial aquatic environments created for aquaculture activities, specifically for the raising of fish and other aquatic animals. Grassland consisted of areas dominated by grasses and herbaceous vegetation, including natural grasslands, pastures, and areas of grazing. Inland water refers to bodies of water located within land boundaries, such as rivers, lakes, ponds, and reservoirs. Finally, open/barren land was represented by areas with little or no vegetative cover, characterized by exposed soil, rock, sand, or other surfaces with limited biological activity, including deserts and quarries.

Table 1. Land Cover classification description

Land Cover Class	Description	Examples
Annual Crop	Land used for cultivating crops that are planted and harvested within a single growing season.	Rice, corn, vegetables
Built-up	Areas covered by man-made structures and infrastructure, indicating human habitation and development.	Residential, commercial, industrial, and transportation areas
Perennial Crop	Land used for cultivating crops that live for more than two years and are harvested multiple times.	Fruit trees, coffee, cacao
Brush/ Shrubs	Areas dominated by woody vegetation of low height.	Shrubs, bushes, thickets
Fishpond	Artificial ponds or enclosures used for aquaculture.	Fish ponds, shrimp farms
Grassland	Areas covered predominantly by grasses and herbaceous (non-woody) plants.	Natural grasslands, pastures
Inland Water	Bodies of water located within the land.	Rivers, lakes, ponds, reservoirs
Open/ Barren	Areas with little to no vegetation cover.	Bare soil, rocks, sand, deserts, quarries

Training data were acquired for each land cover type utilizing visual interpretation, supplementary data, and field surveys. Land cover types include such as annual crop, built-up, perennial crop, brush/shrubs, fishpond, grassland, inland water, and open/barren. All accessible bands were considered for land cover categorization, while thermal and other relevant bands were used for LST retrieval (LST Formula shown in Figure 2), which included emissivity estimation.

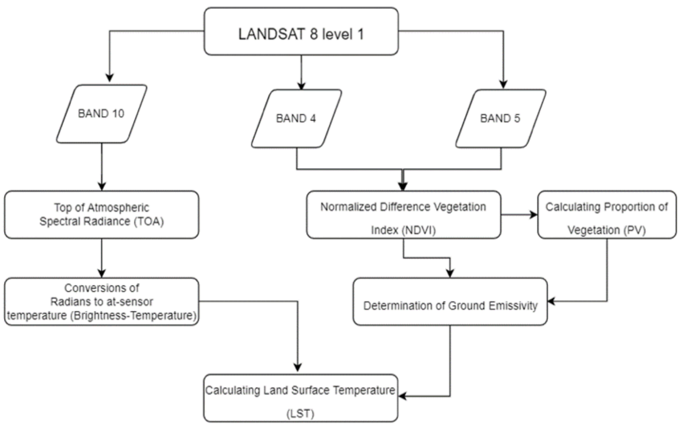

Figure 2. Land Surface Temperature (LST) formula for Urban Heat Island Index

Following classification from 2000 to 2025, accuracy was assessed using a confusion matrix and independent validation data; change detection analysis was performed to quantify land cover changes, and LST trend analysis will be used to discover temperature patterns.

The Support Vector Machine (SVM) algorithm was used for supervised image classification from 2000 to 2025. Representative training areas in a polygon file for each land cover class were defined using a combination of visual interpretation of Landsat imagery, supplemental data (for example, high-resolution imagery from Google Earth, existing land use maps), and field surveys. Using the acquired training data, the SVM algorithm was applied to the pre-processed Landsat images to generate annual land cover maps.

The methodology was applied with ArcGIS and QGIS software. The results provided classified land cover maps and LST maps for Urdaneta City from 2000 to 2025 in a five-year interval, change detection statistics that illustrate land cover area changes, LST trend analysis, and an accuracy assessment analysis.

The gathered data were utilized to determine the land cover and LST for Urdaneta City by 2030. Linear regression and correlation were used to project land cover and land surface temperature by 2030. Recent studies have demonstrated the application of multiple linear regression (MLR) techniques to project land surface temperature (LST) based on land cover variables over time, providing a straightforward approach to modeling urban heat dynamics (Gao *et al.*, 2024; Mohammad *et al.*, 2021). Despite its simplicity and interpretability, MLR's limitations include its assumption of linear relationships and inability to capture complex, non-linear interactions among variables, which may lead to oversimplified projections (Gao *et al.*, 2024). Nonetheless, MLR remains a valuable tool for initial trend analysis and can be complemented by advanced non-parametric or machine learning methods, such as random forests or neural networks, in future research to improve projection accuracy and robustness.

Results and Discussion

Land cover change 2000 to 2025

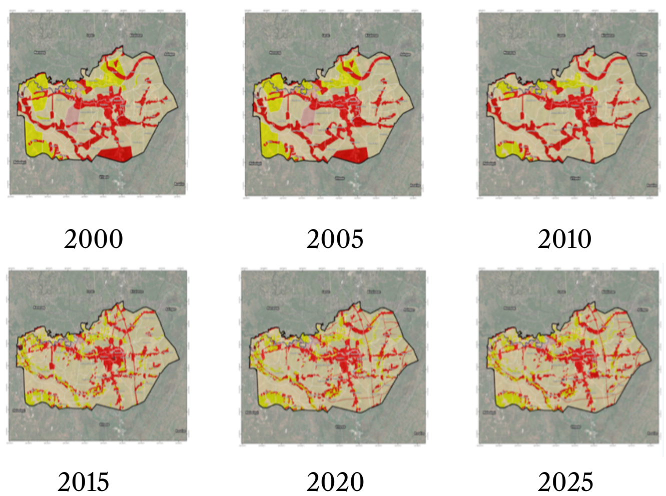

Figure 3. The changes in Land Cover of Urdaneta City from the year 2000 to 2025 using a five-year interval map.

