Investigating the relationship between the Urban Heat Island Effect and its influencing factors: A case study of Perth

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Abstract

Rapid urbanisation significantly alters land surface characteristics and increases heat-related risks, such as the Urban Heat Island (UHI) effect. Urban growth and the resulting UHI elevate surface temperatures in urban environments, exacerbating environmental challenges such as biodiversity loss and poor urban air quality, while also posing risks to human health, including heat-related illnesses and increased vulnerability among susceptible populations. This study investigates the correlation between urban development and summer daytime Land Surface Temperature (LST) in the Perth Metropolitan Region (PMR). Using multi-temporal Land Use Land Cover (LULC) data and factors influencing LST, the spatial patterns of urban growth and their thermal characteristics were analysed. The results of this study showed that newer developments experience higher surface temperatures than older neighbourhoods due to higher impervious surfaces and limited vegetation cover. Statistical analysis was quantified using the Ordinary Least Squares (OLS) regression model, which identified tree canopy cover, surface moisture, building density and population density as the most influential predictors of LST. Surface moisture and tree canopy cover showed a negative correlation, whereas building and population density showed a positive relationship with LST, particularly in the newer neighbourhoods. The findings from this study underscore the vital need to integrate urban planning strategies to enhance urban green infrastructure and to incorporate climate-resilient designs in newer developments to combat rising LST and the associated public health and environmental impacts in rapidly evolving cities like Perth.

1. Introduction

Urbanisation is accelerating globally and is a defining feature of modern cities. In 2016, 55% of the global population lived in cities, and it is projected to reach nearly 70% by 2050 (Heilig, 2012). Rapid urban and population growth pose major challenges for sustainable development. By 2030, global urban land cover is expected to reach 1.2 million km², three times that of 2000 (Seto et al., 2012). This transformation involves significant Land Use Land Cover (LULC) changes, often converting natural vegetation into impervious surfaces like buildings and roads.

The conversion of natural vegetation into impervious surfaces contributes to elevated surface temperatures in urban core areas compared to surrounding rural areas, a phenomenon known as the Urban Heat Island (UHI) effect (Alavipanah et al., 2015). The UHI effect is primarily driven by impervious surfaces such as asphalt and concrete that absorb incoming shortwave radiation and re-radiate it as heat, increasing both surface and ambient temperatures in urban areas (Ranagalage et al., 2018). Hence, urbanisation strongly correlates with rising Land Surface Temperature (LST) and intensified Urban Heat Island (UHI) (Zhao et al., 2016).

This urban warming has significant implications for both human well-being and the environment, including reduced thermal comfort, increased heat-related illnesses, particularly among vulnerable populations, urban air pollution, and greater energy consumption for cooling purposes (Carleton & Hsiang, 2016; Estoque et al., 2017). As urban areas continue to grow and redevelop, a large proportion of the global population will be exposed to heat-related hazards, highlighting the urgent need for urban planners and policymakers to make informed decisions and implement heat-mitigation strategies to safeguard public health and the environment.

Despite global attention to Urban Heat Island (UHI) effects, few studies have examined the spatio-temporal dynamics of Land Surface Temperature (LST) in relation to recent urbanisation in Perth. Duncan et al. (2019) used Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data, which indicated that increased tree and shrub cover has a significant cooling effect, with notable spatial variability of surface temperature across the city. Similarly, MacLachlan et al. (2017) applied a multi-sensor approach, suggesting that vegetation-to-urban land conversions drive the largest temperature increases. However, these studies focus mainly on vegetation and land cover, neglecting other urban growth factors such as building density, population density, and impervious surface expansion, and they do not distinguish thermal behaviours between older and newer developments. Moreover, both studies predate Perth’s rapid suburban expansion from 2005 to 2024, limiting their relevance for current urban planning.

Hence, this study aimed to address this gap by:

- Identifying and delineating the areas of new development in Perth between 2005 and 2024,
- Analysing and comparing LST patterns between long-established older and newly developed areas
- Investigating the relationship between LST and its contributing factors, such as building and population density, tree canopy cover, surface moisture, albedo, and proximity to rivers

To achieve these aims, the study evaluated urban expansion between 2005 and 2024 and quantified thermal differences using multi-temporal Landsat-derived LST. Ordinary Least Squares (OLS) regression is applied to examine statistical relationships between LST and its predictor variables. The findings advance knowledge of Perth’s thermal landscape and provide evidence-based insights into the spatial drivers of urban heat.

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The paper is structured as follows: Section 2 covers the background, followed by an overview of the data in Section 3 and the method in Section 4. Results are presented in section 5, followed by the conclusion in section 6.

