Spatiotemporal landscape pattern changes and their effects on land surface temperature in greenbelt with semi-arid climate: A case study of the Erbil City, Iraq Postprint

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Abstract

Urban expansion of cities has caused changes in land use and land cover (LULC) in addition to transformations in the spatial characteristics of landscape structure. These alterations have generated heat islands and rise of land surface temperature (LST), which consequently have caused a variety of environmental issues and threated the sustainable development of urban areas. Greenbelts are employed as an urban planning containment policy to regulate urban expansion, safeguard natural open spaces, and serve adaptation and mitigation functions. And they are regarded as a powerful measure for enhancing urban environmental sustainability. Despite the fact that, the relation between landscape structure change and variation of LST has been examined thoroughly in many studies, but there is a limitation concerning this relation in semi-arid climate and in greenbelts as well, with the lacking of comprehensive research combing both aspects. Accordingly, this study investigated the spatiotemporal changes of landscape pattern of LULC and their relationship with variation of LST within an inner greenbelt in the semi-arid Erbil City of northern Iraq. The study utilized remote sensing data to retrieve LST, classified LULC, and calculated landscape metrics for analyzing spatial changes during the study period. The results indicated that both composition and configuration of LULC had an impact on the variation of LST in the study area. The Pearson’ s correlation showed the significant effect of Vegetation 1 type (VH), cultivated land (CU), and bare soil (BS) on LST, as increase of LST was related to the decrease of VH and the increases of CU and BS, while, neither Vegetation 2 type (VL) nor built-up (BU) had any effects. Additionally, the spatial distribution of LULC also exhibited significant effects on LST, as LST was strongly correlated with landscape indices for VH, CU, and BS. However, for BU, only aggregation index metric affected LST, while none of VL metrics had a relation. The study provides insights for landscape planners and policymakers to not only develop more green spaces in greenbelt but also optimize the spatial landscape patterns to reduce the influence of LST on the urban environment, and further promote sustainable development and enhance well-being in the cities with semi-arid climate.

Full Text

Preamble

Spatiotemporal landscape pattern changes and their effects on land surface temperature in greenbelt with semi-arid climate: A case study of the Erbil City, Iraq

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Abstract: Urban expansion has caused changes in land use and land cover (LULC) and transformations in landscape structure spatial characteristics. These alterations have generated heat islands and increased land surface temperature (LST), causing various environmental issues and threatening sustainable urban development. Greenbelts serve as urban planning containment policies to regulate expansion, safeguard natural open spaces, and provide adaptation and mitigation functions, making them powerful measures for enhancing urban environmental sustainability. Although many studies have examined the relationship between landscape structure change and LST variation, research is limited concerning this relationship in semi-arid climates and greenbelts, with a lack of comprehensive studies combining both aspects. Accordingly, this study investigated spatiotemporal changes in LULC landscape patterns and their relationship with LST variation within an inner greenbelt in semi-arid Erbil City, northern Iraq. Remote sensing data were used to retrieve LST, classify LULC, and calculate landscape metrics for analyzing spatial changes during the study period. Results indicated that both LULC composition and configuration affected LST variation. Pearson' s correlation showed significant effects of Vegetation 1 type (VH), cultivated land (CU), and bare soil (BS) on LST, as increased LST was related to decreased VH and increased CU and BS, while neither Vegetation 2 type (VL) nor built-up (BU) had significant effects. Additionally, LULC spatial distribution exhibited significant effects on LST, as LST was strongly correlated with landscape indices for VH, CU, and BS. For BU, only the aggregation index metric affected LST, while no VL metrics showed any relationship. The study provides insights for landscape planners and policymakers to develop more green spaces in greenbelts and optimize spatial landscape patterns to reduce LST influence on urban environments, promoting sustainable development and enhancing well-being in semi-arid climate cities.