The land cover change data from 2000 to 2025 is shown in Figure 3, providing a visual representation of environmental transitions. It includes eight land cover types: annual crop, built-up, perennial crop, brush/shrubs, fishpond, grassland, inland water, and open/barren land. This data highlights the complex relationship between human activities and natural environments, underscoring the need for proactive and integrated land management.

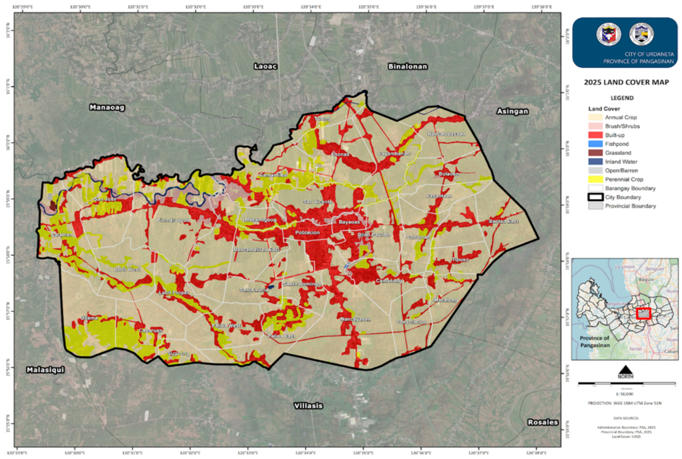

Figure 4. The 2025 land and cover map of Urdaneta City

Between 2000 and 2025, Urdaneta City's land cover remained dominated by annual crops, with a net increase from 5,291.34 ha in 2000 to 6,348.67 ha in 2025 (20.0% increase). The largest expansion occurred between 2005 and 2010, when annual crops grew by 1,220.77 ha (22.87%), coinciding with reductions in built-up, perennial crop, and brush/shrub areas, suggesting conversion of other land covers to annual agriculture. Built-up areas exhibited changes along major roads and concentrated along urban barangays. Bagarinao (2020) mentioned that the development of extensive built-up areas predominantly occurred in barangays undergoing considerable shifts in population sizes. For instance, Barangay Canlubang, which has been labeled as an urban barangay with the most substantial population shift between 2003 and 2010, experienced nearly 19% of its total land transitioned from annual cropland to developed areas in 2010. The 2025 land and cover map of Urdaneta City provides visual information that barangay Bayaoas, Dilan-Paurido, Mabanogbog, Poblacion, and San Vicente experienced developments of built-up areas through visual analysis in Figure 4.

Table 2. Land Cover derived through satellite images from 2000 to 2025

Land Cover Type	2000 (ha)	2005 (ha)	2010 (ha)	2015 (ha)	2020 (ha)	2025 (ha)
Annual Crop	5291.34	5336.7	6557.47	6567.18	6439.57	6348.67
Built-up	2358.23	2355.09	2095.83	1700.72	1829.58	1871.86
Perennial Crop	1400.11	1369.97	646.69	1024.3	1023.34	1071.95
Brush/shrubs	436.63	424.55	186.33	178.65	193.81	193.81
Fishponds	1.49	1.49	1.49	1.46	1.49	1.49

Grassland	5.51	5.51	5.51	20.54	5.51	5.51
Inland Water	63.24	63.24	63.24	63.71	63.24	63.24
Open/Barren	6.53	6.53	6.53	6.53	6.53	6.53

Table 2 shows the land cover type derived from satellite images from 2000 to 2025. The most striking pattern in this dataset is the fluctuation of agricultural fields. Perennial crops showed a sharp contraction from 1,400.11 ha in 2000 to 646.69 ha in 2010 (−52.80%), followed by partial recovery to 1,071.95 ha in 2025. Brush/shrub areas declined from 436.63 ha to 193.81 ha over the same period (−55.6%), with only minor increases after 2015, while fishponds, inland water, and open/barren areas remained nearly constant. Built-up land decreased from 2,358.23 ha in 2000 to a minimum of 1,700.72 ha in 2015, before recovering slightly to 1,871.86 ha by 2025. A comparable trend is observed in Tuguegarao City, where from 1990 to 2016, there was a notable increase in built-up areas and cropland, accompanied by a significant decrease in grassland, forested land, and barren areas (Landicho & Blanco, 2019).

These patterns indicate a long-term tendency toward agricultural expansion at the expense of semi-natural covers and, to some extent, built-up land. However, the apparent decline in built-up area between 2000 and 2015 must be interpreted carefully, because early Landsat sensors have coarser spatial resolution and greater geometric and radiometric uncertainty, which can affect the delineation of narrow or fragmented urban features. Consequently, the built-up time series likely underestimates the true extent of urbanization in the early years.