2. Background

Traditionally, UHI effects have been estimated using in situ measurements of air temperature data collected from weather stations. However, this point-based method, with sparse and uneven distributions of weather stations, often lacks the spatial coverage and resolution required for comprehensive analysis (Singh et al., 2024). Remotely sensed satellite images address this limitation by providing synoptic, consistent and repeatable data observation over time. These datasets provide a reliable proxy for quantifying the UHI effect across a broader geographic area with high temporal resolution. A wide variety of satellites with thermal sensors such as Moderate Resolution Imaging Spectroradiometer (MODIS), Advanced Very High-Resolution Radiometer (AVHRR), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), and Landsat series (e.g., Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI/TIRS), have been commonly used to monitor and investigate UHI effects across urban landscapes (Li et al., 2023).

In response to growing concerns about heat vulnerability in cities and its impact on liveability and sustainability, numerous studies have quantified the relationship between urban landform characteristics and LST. A consensus has emerged that artificial and impervious surfaces (e.g. asphalt, concrete and rooftops) amplify the UHI effect, while natural vegetation, including tree canopy and urban green spaces, contributes to urban cooling (Bounoua et al., 2015).

Empirical evidence suggests that urban forms such as building density are positively correlated with higher LST, while urban green spaces and water bodies exhibit stronger cooling effects within cities, particularly during summer seasons (Sun et al., 2019). Effective heat mitigation strategies, such as increasing urban vegetation cover, using cool roofs and pavements, and designing ventilation corridors within the urban environment, have demonstrated significant reductions in surface temperatures (Hong & Lin, 2014).

Several studies have examined how urban land use types and urban morphology influence LST. Factors such as building density, impervious surface fraction, road density, building height, and urban vegetation cover, together with land use categories, have been widely assessed for their impact on urban LST (Gao et al., 2022; Yin et al., 2018).

The aim of this study is to focus on Perth, Western Australia (WA). The Perth Metropolitan Region, historically regarded as a globally isolated city, is located on the southwestern coast of Australia. The region spans about 125km. Perth's climate is classified as Mediterranean (Köppen-Geiger classification Csa), with cool, wet winters and hot, dry summers. Winters generally last from May to September, while summers extend from December to March. During the hot summer months, the region frequently experiences extreme heat events, posing significant risks to public health, ecosystems and infrastructure (Cleugh et al., 2006).

As the state capital, the region experienced substantial economic growth (Department of Mines and Petroleum, 2015) between 2002 and 2012, the urban footprint of Perth and the Peel region expanded from 631 km² to 870 km², positioning it among the fastest-growing metropolitan areas in Australia (Perth and Peel @ 3.5 million Frameworks, 2022). Perth currently has a population of more than 2 million residents. Population growth in this region of Western Australia has led to an outward, low-density development pattern outpacing other major Australian cities, raising concerns about the region's long-term sustainability (Dhakal, 2014; MacLachlan et al., 2017).

The Perth and Peel @ 3.5 million land-use planning and infrastructure frameworks aim to accommodate 3.5 million people by 2050. This projected growth is expected to have considerable implications on land use planning, transportation networks and urban development. Hence, it is important to better understand the factors contributing to the UHI effect, considering the current low-density developments in the Perth Peel region.

This study will focus on the Perth Metropolitan Region, where low-density urban developments are commonly present. For this reason, we included data from 2005 to 2024 to identify growth hotspots and compare the UHI performance of those areas with established areas in the inner Perth area. As a long-term trend is investigated, we utilise Landsat imagery for the key dates of 2006, 2010, 2015, 2020 and 2024, focusing on summer months (December–February) when UHI intensity is typically highest. Any additional data will be open-sourced data to ensure that the results can be reproduced.

3. Datasets

The study integrated remotely sensed satellite imagery (Landsat), land-use land-cover (LULC) datasets (Digital Earth Australia, DEA), and auxiliary datasets for the years 2006, 2010, 2015, 2020, and 2024.

3.1 Image data

LST and several indices were estimated using Landsat imagery with minimal cloud during the hot summer months (December to February) (Table 1). For Landsat 5 TM, we utilised Band 1 (B), Band 2 (G), Band 3 (R), Band 4 (NIR), Band 5 (SWIR1), Band 6 (TIRS1) and Band 7 (SWIR2). For Landsat 8 OLI/TIRS we utilised Band 2 (B), Band 3 (G), Band 4 (R), Band 5 (NIR), Band 6 (SWIR1), Band 7 (SWIR2), Band 10 (TIRS1).

TIRS1 was used to estimate LST (Alademomi et al., 2022; ObiefuNa et al., 2021).