Keywords: land use and land cover change; landscape pattern; land surface temperature; greenbelt; remote sensing

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1 Introduction

In recent decades, urbanization and its environmental effects have gained worldwide recognition and concern due to their substantial global influence. Urban expansion leads to significant alterations in land use and land cover (LULC), a vital factor in regional and global climate change that affects local ecosystems and human well-being (Rimal et al., 2019). Urban land expansion is directly associated with decreased natural vegetation and increased man-made surfaces in city surroundings (Abebe et al., 2022). The main consequences of LULC changes include landscape deterioration, deforestation, soil loss, and natural habitat destruction. At the regional level, transition from greenery to built-up areas modifies local climate and can alter local atmospheric conditions (Senanayake et al., 2013). Furthermore, thermal condition variations, such as heat island formation and LST alteration, represent additional outcomes of significant surface cover modifications (Kumari and Sarma, 2017; Bhagat and Prasad, 2023). For instance, LST increases when forest cover is removed and replaced due to alterations in land surface physical qualities (Debie et al., 2022). Similarly, elevated LST in cities leads to negative implications including anthropogenic heat production, decreased air quality from increased greenhouse gas emissions, and air contaminants (Balany et al., 2020). These factors have caused various environmental issues, threatening sustainable urban development.

Green spaces play crucial roles in regulating urban thermal environments and enhancing local microclimates. They modulate air flow and heat exchange to produce cooling island effects through evapotranspiration and emissivity, combined with reduced thermal inertia (Li and Zhou, 2019). Consequently, green spaces have proven most efficient in minimizing urban heat island (UHI) impacts and decreasing LST. Urban areas absorb and transform greater amounts of solar radiation to thermal energy because impermeable surfaces typically contain both heat-absorbing and heat-reflecting elements (Galvez et al., 2024).

Planners and policymakers have adopted diverse urban containment strategies to regulate expansion, safeguard green spaces, and influence urban spatial development (Bengston and Youn, 2006). Among various planning policies, greenbelts represent the most common strategies for managing urban development. These development-restricted zones aim to minimize urban sprawl and create healthy living environments by conserving natural surroundings. Amati (2016) states that greenbelts are important tools for protecting the environment, creating open space, controlling excessive urban growth, and ensuring sustainability of larger green spaces around urban areas. In the 21st century, climate change and sustainability issues reinforce the urgency to minimize sprawl, as greenbelts provide ecological restoration, mitigate UHI effects, and address climate change. Consequently, greenbelts serve various adaptation and mitigation functions, regarded as powerful measures for enhancing urban environmental sustainability (Han et al., 2017). Greenbelt studies have aimed to manage LULC changes, create and protect green surfaces primarily by scale and proportion, and decrease urbanization effects on landscapes.

Human activities have caused not only LULC changes but also significant variations in landscape structure spatial aspects (Wang et al., 2023). Landscape ecology seeks to understand and enhance the interdependence between landscape patterns and ecological processes (Turner, 2005). Within landscape ecology, landscape pattern studies center on quantifying and analyzing land feature composition and configuration alterations using landscape metrics (Fan and Myint, 2014). These metrics are essential tools for comprehending landscape structure, function, and changes (O' Neill et al., 1988). Humans play crucial roles in landscape formation, as land use practices significantly impact landscape structure and function. Landscape ecology offers comprehensive methods for examining connections between environmental condition changes from human land use activities and landscape patterns (Abdullah and Nakagoshi, 2006). For instance, increased surface temperature from landscape pattern alterations can create numerous ecological consequences with harmful impacts on environmental sustainability (Jia et al., 2022). Recognizing connections between land use, landscape patterns, and urban planning policies is essential for enhancing environmental sustainability (Abdullah and Nakagoshi, 2006).