In addition, the expansion of built-up areas, while shifting, generally reflects continued urbanization. Nuissl's research on urbanization and land use change indicated that a notable result of the spatial expansion of built-up areas contributes to the rising urbanization (Nuissl & Siedentop, 2020). Results show that the built-up area in Urdaneta City declined to 1700.72 hectares in 2015. This decline is due to the limitation of the spatial resolution of the satellite imagery; the lower resolution and the sensor instability of early Landsat satellites contributed to issues such as geometric distortions and inconsistencies in radiometric calibration, ultimately impacting data reliability (Loveland *et al.*, 1991).

To further analyze the changes in land cover in Urdaneta City, Table 3 provides the area change in hectares and the percentage of land cover changes between 2000-2005, 2005-2010,2010-2015, 2015-2020, and 2020-2025.

Table 3. Land Cover Changes in Urdaneta, Pangasinan from 2000 to 2025

	2000-2005		2005-2010		2010-2015		2015-2020		2020-2025	
Land Cover Type	**Area Change (ha)**	**% Change**	**Area Change (ha)**	**% Change**	**Area Change (ha)**	**% Change**	**Area Change (ha)**	**% Change**	**Area Change (ha)**	**% Change**
Annual Crop	45.36	0.86%	1220.77	22.87%	9.71	0.15%	-127.61	-1.94%	-90.9	-1.41%
Built-up	-3.14	-0.13%	-259.26	-11.01%	-395.11	-18.85%	128.86	7.58%	42.28	2.31%
Perennial Crop	-30.14	-2.15%	-723.28	-52.80%	377.61	58.39%	-0.96	-0.09%	48.61	4.75%
Brush/Shrubs	-12.08	-2.77%	-238.22	-56.11%	-7.68	-4.12%	15.16	8.49%	0	0.00%
Fishpond	0	0.00%	0	0.00%	-0.03	-2.01%	0.03	2.05%	0	0.00%
Grassland	0	0.00%	0	0.00%	15.03	272.78%	-15.03	-73.17%	0	0.00%
Inland Water	0	0.00%	0	0.00%	0.47	0.74%	-0.47	-0.74%	0	0.00%
Open/Barren	0	0.00%	0	0.00%	0	0.00%	0	0.00%	0	0.00%

Based on the gathered data, there have been minimal changes in the land cover areas from 2000 to 2005, with the annual crop increasing by 45.36 ha, or 0.86%, compared to the year 2000. There were minimal decreases also in the Built-up areas with -0.13%, Perennial Crop with -2.15%, and Brush/Shrubs with -2.77%. No changes were observed in the areas of Fishponds, Grasslands, Inland water, and Open/Barren spaces. Other research also demonstrated that these land covers often remained stable and experienced significant expansion or reduction over the years. In 2005-2010, there was a substantial increase in the annual crop area of 1220.77 ha or 22.87%, which can be attributed to a decrease in the other land cover areas. It is apparent that some areas used for built-up, perennial crops, and brush/shrubs were converted to annual crops, thus increasing the agricultural productivity of the land. The expansion of annual crops used for agricultural purposes was also exhibited in research where grasslands are being converted into agricultural fields (Foley *et al.*, 2005). In the years 2010-2015, more resources were used to grow perennial crops (an increase of 58.39%), which contributed to a slowdown of growth in the area of annual crops (an increase of 0.15% only). Continued decreases were seen in Built-up areas, Brush/Shrubs, Fishponds, Grasslands, and Inland water. In the years 2015-2020, the areas of annual crops, perennial crops, and grasslands decreased, in exchange for an increase in Brush/shrubs and built-up areas. The amount of grassland significantly decreased, which could have been converted to built-up areas during this period. The years 2020-2025 still see a minimal decrease in the annual crop areas of -1.41%, with a slight increase in the built-up areas of 2.31% and perennial crops of 4.75%. Overall, from 2000 to 2025, there is an increase in the areas devoted to annual and perennial crops with a combined increase of 28.63%, while built-up areas have a general decrease of 20.11%. These changes show that although there are slight increases in the built-up areas from 2015 to 2025, there is an effort to increase the agricultural productivity of the land and thus improve the state of food security in the region. A huge increase in the grassland areas also indicates that these are potential lands that can be cultivated for either annual or perennial crops.

Land Surface Temperature 2000 to 2025

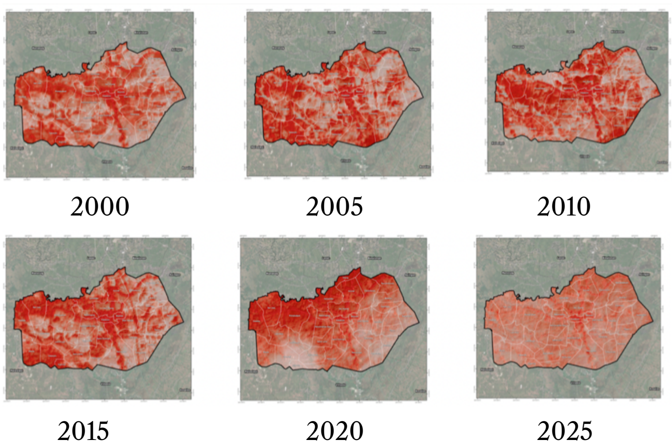

Figure 5. The changes in Land Surface Temperature of Urdaneta City from the year 2000 to 2025 using a five-year interval map.

Land surface temperature changes were analyzed using satellite imagery with less than 10% cloud cover, as shown in Figure 5. The imagery was selected specifically for the research area to ensure accuracy. Since the Philippines experiences summer from March to May, the best satellite data were obtained during this period.