3.2 Vector data

Urban expansion was mapped using Digital Earth Australia's (DEA) land-use land-cover (LULC) dataset (https://knowledge.dea.ga.gov.au). For the analysis, the classes related to artificial surfaces (including built surfaces and roads) were selected as urban areas.

Satellite/ sensor	Date	Path/ Row	Spatial Res	Cloud Cover (%)
Landsat 5 TM	2006-01-20	112 / 082	30 m	0
Landsat 8 OLI/TIRS	2010-11-15	112 / 082	30 m	0
Landsat 8 OLI/TIRS	2015-12-31	112 / 082	30 m	0.14
Landsat 8 OLI/TIRS	2020-12-28	112 / 082	30 m	0.06
Landsat 8 OLI/TIRS	2024-12-31	112 / 082	30 m	0.01

Table 1: Landsat imagery utilised in the study.

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Census data were acquired from the Australian Bureau of Statistics (ABS, https://www.abs.gov.au/). The mesh block scale was selected as it is the smallest geographic area defined by the ABS and forms the building blocks for the larger regions of the Australian Statistical Geography Standard (ASGS). Mesh Blocks reflect dominant land use where possible. For example, residential areas are separated from commercial or industrial areas. Wherever possible, each Mesh Block is designed to have a single land use.

Auxiliary datasets were obtained from DataWA (https://data.wa.gov.au) and included building footprints (LGATE-483), tree canopy and grass cover data (DPLH-109).

An overview of all the vector datasets used is provided in Table 2.

Source	Dataset	Content/Information
Digital Earth Australia	LULC	LULC classes indicating artificial surfaces
ABS	Mesh block	Area
		Population Density
		Dwelling Density
Landgate	LGATE-053	Location of rivers
Landgate	LGATE-483	2D Building Outlines
CSIRO Urban Monitor	DPLH-109	Vegetation coverage with the classes 0 – 3 m, 3 – 8 m, 8 – 15 m and 15+ m

Table 2: Overview of vector datasets.

3.3 Urban Growth Detection

The urban land cover classes were extracted from the LULC datasets to examine the extent of the urban area at each specific year. Differencing was applied to detect changes in urban areas across the intervals 2006-2010, 2011-2015, 2016-2020, and 2021-2024. The results were validated using alternative sources. Based on the results of the urban growth patterns, newly developed neighbourhoods were identified (Figure 1).

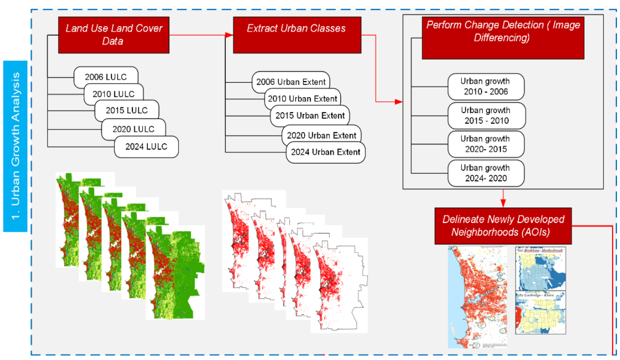

Figure 1: Urban Growth Detection.

4. Methodology

4.1 Spatial predictors

To investigate the drivers for increased LST, relevant spatial predictors were extracted. Next to standard indices such as building density (BD) and Normalised Difference Vegetation Index (NDVI), we also used:

- Normalised Difference Moisture Index (NDMI): Soil and vegetation water retention can influence LST.
- Surface Albedo (SA): The amount of radiation reflected or absorbed by the surface materials is an indicator of LST (a high albedo surface reflects a larger portion of sunlight and therefore is cooler, while a low albedo surface absorbs more radiation and shows higher LST).
- Tree coverage (TC) and grass coverage (GC): Trees and grass moderating the temperature within urban environments through shading and evapotranspiration.
- Population Density (PD): Regions with high population density are generally associated with higher heat emissions due to residential, industrial and transportation-related activities.
- Dwelling Density (DD): Higher dwelling densities are usually associated with higher temperatures.
- Distance to rivers (RD): Water bodies, such as rivers, can influence the microclimatic conditions by producing a cooling effect on the surrounding areas.

These predictor variables were widely used in previous studies (Jamei et al., 2022; Sun et al., 2019). All predictor variables were spatially aggregated at the residential mesh block level.

An overview of all the used drivers is provided in Table 3.