Recent advances in remote sensing techniques and free time series data availability provide essential knowledge and instruments for studying LULC and landscape pattern changes. Thermal data in satellite images serve as foundations for calculating LST, valuable for environmental and climate change research in urban areas through UHI examination to detect landscape alterations (Quattrochi and Luvall, 2014). Scholars have conducted intensive research on landscape pattern-LST relationships, thoroughly exploring landscape composition and configuration influences on LST across many climatic situations (Connors et al., 2013; Estoque et al., 2017; Amani-Beni et al., 2019; Effati et al., 2021). These studies generally indicate that landscape pattern metrics can efficiently explicate LST in urban settings across diverse climates, though some cases show conflicting outcomes. For instance, shape mean index measuring shape complexity showed negative correlation with LST in green areas with trees in Accra, Ghana, a tropical sub-Saharan city (Athukorala and Murayama, 2020), but positive correlation in Beijing, China, a monsoon-influenced humid continental climate city (Liu et al., 2022b). Azhdari et al. (2018) investigated landscape structure and urban form effects on LST in Shiraz City, Iran, finding positive correlation between landscape shape index (LSI) and LST for built-up land. Conversely, Li et al. (2012) found positive association between LSI for green space and LST in Beijing City, with the same finding observed in Hangzhou City, China, characterized by monsoon climate (Song et al., 2020). The largest patch index (LPI), representing dominance, exhibited negative correlation with LST in green spaces of Hangzhou City (Song et al., 2020), Fuzhou City (Liu et al., 2022a), and Accra City (Athukorala and Murayama, 2020), with monsoon, subtropical marine monsoon, and tropical sub-Saharan climates respectively, but showed positive correlation in Beijing City (Li et al., 2013b).

These findings indicate that particular landscape metrics may have varying and even opposite impacts on thermal environments. Previous studies attribute these variations to diverse climatic conditions (Zhou et al., 2017), limiting research findings' applicability for urban planning. Hence, additional studies are vital for effective urban landscape development and management across various climates. However, research is constrained in arid and semi-arid areas. Li et al. (2023) conducted a systematic review of 167 studies on landscape metrics' significance in evaluating how urban green space configuration influences LST, finding significantly fewer studies in arid climatic areas compared to other zones, with complete absence of research in Iraq, highlighting urgent need for more arid area studies and addressing knowledge gaps in Iraq.

Prior studies have thoroughly stated greenbelts' importance for urban development. Han et al. (2017) analyzed greenbelt deregulation impacts on urban land growth in Seoul, South Korea, revealing land use expansion differences. Wang et al. (2014) investigated Shanghai City to understand land use, land cover, and socioeconomic factors' influence on greenbelt evolution. Yang and Jin (2007) analyzed spatial and temporal greenbelt variations in Beijing City using remote sensing data. These studies investigated greenbelt impacts on urbanization and land development. Additionally, previous greenbelt studies linked land use change with environmental factors such as LST, carbon dioxide (CO_2) emissions, and air pollution. Research in the United States evaluated greenbelt effectiveness in six counties for controlling urban expansion and preserving open land, finding that land use priorities should be conserved and safeguarded in these greenbelts (Han et al., 2022). Kardani-Yazd et al. (2019) examined urban greenbelt planning in Mashhad City, Iran, utilizing environmental change indices to evaluate sensitivity and environmental modifications. These studies demonstrated greenbelts' beneficial roles in managing urban expansion, land use changes, and preserving urban environmental quality.

Ultimately, although general relationships between landscape spatial characteristics and LST have been thoroughly examined, literature limitations exist concerning this relationship in semi-arid climates and greenbelts, lacking comprehensive research combining both aspects. Using Erbil City' s greenbelt with semi-arid climate as the study area, this research investigated spatiotemporal LULC landscape pattern changes and their relationship with LST. Specific aims include: (1) quantifying spatial and temporal LULC variations in Erbil City' s greenbelt; (2) assessing spatial and temporal LST changes; (3) analyzing LULC change impacts on LST; (4) determining relationships between landscape pattern changes and LST; and (5) identifying primary spatial metrics influencing LST through landscape characteristics. The study provides urban planners and policymakers with insights for reducing LST effects through LULC landscape spatial patterns in greenbelts, promoting sustainable development and enhancing well-being.