The thermal characteristics of various land surface types differ. For instance, a study shows that the urban heat island effect is exacerbated by the tendency of built-up areas to absorb and retain more heat than green areas (Jabbar *et al.*, 2023; Aram *et al.*, 2019). Central Business Districts (CBDs) highlight how land cover change influences LST. CBDs feature a higher concentration of impermeable surfaces such as concrete and asphalt, which absorb and retain substantially more solar radiation than natural surfaces, adding to the urban heat island effect. This effect is increased by diminished vegetation, which limits evapotranspiration, as well as anthropogenic heat sources such as vehicles and air conditioning. For instance, the UHI phenomenon in Baguio City will worsen from 2019 to 2022 due to an increase in built-up areas despite its cool weather conditions (Vergara *et al.*, 2023). In addition, a study conducted in Nueva Ecija, Philippines, showed an average SUHI intensity of 12.42°C, with urban areas reaching peak temperatures of 53.62°C, while rural regions recorded lower maximums at 49.91°C, indicating that developed areas experience higher temperatures (Bensi & Esquivel, 2024). Tall structures in CBDs can trap more heat and impede wind flow, while the conversion of natural land cover to built-up infrastructure fundamentally affects the area's energy balance. The heat generated from buildings, vehicles, and other urban infrastructure contributes to the warming effect. Oke (1982) has noted that the configuration of tall buildings can exacerbate this effect by creating "canyons" that trap heat and inhibit cooling through wind flow. Furthermore, the Poblacion barangay of Urdaneta City serves as the primary growth center of the city, allowing massive change and allocating built-up areas for urbanization, catering to the increasing population of the city. In contrast, replacing built-up areas with vegetation, as seen by the turnaround of perennial crops and brush/shrubs in the data, could potentially offset temperature increases. Research shows that an increase of vegetation cover in the city can reduce the Universal Thermal Climate Index (Meili *et al.*, 2021). The transition from annual crops to other land cover types may also have an impact on LST, as various crops and vegetation have varied evapotranspiration rates and albedo (reflectivity), which alter heat absorption and retention.

Table 4. The lowest, highest, and average temperatures recorded from 2000 to 2025.

Years	Lowest Temperature °C	Highest Temperature °C	Average	Change %
2000	23	25	24	
2005	24	26	25	4.17% (2000-2005)
2010	26	28	27	8.00% (2005-2010)
2015	25	29	27	0.00% (2010-2015)
2020	24	27	25.5	-5.56% (2015-2020)
2025	28	31	29.5	15.69% (2020-2025)
Cumula-tive Change, °C (2000-2025)	5	6	5.5	22.92% (2000-2025)

Table 4 records the lowest, highest, and average temperatures recorded from 2000 to 2025. It also includes the percentage of changes every five-year interval starting from 2000 to 2025 was computed to differentiate each period.

The lowest temperatures recorded were in the base year 2000, where the average land temperature was 24 ˚C. There was a 1˚C increase in the average land temperature from 2000 to 2005, evidence of a general rise in land temperature. Similarly, in Metro Manila, the annual land temperature increased by approximately 0.18˚C between 1997 and 2019 (Landicho & Blanco, 2019), further supporting evidence of sustained warming over time.

The temperature increase was even more significant from 2005 to 2010, reaching 2˚C. There were no changes in the average land temperature from 2010 to 2015, where a substantial increase in the number of annual and perennial crop areas and a significant decrease in the number of built-up areas were observed. The year 2020 demonstrated a considerable decline in average land temperature, which may be attributed to a significant reduction in human activity brought about by the pandemic. However, a massive increase of 4˚C in average land temperature was observed as 2025 approaches. This could be attributed to increased human activity and urbanization in the post-pandemic era. Incidentally, the land cover changes also indicated a steady rise in the number of built-up areas during this period, while a decrease in annual crop areas was also apparent.

Land cover change and land surface temperature by 2030

Table 5. Correlation and Linear Regression Model for Land Cover (Li) and Year (y)

Land Cover	Correlation Coefficient, r	Coefficient of Determination, r^2	p-value (F-test)	Linear regression model equation	Projected Land cover (ha) by 2030
Built-up	0.841 (H)	0.708	0.036 (S)		1,519.4
Brush/ Shrubs	0.816 (H)	0.666	0.048 (S)		153
Annual Crop	0.758 (H)	0.575	0.081*		7,009
Perennial Crop	0.446 (M)	0.199	0.375 (NS)	N/A	N/A
Fishpond	0.131 (VL)	0.0171	0.805 (NS)	N/A	N/A
Grassland	0.131(VL)	0.0171	0.805 (NS)	N/A	N/A
Inland Water	0.131 (VL)	0.0171	0.805 (NS)	N/A	N/A
Open/ Barren	N/A	N/A	N/A	N/A	N/A

**Projection for Annual Crop applies only to the 8.1% significance level.*

Linear regression and correlation were used to project land cover and land surface temperature by 2030. Pearson correlation coefficient was used to determine the strength of the relationship between land cover and time, as well as between land surface temperature and time. The advantage of using correlational analysis is that it shows the strength of the relationship between the dependent variable (land cover) and the predictor variables (time). It finds what predictor variables are significantly related to the dependent variable under study. Also, the linear regression models considered in this study project highly significant results, demonstrating a p-value of less than 5%.