Dataset	Source	Definition
Building Density (BD)	ABS, LGATE-483	Total area of building footprints within each mesh block area
Normalised Difference Vegetation Index (NDVI)	Landsat	$NDVI = \frac{NIR - R}{NIR + R}$
Normalized Difference Built-Up Index (NDBI)	Landsat	$NDBI = \frac{SWIR1 - NIR}{SWIR1 + NIR}$
Normalised Difference Moisture Index (NDMI)	Landsat	$NDMI = \frac{NIR - SWIR1}{NIR + SWIR1}$
Surface Albedo (SA)	Landsat	$SA = 0.2453B + 0.0508G + 0.1804R + 0.3081NIR + 0.1332SWIR1 + 0.0521SWIR2 + 0.0011$
Tree coverage (TC)	ABS, DPLH-109	Percentage of tree coverage within each mesh block area
Grass coverage (GC)	ABS, DPLH-109	Percentage of grass coverage within each mesh block area
Population Density (PD)	ABS	Per mesh block area, the number of persons/km^2
Dwelling Density (DD)	ABS	per mesh block area number of residential units (dwelling / km^2)
Distance to rivers (RD)	ABS,	Euclidean distance to the nearest river

Table 3: Overview of the investigated drivers of LST.

4.2 Statistical Analysis

Statistical analysis was performed using Ordinary Least Squares (OLS) regression to assess how spatial variables influence LST patterns. The OLS model has been widely adopted in previous studies to quantify the statistical associations between LST and its influencing factors (Sun et al., 2019). The analysis especially focuses on comparing newer and older developments to assess variations in LST across neighbourhood types.

It was hypothesised that older developments would demonstrate lower LST due to more established tree canopy and vegetation cover. Based on this conceptual framework, the OLS model was developed as follows:

$$LST = \beta_0 + \beta_1 BD + \beta_2 NDVI + \beta_3 NDMI + \beta_4 SA + \beta_5 TC + \beta_6 GC + \beta_7 PD + \beta_8 DD + \beta_9 RD + \varepsilon \quad \text{Equation (1)}$$

Where LST is the dependent variable, β_n are the variables influencing LST (Table 3), and ε is the error term. The model performance was evaluated using the adjusted coefficient of determination (Adjusted R2).

5. Results

5.1 Urban Growth Analysis

The spatial analysis of urban growth patterns in Perth between 2005 and 2024 revealed significant urban expansion. Figure 2 shows the areal changes in urban area based on the DEA urban land cover class, with urban footprint increasing from approximately 514.72 km² in 2005 to 744.42 km² in 2024. This represents a substantial growth of about 44.62%. To validate the estimates, comparisons were made with the Urban Growth Monitor 15 report (Western Australian Planning Commission, 2024) which reported around 77140 hectares (771.4 km²) of urbanised land in 2022. DEA's estimates align closely with these official figures and were therefore adopted in this study for detailed analyses of urban growth.

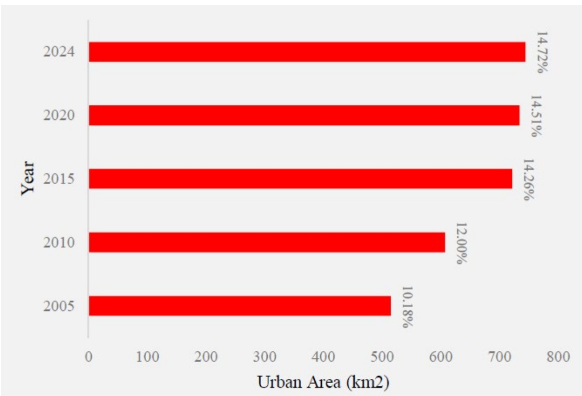

Figure 2: Areal changes in urban land cover classes between 2025 and 2024. The percentage shows the increase compared to the previous time point.

In contrast, the Global Human Settlement (GHS, https://human-settlement.emergency.copernicus.eu, 100 m resolution) and ESRI global land cover (ESRI, https://livingatlas.arcgis.com/landcover/, 10 m resolution) overestimated the urban extents, reporting approximately 1700 km² by 2024. Figure 3 illustrates differences in urban extent estimates across datasets and clearly shows their dataset-dependent nature.

Urban growth patterns are shown in Figure 4 and suggest that by 2005, regions along the coastal zones on the west were largely developed. Subsequent developments radiating outwards into peripheral zones, including areas in the northwest (Alkimos), northeast (Brabham, Caversham), southwest (Success, Piara Waters, Baldivis), and southeast (Byford). The findings indicate a clear outward urban growth trend, with significant development occurring after 2010, particularly within the outer peripheral zones.