2.1 Study area

Erbil, the fourth largest city in northern Iraq, serves as the Kurdistan Region capital (36°06 54 -36°16 45 N, 43°55 15 -44°05 31 E). It has a semi-arid continental climate with dry, warm summers and rainy, chilly winters. The lowest temperature was 6.20°C in January, while the highest was 42.70°C in July 2021. Maximum precipitation was 91.70 mm in December and minimum was 0.00 mm in June (https://krso.gov.krd/en/statistics/environment).

The city experienced significant economic growth since 2003 (Baper et al., 2013), resulting in rapid urban expansion affecting surrounding green spaces. The Erbil Inner Greenbelt (EIGB) was proposed as a key project in the 2007 City Master Plan and approved on 9 January 2013, aiming to regulate urban growth and ensure survival of larger green spaces near Erbil City. According to the 2007 City Master Plan, the EIGB spans 12.00 km from Erbil City center and is bounded by Ring Ways 8 and 9. Located in city surroundings outside urbanized areas, it has a 2.00 km width and 164.75 km^2 area. Vegetation in the study area comprises shrubs, crops, and grains with small tree patches, while grass occupies the largest portion within vegetation cover.

2.2 Data sources and preprocessing

Two Landsat satellite images from the United States Geological Survey (USGS) Earth Explorer website (https://earthexplorer.usgs.gov/) served as primary data: Landsat-7 on 16 April 2000 and Landsat-8 on 21 April 2022 (Table 1). The remotely sensed datasets used various sensors, including L7 enhanced thematic mapper plus (ETM+) and L8 operational land imager (OLI) with thermal infrared sensor (TIRS) at 30 m spatial resolution. Images had relatively cloud-free scenes with 2.00% cloud cover for L7 and 0.14% for L8, associated with path/row combination 169/35.

A 22-year gap was selected between 2000 and 2022 to detect changes before and after EIGB approval in 2013. Images were acquired in April when vegetation growth peaked in the study area (Gaznayee et al., 2022). Secondary data included the EIGB map, 2007 Erbil Master Plan, geometrically corrected Erbil City map, and high-resolution Erbil City map. High-resolution maps from Google Earth Pro were also used.

Table 1 Satellite images and descriptions

Satellite/Sensor	Image ID	Path/Row	Date acquired (dd/mm/yyyy)	Scene center time (LST)	Cloud cover (%)	Projection	Ellipsoid	Resolution (m)
Landsat-7 ETM+	LE07_{{L1TP}}_{{169035}}_{{20000416}}_{{20170918}}_{{02}}_{{T1}}	169/35	16/04/2000	07:31:00 AM	2.0	UTM Zone 38	WGS 84	30
Landsat-8 OLI TIRS	LC08_{{L1TP}}_{{169035}}_{{20220421}}_{{20220428}}_{{02}}_{{T1}}	169/35	21/04/2022	07:38:00 AM	0.4	UTM Zone 38	WGS 84	30

Note: ETM+, enhanced thematic mapper plus; OLI, operational land imager; TIRS, thermal infrared sensor; ID, identification card; UTM, universal transverse Mercator; AM, ante meridiem; WGS 84, world geodetic system 1984. The images are cited from the website of https://earthexplorer.usgs.gov/.

Following satellite image download, preprocessing was vital to prepare images for spatiotemporal analysis, as Landsat 7 and 8 data are Level 1 products (Fig. 1 [Figure 1: see original paper]). Preprocessing comprises geometric and atmospheric corrections that reduce instrumental errors, noise from various sources, and lens distortions (Moravec et al., 2021).

Initially, atmospheric correction transformed digital numbers to radiance values using metadata information. Subsequently, radiance values were converted to top-of-atmosphere reflectance using the fast line-of-sight atmospheric analysis of spectral hypercubes (FLAASH) module in ENVI v.5.3 software. Before land surface temperature calculations, thermal atmospheric correction in ENVI software corrected thermal infrared bands in Landsats 7 and 8. After appropriate atmospheric adjustments and temporal variation handling, proper pixel alignment was critical (Liang and Wang, 2019). An image-to-image registration method was implemented, making the research image correspond to an accurately adjusted image of the study area using ground control points in 2000 and 2022 with root mean square errors (RMSE) of 0.28 and 0.26, respectively.