The projections in Table 5 were only based on the year (time) as the predictor variable. Other variables have not been factored into the model, such as the city's development plans. Using the Linear Regression equation for the Built-up areas, 1,519.5 ha is projected for the year 2030 since the model exhibited a decrease in values from 2000-2015, with only a slight increase from 2020-2025. Because the linear regression model follows the general behavior of the data through time, a lower value was projected for 2030. The same is true with Brush/Shrubs. The data exhibited a steady decrease in the brush/shrubs area from 2000-2025, which slightly increased in 2020-2025. Hence, the projection is also a decrease in the land cover for brush/shrubs by 2030. The land cover for Annual Crop has seen a steady increase from 2000-2025, which indicates that through time, an upward trend in annual crop areas is demonstrated. According to FAO (2023), from 2000 to 2025, the global area dedicated to annual crops has consistently increased, demonstrating a clear upward trend in agricultural practices focused on short-term crop production. This growth trend is indicative of evolving agricultural strategies aimed at meeting the rising global demand for food and sustainable resource management. In light of these findings, it is evident that the trajectory of annual crop expansion is influenced not only by demand but also by adaptations to agricultural technology and policy frameworks aimed at increasing agricultural productivity (OECD, 2020). However, the results of the increase in annual crop in Urdaneta City from 2000 to 2025 are true only at the 8.1% significance level, as far as the linear regression model is concerned.

Correlation analyses suggest that, across the six observation years, built-up and annual crop areas tend to co-vary with higher LST, while vegetation-dominated covers (perennial crops and brush/shrubs) are associated with lower LST values. For example, years with higher average LST (2010 and 2025) coincide with reduced perennial crop and brush/shrub extents, whereas the relative stabilization of LST around 2015 occurs during a period of recovering perennial crops and declining built-up area.

Because the number of time points is small (n = 6), correlation coefficients and p-values have low statistical power and are sensitive to individual years. We therefore treat these associations as indicative patterns consistent with previous findings in Philippine and international studies, which also report warming in densely built-up areas and cooling effects from vegetation and water bodies.

Simple linear regression models were used to explore short-term extrapolations of land cover and LST to 2030, using time as the sole predictor. For land cover, regression models were retained only for classes with high correlation coefficients and statistically significant or marginal p-values (built-up, brush/shrubs, and annual crops), whereas classes with non-significant relationships were not extrapolated. For LST, only maximum and average temperatures exhibited sufficiently strong relationships with time to justify exploratory regression.

Given the limited number of temporal observations (n = 6) and the absence of additional drivers (e.g. population growth, zoning, infrastructure development), these 2030 values should be interpreted as illustrative continuations of recent trends rather than as precise forecasts. More robust prediction of land cover and LST dynamics in Urdaneta City would require transition-based models such as CA–Markov or machine-learning approaches, coupled with higher-resolution spatial data and ground-based validation.

Table 6. Correlation and Linear Regression Model for Land Surface Temperature (T) and Year (y)

Land Surface Tempera-ture	Correlation Coefficient, r	Coefficient of Determina-tion, r^2	p-value (F-test)	Linear regression model equation	Projected Land Surface Tempera-ture by 2030 (°C)
Lowest Temper-ture	0.717 (H)	0.514	0.109 (NS)		N/A
Highest Temper-ture	0.841 (H)	0.708	0.036 (S)		30.49
Average Temper-ture	0.799 (H)	0.638	0.057*		29.813

**The projection for Average Temperature is significant only at the 5.7% level.*

From the correlational analysis, as shown in Table 6, only the Highest Temperature has a significant relationship with Time as the predictor variable. This is why a linear regression model was not built anymore for the Lowest Temperature, although the correlation coefficient was also high. From the linear regression equation for Highest Temperature, the predicted value for 2030 is 30.49°C, 0.51°C lower than the 2025 highest temperature. This is because the model takes into account the decrease in the highest temperature from 29°C to 27°C during the year 2020. The COVID-19 pandemic resulted in significant reductions in human activity that contributed to temporary decreases in global temperatures. According to a study conducted by the Global Carbon Project, global carbon emissions fell by approximately 7% in 2020, marking the largest annual decrease since World War II. This decline was primarily attributed to decreased transportation and industrial activities as countries enacted lockdowns (Friedlingstein *et al.*, 2020). The p-value for the correlation between average temperature and time is 0.057, which is still at the boundary of significance and insignificance, so the linear regression model was still built for this variable. The projected average temperature for 2030 from the linear regression model is 29.813 °C, which is slightly higher than the average temperature of 29.5 °C in 2025. Generally, an upward trend is seen in the land surface temperatures as demonstrated by linear regression models. The result corroborates the projected mean temperature of the Climate Change Commission of the Philippines, that the country could experience an increase in average temperatures ranging from 0.9 °C to 1.1 °C in 2020 and by 1.8 °C to 2.2 °C in 2050 (Climate Change Commission, 2021).