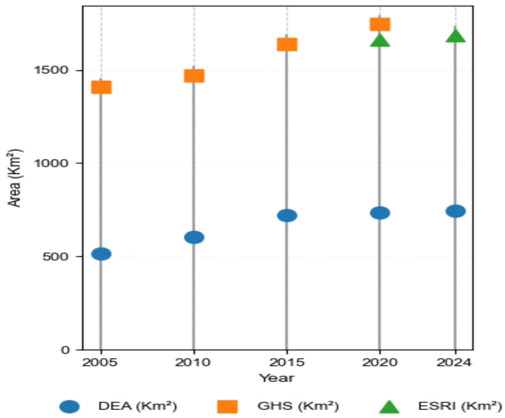

Figure 3: Urban Area estimates from different sources DEA (blue), GHS (orange), ESRI land cover (green).

This trend suggests the transformation of vegetated lands into impervious built-up surfaces, which typically retain more heat and elevate the local surface temperature. Notably, regions such as Byford, Piara Waters and Brabham experienced extensive development between 2015 and 2024, while Baldivis and Success also saw continuous development since around 2010.

Representative Areas of Interest (AOIs) were selected based on observed spatial patterns of urban growth, including older (Highgate, Mosman Park, Nedlands, Shenton Park) and newer (Brabham, Success, Kiara Waters) neighbourhoods. These selected AOIs were subsequently used to compare thermal behaviour across different development periods.

5.2 Spatial Patterns of Land Surface Temperature (LST)

To analyse spatial differences in surface temperature, the difference between the mean urban LST for the larger Perth area and each pixel value in the AOIs was calculated. This approach highlighted how the surface temperatures of specific locations deviated from the average urban LST.

The results revealed significant spatial variation in surface temperatures throughout Perth (Figure 5), with older urban areas including Shenton Park, Highgate, Nedlands and Mosman Park, consistently exhibiting temperatures 2 °C to 4 °C cooler than the average. In contrast, recently developed outer suburbs such as Success, Piara Waters and Brahmans usually recorded hotter-than-average temperatures, often exceeding 3 °C. The cooler conditions observed in older, inner-city neighbourhoods may be influenced by factors such as coastal proximity, mature street trees and the shading effect of taller buildings.

Additionally, a notable trend observed in the older neighbourhoods is that their negative deviations are becoming smaller over time. For example, Shenton Park's deviation declined from -3.4 °C in 2006 to -1.1 °C in 2024, and a similar pattern was observed in Nedlands and Highgate. This shift may reflect the impacts of urban infill and densification, which increase building footprints and diminish the thermal advantage previously enjoyed by these established areas.