2.3.1 LULC classification

Two satellite images from 2000 and 2022 were divided into five distinct types (Fig. 2 [Figure 2: see original paper]): built-up (BU), bare soil (BS), cultivated land (CU), vegetation 1 (VH), and vegetation 2 (VL) (Table 2). VH includes various plant life forms such as crops, grains, shrubs, and dispersed trees, while VL primarily comprises grasslands (Anderson et al., 1976). Supplementary data from Google Earth Pro and high-resolution Erbil City images were used throughout. Classification accuracy was evaluated using a confusion matrix (Ali and Johnson, 2022). Results indicate overall accuracies of 92.00% in 2000 and 94.60% in 2022, with Kappa coefficients of 0.90 and 0.93, respectively (Table 3).

Table 2 LULC classification of greenbelt and description

LULC classification	Description
Built-up (BU)	Settlements like built-up village lands, roadways, and dispersed residential areas
Bare soil (BS)	Areas characterized by vegetation absence with surfaces comprising rock, sand, or clay
Cultivated land (CU)	Areas specifically prepared for agricultural use
Vegetation 1 (VH)	Various plant life forms including crops, grains, shrubs, and dispersed trees
Vegetation 2 (VL)	Areas primarily comprising grasslands

Table 3 Accuracy of classification of LULC of greenbelt in 2000 and 2022

Accuracy	2000	2022
Overall accuracy (%)	92.00	94.60
Kappa coefficient	0.90	0.93

Note: UA, user’ s accuracy; PA, producer’ s accuracy; OA, overall accuracy; KC, Kappa coefficient; -, no value.

Research area images were divided into polygon grids using ArcGIS v.10.8.1 by generating a 0.9 km$×$0.9 km fishnet. A random sampling approach selected 136 samples from 205 total samples for each year. Data extraction was conducted to calculate class-level spatial metrics using Fragstats v.4.2 software.

2.3.2 Landscape metrics

Landscape metrics serve as valuable tools for quantifying LULC categories’ spatial attributes, functioning as indicators of landscape pattern composition and configuration to assess spatial and temporal landscape variations (McGarigal and Marks, 1995). Landscape composition focuses on land cover type occurrence and proportion characteristics without clearly defining spatial attributes. Landscape configuration conversely refers to patch spatial organization and distribution within the landscape (Vanderhaegen and Canters, 2010). Metrics can be computed at class and landscape levels, with class-level metrics beneficial for studying landscape development as they indicate specific land cover type spatial distribution and patterns.

This study examined several landscape measures based on literature significance and prior research, selecting seven class-level metrics according to study objectives. These commonly used metrics evaluate landscape pattern-LST relationships (Estoque et al., 2017; Yang et al., 2017). Selected metrics include largest patch index (LPI), mean shape index (SHAPE_{MN}), landscape shape index (LSI), division index (DIVISION), aggregation index (AI), number of patches (NP), and patch density (PD) (McGarigal, 2014; Song et al., 2020; Table 4).

Table 4 Landscape metrics of greenbelt for the study

Landscape metric	Abbreviation	Description	Category	Range
Largest patch index	LPI	Percentage of landscape comprised by the largest patch	Dominance	0<LPI$ 100||*Meanshapeindex*|*SHAP* 1||*Numberofpatches*|*NP*|*Countoftota*
Aggregation index	AI	Number of similar adjacencies involving landscape class type, divided by maximum possible similar adjacencies, multiplied by 100	Aggregation	0≤AI$ $100

Chosen landscape metrics were computed using Fragstats v.4.2 software for quantitative landscape structure analysis. The eight-cell neighborhood rule and non-sampling strategy computed these metrics for all sampled polygons in 2000 and 2022 (McGarigal et al., 2023). T-test statistical analysis showed landscape pattern change significance during the study period. Bivariate correlation analysis identified statistical associations between land use class landscape metric changes and mean LST.