Table 7. Relationship Between Land Cover and Lowest Temperature

Land Cover	r	r^2	p-value (F-test)	Linear Regression Equation
Annual Crop	0.598 (M)	0.357	0.21 (NS)	N/A
Built-Up	0.476 (M)	0.226	0.34 (NS)	N/A
Perennial Crops	0.54 (M)	0.291	0.261 (NS)	N/A
Bush/Shrubs	0.645 (M)	0.417	0.166 (NS)	N/A
Fishponds	N/A	N/A	N/A	N/A
Grassland	N/A	N/A	N/A	N/A
Inland Water	N/A	N/A	N/A	N/A
Open/Barren	N/A	N/A	N/A	N/A
Overall (Annual Crop, Built-up, Perennial Crop, Bush/Shrubs As Predictors of Lowest temperature)	1.00 (Perfect)	1.00 (Perfect)	0.033 (S)	

Where: AC- Annual Crop
BU- Built-Up
PC- Perennial Crops
BS- Bush/Shrubs
Lt - Lowest temperature

Based on Table 7, results show that individually, the different land covers do not have a strong or significant relationship with the lowest land surface temperature. This means that no individual land cover can predict the lowest temperature on the land surface. However, when taken together, the four areas (annual crop, built-up, perennial crop, and bush/shrubs) which occupy most of the land areas can significantly project the lowest temperature, as evidenced by a perfect correlation coefficient when the four land covers interact with the lowest land surface temperature. The coefficients of the linear regression model for the lowest temperature are given in the last column of the table.

The projection of the lowest land surface temperature by 2030 will be in the form of a multiple linear regression equation, which was determined using the R analytical software (2024) used in the statistical analysis. Only Annual crops, Built-up, Perennial Crops, and Bush/Shrubs were accepted by the model since the other land covers did not affect the dependent variable, which is the temperature. The multiple regression equation will be used to forecast the Lowest Temperature value by 2030.

Where: AC- Annual Crop
BU- Built-Up
PC- Perennial Crops
BS- Bush/Shrubs
Lt - Lowest temperature

However, the actual numerical values for Annual Crop, Built-Up, Perennial Crops, and Bush/Shrubs by 2030 should be input into the multiple linear regression model to predict the lowest temperature by 2030.

Table 8. Relationship Between Land Cover and Highest Temperature

Land Cover	r	r^2	p-value (F-test)	Linear Regression Equation
Annual Crop	0.733 (H)	0.538	0.097	N/A
Built-Up	0.737(H)	0.544	0.094	N/A
Perennial Crops	0.519(M)	0.269	0.292	N/A
Bush/Shrubs	0.779 (H)	0.607	0.068	N/A
Fishponds	0.302 (L)	0.0914	0.56	N/A
Grassland	0.302 (L)	0.0914	0.56	N/A
Inland Water	0.302 (L)	0.0914	0.56	N/A
Open/Barren	N/A	N/A	N/A	N/A
Overall (Annual Crop, Built-up, Perennial Crop, Bush/Shrubs As Predictors of Lowest temperature)	1.00 (Perfect)	1.00 (Perfect)	0.029 (S)	

Where: AC- Annual Crop
BU- Built-Up
PC- Perennial Crops
BS- Bush/Shrubs
Ht - Highest temperature

The projection of the highest land surface temperature by 2030 will be in the form of a multiple linear regression equation, which was determined using the R analytical software (2024) used in the statistical analysis. Only Annual crops, Built-up, Perennial Crops, and Bush/Shrubs were accepted by the model since the other land covers did not affect the dependent variable, which is the temperature. The multiple regression equation will be used to forecast the Highest Temperature value by 2030.

Where: AC- Annual Crop
BU- Built-Up
PC- Perennial Crops
BS- Bush/Shrubs
Ht - Highest temperature

However, the actual numerical values for Annual Crop, Built-Up, Perennial Crops, and Bush/Shrubs by 2030 should be input into the multiple linear regression model to predict the highest temperature by 2030.

Table 9. Relationship Between Land Cover and Average Temperature

Land Cover	r	r^2	p-value (F-test)	Linear Regression Equation
Annual Crop	0.684 (M)	0.467	0.134 (NS)	N/A
Built-Up	0.63 (M)	0.396	0.18 (NS)	N/A
Perennial Crops	0.537 (M)	0.289	0.272 (NS)	N/A
Bush/Shrubs	0.731 (H)	0.534	0.099 (NS)	N/A
Fishponds	0.168 (VL)	0.117	0.75 (NS)	N/A
Grassland	0.168 (VL)	0.117	0.75 (NS)	N/A
Inland Water	0.168 (VL)	0.117	0.75 (NS)	N/A
Open/Barren	N/A	N/A	N/A	N/A
Overall (Annual Crop, Built-up, Perennial Crop, Bush/Shrubs As Predictors of Lowest temperature)	1.00 (Perfect)	1.00 (Perfect)	0.031 (S)	

Where: AC- Annual Crop
BU- Built-Up
PC- Perennial Crops
BS- Bush/Shrubs
At - Average temperature

Furthermore, in Table 9, results show again that individually, the different land covers do not have a strong or significant relationship with the average land surface temperature. This means that no individual land cover can predict the average temperature on the land surface. However, when taken together, the four areas (annual crop, built-up, perennial crop, and bush/shrubs) which occupy most of the land areas can project the average land temperature significantly, as evidenced by a perfect correlation coefficient when the four land covers interact with the average land surface temperature. The coefficients of the linear regression model for the Average temperature are given in the last column of the table.

The projection of the average land surface temperature by 2030 will be in the form of a multiple linear regression equation, which was determined using the R analytical software (2024) used in the statistical analysis. Only Annual crops, Built-up, Perennial Crops, and Bush/Shrubs were accepted by the model since the other land covers did not affect the dependent variable, which is the temperature. The multiple regression equation will be used to forecast the Average Temperature value by 2030.