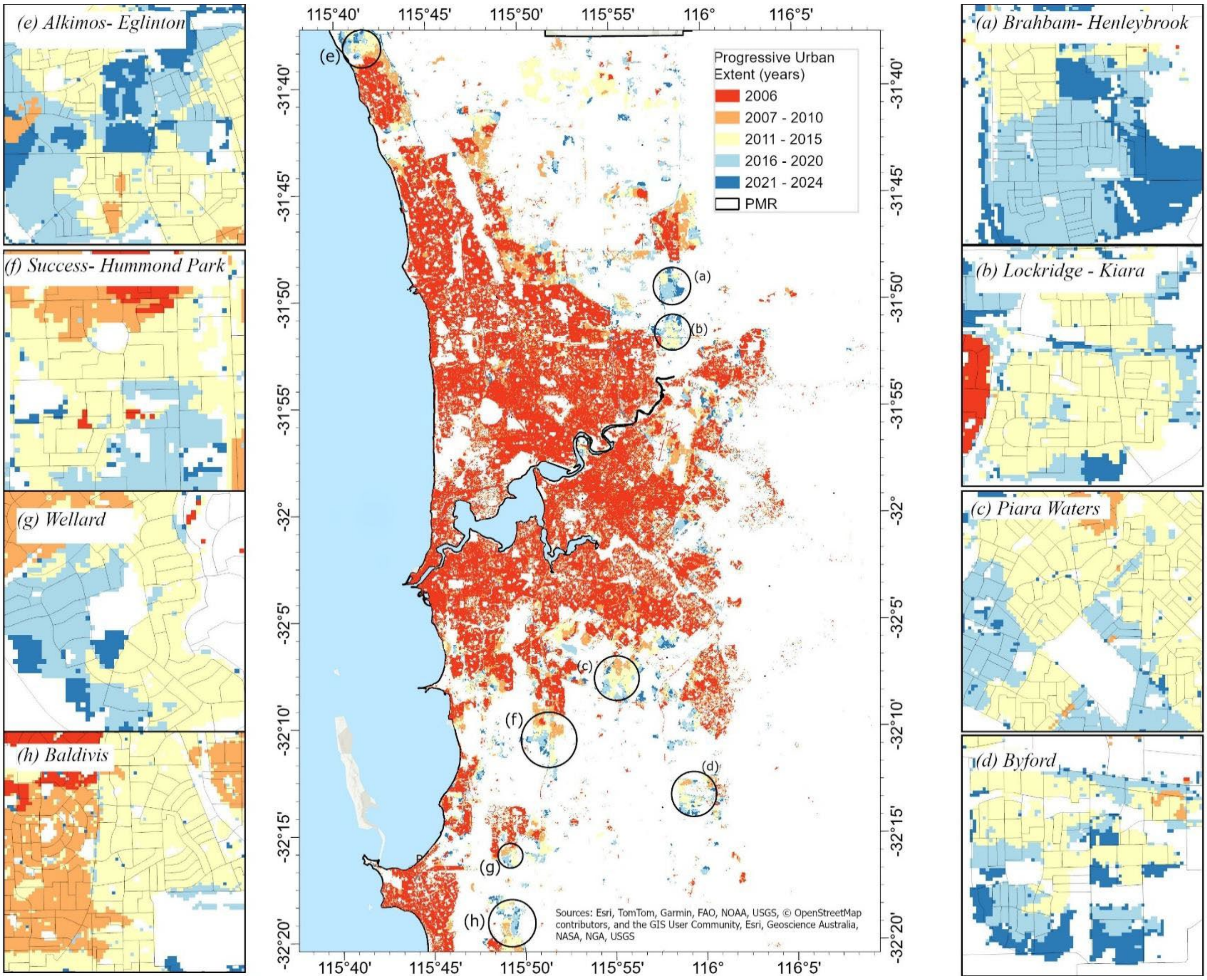

Figure 4: Urban land growth analysis in Perth between 2005 and 2024.

5.3 Statistical Modelling of LST Drivers

The comparative analysis of LST variations across Perth revealed that newer neighbourhoods tend to be hotter than the older neighbourhoods. To understand the underlying factors contributing to these distinct thermal patterns, an OLS regression model was applied separately to both neighbourhood types.

Among the selected explanatory variables, mean NDVI, mean NDBI, and Dwelling Density (DD) exhibited high multicollinearity with Pearson correlation coefficients (r) exceeding 0.7. These variables were subsequently excluded from the final regression model, and the refined model included seven explanatory variables: Tree Coverage (TC), Grass Coverage (GC), Building Density (BD), mean NDMI, mean Surface Albedo (SA), Population Density (PD) and River Distance (RD).

5.3.1 Older Neighbourhoods

Table 4 presents a summary of OLS regression results for the older neighbourhoods, with the model explaining approximately 31% of the variability in morning LST (Adjusted $R^2 = 0.3085$). The result revealed four statistically significant ($p < 0.01$) predictors, including Tree Coverage (TC), mean Surface Albedo (SA), Building Density (BD) and mean NDMI.

Variable	Coefficient	Std Error	t-Statistics	Probability	Robust SE	Robust	Robust Probability	VIF
Inter-cept	30.20	0.46	66.10	0.00	0.48	63.44	0.00	--
TC	-0.02	0.00	-4.08	0.00	0.00	-4.52	0.00*	1.14
GC	-0.01	0.01	-0.76	0.45	0.01	-0.55	0.59	1.33
BD	-0.05	0.00	-10.19	0.00	0.01	-9.50	0.00	1.71
SA	10.01	2.69	3.72	0.00	2.79	3.59	0.00	1.49
NDMI	-10.45	0.93	-11.18	0.00	1.08	-9.65	0.00	1.43
RD	0.00	0.00	0.99	0.32	0.00	1.01	0.31	1.09
PD	0.00	0.00	1.59	0.11	0.00	1.44	0.15	1.14

Table 4: Summary statistics OLS for older neighbourhoods. All variables are statistically significant at $p < 0.01$.

Among the variables, Tree Coverage (TC) and NDMI exhibited the strongest negative correlation with LST, suggesting that increased vegetation cover and surface moisture contribute to a localised cooling effect. This result is consistent with previous studies (Duncan et al., 2019). Interestingly, Building Density (BD) also showed a reverse relationship with LST, which may be attributed to factors such as closely spaced urban layouts with narrower streets that enhance shading and the prevalence of light-coloured roofing materials.

In contrast, mean Surface Albedo (SA) showed a positive correlation with LST, suggesting that surfaces such as light-coloured rooftops and aged concrete may reflect shortwave solar radiation while still retaining and re-radiating heat, thereby contributing to elevated surface temperatures.

Diagnostic tests indicated heteroskedasticity (Koenker, $p < 0.001$) and non-normal residuals (Jarque-Bera, $p = 0.000098$), suggesting spatial non-stationarity and the likelihood that unobserved variables are influencing the relationship.

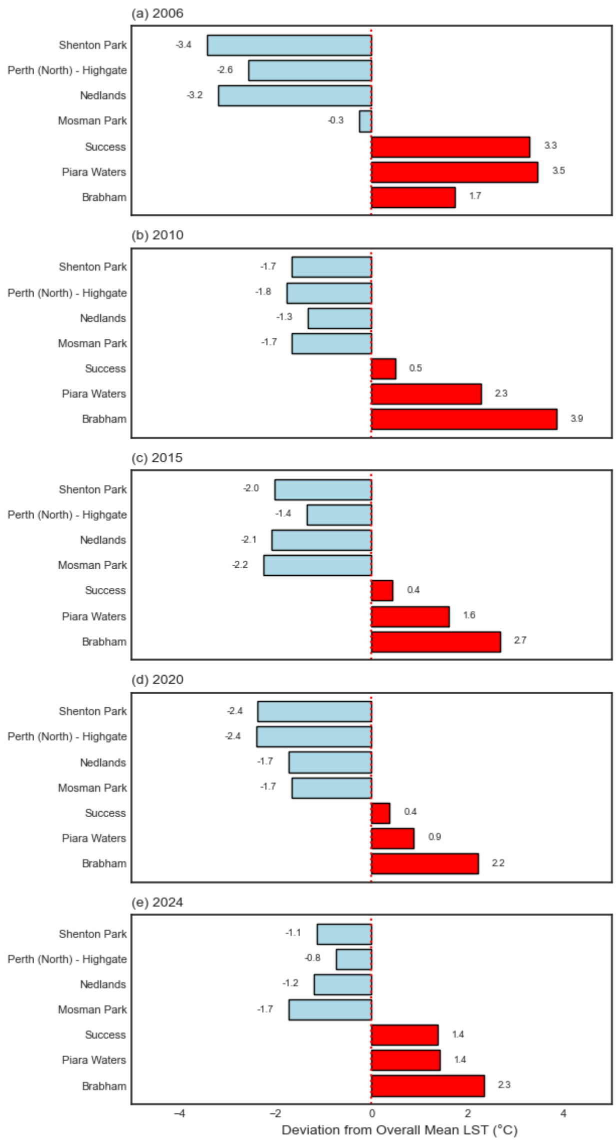

Figure 5: Spatial variation in surface temperatures (deviation from mean) for older suburbs (Shenton Partk, Highgate, Nedlands, Mosman Park) and newer suburbs (Success, Piara Waters, Brabham).

Overall, older neighbourhoods in Perth benefit from cooler surface temperatures, largely due to well-established tree canopies and higher moisture content. A representative image of such a neighbourhood is presented in Figure 6.

Figure 6: Google Earth imagery of Mosman Park.

5.3.2 Newer Neighbourhoods

In contrast to older neighbourhoods, the regression analysis performed on the newer developments showed a slightly higher model fit, with an Adjusted R^2 of 0.419 (approximately 42%) (Table 5).

Variable	Coefficient	Std Error	t-Statistics	Probability	Robust SE	Robust	Robust Probability	VIF
Inter-cept	32.26	0.42	77.16	0.00	0.43	74.79	0.00	--
TC	-0.02	0.01	-1.53	0.13	0.01	-1.70	0.09	1.19
GC	0.01	0.01	1.30	0.19	0.00	1.32	0.19	1.07
BD	0.40	0.42	-0.95	0.34	0.37	-1.09	0.28	2.46
SA	1.05	2.13	0.49	0.62	2.13	0.49	0.62	1.37
NDMI	-18.39	1.17	-15.68	0.00	1.34	-13.75	0.00	1.33
RD	0.00	0.00	0.89	0.38	0.00	1.02	0.31	1.06
PD	0.00	0.00	2.16	0.03	0.00	2.40	0.02	2.68

Table 5: Summary statistics for OLS in newer neighbourhoods. All variables are statistically significant at $p < 0.01$.

As in older neighbourhoods, a stronger negative correlation was observed between mean NDMI and Tree Coverage (TC), suggesting that vegetation cover has a cooling effect, which is often sparse in these regions. In contrast, Population Density (PD) and Building Density (BD) showed a positive relationship with LST, indicating that increasing population and impervious surfaces in these new developments contribute strongly to warming.

Newer developments are often characterised by extensive impervious surface and exposed bare grounds, with reduced or immature vegetation. Additionally, ongoing construction activities and exposed soils can increase the surface temperatures in these regions. A representative image of such a neighbourhood is presented in Figure 7.

Figure 7: Google Earth imagery of Piara Waters.