Where: AC- Annual Crop
BU- Built-Up
PC- Perennial Crops
BS- Bush/Shrubs
At - Average Temperature

However, the actual numerical values for Annual Crop, Built-Up, Perennial Crops, and Bush/Shrubs by 2030 should be input into the multiple linear regression model to predict the average temperature by 2030.

In summary, the land cover areas that have a predictive value for the lowest, highest, and average land surface temperatures are Annual Crop, Built-up, Perennial, and Bush/Shrubs by the year 2030. However, all four land covers must be input together in the linear regression equation because their predictive effect is only certain if all four of them are used together in the model.

Conclusion

Landsat-based analysis indicates that, from 2000 to 2025, Urdaneta City experienced a net expansion of annual and perennial crops and a modest decline followed by partial recovery of built-up land, together with a general increase in land surface temperatures despite temporary cooling around 2020. These patterns are consistent with the broader literature on the thermal impacts of land cover change, in which urban and intensively used surfaces tend to warm faster than vegetated and water-dominated areas.

However, several methodological limitations constrain the strength of our inferences. First, Landsat thermal bands have relatively coarse spatial resolution and sensor-specific calibration differences, and no in situ temperature data were available for direct validation of retrieved LST. Second, the analysis relies on only six time steps, which limits the statistical robustness of correlation and regression results and makes 2030 extrapolations highly uncertain. Third, the regression-based projections use time as the only predictor and do not capture spatial transition processes or policy-driven land use changes.

Within these constraints, the study still provides a city-specific, multi-decadal baseline of land cover and LST dynamics that can support local planning under SDGs related to food security, sustainable cities, and climate action. Future research in Urdaneta City and similar secondary Philippine cities should integrate higher-resolution imagery, ground measurements, and more advanced modelling frameworks to improve the reliability of land cover and LST projections and to better guide adaptation strategies.

Ethical Statement

Since this study utilizes satellite data and does not involve direct interaction with human participants, ethical considerations related to informed consent and confidentiality are not applicable. However, all data sources will be properly cited and used in accordance with relevant data usage policies. The research will ensure that no identifiable personal information is collected or disclosed, and the study will adhere to ethical standards for responsible and respectful use of satellite imagery and geospatial data.

Conflict of Interest Statement

The authors declare no conflict of interest related to the conduct and publication of this research. All procedures followed were in accordance with institutional and ethical standards, and there were no financial or personal relationships that could have influenced the outcomes of this study.

Acknowledgements

The author would like to express his sincere gratitude to the Local Government of Urdaneta City for providing the essential data that greatly contributed to the success of this project. The author also extend his heartfelt appreciation to Ms. Risselle B. Edullantes for her invaluable guidance and support in analyzing theGIS-generated maps.

Declaration of Generative AI and AI-Assisted Technologies

This work was prepared entirely by the author without the use of generative AI or AI-assisted technologies.

Data Availability

All data supporting the findings of this study are available within the paper.

Author Contributions

JED: Conceptualization and Writing

Funding

The author declared that no specific grant from public, commercial, or nonprofit organizations was received for this study.

References

Aram, F., Garcia, E., Solgi, E., & Mansournia, S. (2019, April 8). *Urban green space cooling effect in cities*. Heliyon. https://www.sciencedirect.com/science/article/pii/S2405844019300702

Bagarinao, R.T. (2015). A spatial analysis of the population growth and urbanization in Calamba City using GIS. *Journal of Nature Studies*. 14 (2): 1-13. https://journalofnaturestudies.org/files/JNS14-2/14(2)%201-13%20Bagarinao-fullpaper.pdf

Bensi, L., & Esquivel, R. (2024, December 11). Rsisinternational. https://rsisinternational.org/journals/ijrias/DigitalLibrary/volume-9-issue-11/427-433.pdf

Climate Change Commission. (2011). *National Climate Change Action Plan 2011-2028*. https://climate.emb.gov.ph.https://climate.emb.gov.ph/wp-content/uploads/2016/06/NCCAP-1.pdf

Digra, A., & Kaushal, A. (2021). Land Use and Land Cover Change Analysis using Remote Sensing and GIS Techniques. In *Biol. Forum. Int. J* (Vol. 13, No. 3b, pp. 134-138). https://www.researchgate.net/publication/374197903_Land_Use_and_Land_Cover_Change_Analysis_using_Remote_Sensing_and_GIS_Techniques

Ellis, E. C. (2015). Ecology in an anthropogenic biosphere. *Ecological Monographs*, *85*(3), 287–331. https://doi.org/10.1890/14-2274.1

Foley, J., DeFries, R., Asner, G., Barford, C., Bonan, G., Carpenter, S., Chapin, S., Coe, M., Daily, G., Gibbs, H., Helkowski, J., Holloway, T., Howard, E., Kucharik, C., Monfreda, C., Patz, J., Prentice, C., Ramankutty, N., & Snyder, P. (2005, July 22). *Global consequences of land use | science*. science.org. https://www.science.org/doi/10.1126/science.1111772

Friedlingstein, P., O'Sullivan, M., Jones, M. W., Andrew, R. M., Hauck, J., Olsen, A., Peters, G. P., Peters, W., Pongratz, J., Sitch, S., Le Quéré, C., Canadell, J. G., Ciais, P., Jackson, R. B., Alin, S., Aragão, L. E. O. C., Arneth, A., Arora, V., Bates, N. R., ... Zaehle, S. (2020, December 11). *Global Carbon Budget 2020*. Earth System Science Data. https://essd.copernicus.org/articles/12/3269/2020/

Gao, Y., Li, N., Gao, M., Hao, M., & Liu, X. (2024). Modelling future land surface temperature: a comparative analysis between parametric and non-parametric methods. *Sustainability*, 16(18), 8195. https://doi.org/10.3390/su16188195

Jabbar, H., Hamoodi, M., & Al-Hameedawi, A. (2023). *Urban heat islands: a review of contributing factors, effects and data*. iopscience.iop.org. https://iopscience.iop.org/article/10.1088/1755-1315/1129/1/012038/pdf

Landicho, K. P., & Blanco, A. C. (2019). Intra-urban heat island detection and trend characterization in Metro Manila using surface temperatures derived from multi-temporal Landsat Data. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLII-4-W19, 275–280. https://doi.org/10.5194/isprsarchives-XLII-4-W19-275-2019

Lasco, R., Guillermo, I. Q., Cruz, R., & Bantayan, N. (2004, January). *Carbon stocks assessment of a secondary forest in Mount Makiling Forest Reserve, Philippines*. Research Gate. https://www.researchgate.net/publication/285748327_Carbon_stocks_assessment_of_a_secondary_forest_in_Mount_Makiling_Forest_Reserve_Philippines

Loveland, T., Merchant, J., Ohlen, D., and Brown, J.F., 1991, Development of a land-cover characteristics database for the conterminous U.S.: *Photogrammetric Engineering and Remote Sensing*, v. 57, no. 11, p. 1453-1463. https://pubs.usgs.gov/publication/70014989?utm

Mohammad, P., & Goswami, A. (2021). A spatio-temporal assessment and prediction of surface urban heat island intensity using multiple linear regression techniques over Ahmedabad City, Gujarat. *Journal of the Indian Society of Remote Sensing*, 49(5), 1091-1108. https://doi.org/10.1007/s12524-020-01299-x

NASA. (2020). Landsat program overview. NASA Earth Science. https://landsat.gsfc.nasa.gov/

NASA. (2024). Landsat data access and updates. NASA Earth Data. https://earthdata.nasa.gov/landsat

Nuissl, H., & Siedentop, S. (2020). Urbanisation and land use change. In *Sustainable land management in a European context: a co-design approach* (pp. 75-99). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-50841-8_5

Organisation for Economic Co-operation and Development. (2020). Agricultural Policy Monitoring and Evaluation 2020. OECD Publishing. https://doi.org/10.1787/928181a8-en

OECD/FAO. (2020, July 16). *OECD-FAO Agricultural Outlook 2020-2029 | OECD*. OECD. https://www.oecd.org/en/publications/2020/07/oecd-fao-agricultural-outlook-2020-2029_bfb66700.html

Oke, T. R. (1982, January). *The energetic basis of urban heat island*. researchgate.net. https://doi.org/10.1002/qj.49710845502

Peng, F., & Weng, Q. (2020). *A time series analysis of urbanization-induced land use and land cover change and its impact on land surface temperature with Landsat imagery*. Remote Sensing, 12(24), 4098. https://doi.org/10.1016/j.rse.2015.12.040

Primavera, J. H. (2000). *Management of Mangroves*. repository.seafdec.org.ph. https://repository.seafdec.org.ph/bitstream/handle/10862/455/primavera2000-mangroves-of-southeast-asia.pdf?sequence=1

PSA (20201). *2020 census of Population | Philippine Statistics Authority*. PHILIPPINE STATISTICS AUTHORITY. https://rsso11.psa.gov.ph/2020-census-population

Seto, K. C., Güneralp, B., & Hutyra, L. R. (2012, October 2). *Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools*. Proceedings of the National Academy of Sciences of the United States of America. https://pmc.ncbi.nlm.nih.gov/articles/PMC3479537/#:~:text=Urban%20land%2Dcover%20change%20threatens,and%20rates%20of%20urban%20expansion.

United States Geological Survey. (2021). Landsat program: Landsat data products and tools. https://www.usgs.gov/landsat-missions

USGS. (2021). Landsat Collections. United States Geological Survey. Retrieved from https://www.usgs.gov/core-science-systems/national-cooperative-drought-task-force/landsat-collections

Vergara, D. C., Blanco, A., Marciano, J. J., Meneses, S., Borlongan, N. J., & Sabuito, A. J. (2023). Assessing and modelling urban head island in Baguio City using Landsat imagery and machine learning. https://isprs-archives.copernicus.org/articles/XLVIII-4-W6-2022/457/2023/isprs-archives-XLVIII-4-W6-2022-457-2023.pdf

Voogt, J.A, Aniello, C., Artis, D. A., Baltsavias, E. P., Bottema, M., Carlson, T. N., Carnahan, W. H., Caselles, V., Chehbouni, A., Cionco, R. M., François, C., Friedl, M. A., Gallo, K. P., Gruen, A., Haala, N., Hoyano, A., ... Fournier, R. A. (2003, June 26). Thermal remote sensing of urban climates. Remote Sensing of Environment. https://www.sciencedirect.com/science/article/abs/pii/S0034425703000798

Voogt, J. A., & Oke, T. R. (2003). Thermal remote sensing of urban climates. *Remote Sensing of Environment*, 86(3), 370–384. https://doi.org/10.1016/S0034-4257(03)00079-8