These findings suggest that newly developed areas in Perth are hotter and more prone to the UHI effect than older neighbourhoods, largely due to high-density new construction, increasing population, and more exposed ground surfaces. The OLS model, however, showed heteroskedasticity and non-normal residuals, as seen in the older neighbourhoods.

6. Discussion

The analysis of urban growth using the DEA urban land cover class shows that Perth’s urban footprint increased by approximately 45% between 2005 and 2024. This expansion was most evident in peripheral suburbs (e.g., Brabham, Piara Waters, Success) and in infill development within established areas. This pattern aligns with previous studies suggesting that Australian cities are increasingly experiencing peri-urban growth driven by population growth and housing demand (Newton et al., 2012).

The spatial growth of urban areas has clear implications for surface thermal patterns. LST analysis (2006–2024) shows that temperatures are higher in recently developed areas, with deviations of up to 3 °C, while older neighbourhoods such as Nedlands, Mosman Park, and Shenton Park remain cooler, with deviations from −0.8 °C to −3.4 °C. This trend is consistent with findings from other Australian cities, such as Sydney and Melbourne, where newer developments exhibit higher surface temperatures (Jamei et al., 2022).

Further analysis by development period and density reinforces this trend: low-density older neighbourhoods show the strongest cooling effects, whereas newer developments remain warmer. This highlights the role of urban form (e.g., larger lots, mature tree canopies) and vegetation in regulating urban temperature. The gradual decline in LST deviation in newer developments, from +0.89 °C (2011–2015) to +0.40 °C (2021–2024), may indicate the onset of vegetative recovery and thermal stabilisation as these neighbourhoods age, consistent with findings by Liao et al. (2021). However, further research is needed to assess the influence of urban design, cool, light coloured building materials, and vegetation maturity on urban heat performance.

The regression models provide further insight into factors influencing LST. In both older and newer neighbourhoods, tree cover and NDMI (surface moisture) show strong negative associations with LST, confirming their cooling effects. In newer areas, higher building and population density significantly increase LST, consistent with previous studies linking impervious surfaces to urban heat (Liang et al., 2020; Zhao et al., 2016), underscoring the need to integrate green infrastructure into new developments. In contrast, older neighbourhoods exhibit a negative correlation between LST and building density, likely due to design features such as narrower streets, closely spaced buildings that enhance shading, and lighter roofing materials that reduce heat absorption.

The presence of spatially non-stationary and non-normal residuals suggests that the Ordinary Least Squares (OLS) model has limitations in capturing complex spatial interactions. These findings, along with the moderate explanatory power (42% in newer and 31% in older neighbourhoods), indicate that key variables, such as roof colour and building material, urban geometry, building height and local wind conditions, may be missing from the model and their inclusion could improve future models.

Additionally, the OLS model provides a single coefficient for the entire study area and often yields higher errors due to spatial dependence (Deilami et al., 2016). This limitation can be addressed using spatially adaptive local regression models that account for spatial heterogeneity, such as the Geographically Weighted Regression (GWR), which provides different correlation coefficients between the dependent and explanatory variables at each specific point (Szymanowski & Kryza, 2012). Therefore, future studies should explore local spatial regression models, such as Geographically Weighted Regression (GWR) or Multi-scale GWR (MGWR), to better capture local variations in LST.

7. Conclusion

This study assessed the influence of urban growth on Land Surface Temperatures (LST) in Perth using multi-temporal Land Use and Land Cover (LULC) data and various LST-influencing factors. The analysis of urban growth patterns in Perth revealed that most new developments are occurring on the outer fringes of the core urban zones, suggesting a dispersed pattern of urban growth. Spatial analysis was then performed to examine whether the timing of development affects the surface temperature. The comparison of LST between older and newer neighbourhoods showed that newer neighbourhoods tend to be relatively warmer, due to extensive impervious surface, ongoing construction activities and limited vegetation within the development zones.

The key drivers influencing LST were identified through regression analysis, with surface moisture (mean NDMI) and tree canopy cover serving as natural cooling agents, while population and building density correlated positively with LST, particularly within newer neighbourhoods. Interestingly, building density showed a positive relationship with LST in older neighbourhoods, which may be attributed to closely spaced urban layouts with narrower streets that provide shading, although this trend required further investigation.

The results of this study advocate planning strategies to prioritise vegetation integration at the lot and precinct scales, preserve tree canopy, and incorporate a multifaceted, holistic urban design approach to precinct design and master planning, to minimise surface temperatures in future developments. As climate change intensifies the risk of extreme heat events, thermal comfort considerations should be incorporated into the urban design framework for climate-resilient communities.

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