2.3.3 LST

LST data for 2000 and 2022 were obtained from Landsat-7 ETM+ and Landsat-8 OLI TIRS (Fig. 3 [Figure 3: see original paper]) through the following stages. The initial stage transforms thermal digital number (DN) values to spectral radiance using metadata information:

$$L_\lambda = M_L \times Q_{cal} + A_L$$

where L_λ is spectral radiance (W/(m^2 • sr • μm)); M_L is the band' s multiplicative scaling factor for radiation; A_L is the band' s additive scaling factor for radiation; and Q_{cal} is the Level 1 pixel value in DN.

The second stage converts radiance to satellite brightness temperature by applying Equation 2 (Aik et al., 2020):

$$T_B = K_2 / \ln((K_1/L_\lambda) + 1)$$

where T_B is top of atmospheric brightness temperature in Kelvin (K); K_2 is band-specific thermal conversion constant 2 (W/(m^2 • sr • μm)); and K_1 is band-specific thermal conversion constant 1 (W/(m^2 • sr • μm)).

The third stage computes normalized difference vegetation index (NDVI) using Landsat imagery' s red (Red) and near-infrared (NIR) bands (Sobrino et al., 2004) through Equation 3:

$$NDVI = (NIR - Red)/(NIR + Red)$$

The subsequent step computes vegetation proportion (P_v) using Equation 4 (Carlson and Ripley, 1997):

$$P_v = (NDVI - NDVI_{min})^2 / (NDVI_{max} - NDVI_{min})$$

where $NDVI_{min}$ is minimum NDVI and $NDVI_{max}$ is maximum NDVI.

The next stage estimates land surface emissivity (ε) through the Valor and Caselles (1996) model. The NDVI-based emissivity method (NBEM) was used to determine surface emissivity (Sekertekin and Bonafoni, 2020). Emissivity is calculated using Equation 5:

$$\varepsilon = 0.985P_v + 0.960(1 - P_v) + 0.06P_v(1 - P_v)$$

The following step calculates LST using Equation 6 (Zhang et al., 2013):

$$LST = T_B/(1 + (\lambda \times T_B/q)\ln\varepsilon)$$

where LST is land surface temperature (K); λ is emitted radiance wavelength (μm); and $q = h \times c/\sigma$ (1.438$×10^{-2}$ m•K), where h is Planck' s constant (6.626$×10^{-34}$ J•s); σ is Boltzmann constant (1.38$×10^{-23}$ J/K); and c is light velocity (2.998$×10^{-8}$ m/s).

The final stage converts LST values from Kelvin to Celsius (Dash et al., 2002):

$$T_c = LST - 273$$

where T_c is LST in Celsius (°C).

3.1 LULC and LST

Table 5 displays area and mean LST variations across LULC classes. In 2000, VL had the highest land area at approximately 56.75% of total area. VH comprised 19.94%, while CU and BS accounted for 12.33% and 9.94%, respectively. BU percentage was lowest at 1.05%. Comparable findings were identified in 2022.

Regarding LST, the lowest value in 2000 was 29.48°C in VH, followed by BU (30.42°C), with the highest in CU (31.76°C). VL and BS showed very slight LST differences. In 2022, the lowest temperature occurred in VH (30.34°C), while the highest was in CU (37.87°C). No noticeable variation appeared in LST values among the other three landscape types.

According to Table 6 , LST variance between VH and CU reached 2.28°C in 2000 and 7.53°C in 2022. Additionally, LST difference between VH and VL was 2.15°C in 2000 and 7.30°C in 2022, and between VH and BS was 2.16°C in 2000 and 7.31°C in 2022.

Table 5 Changes of area and mean LST of different LULC classifications of greenbelt in 2000 and 2022

LULC classification	Area (km^2)	Percentage (%)	Mean LST (°C)	Area (km^2)	Percentage (%)	Mean LST (°C)
VH	32.84	19.94	29.48	29.10	17.67	30.34
VL	93.49	56.75	31.63	79.12	48.03	37.64
CU	20.30	12.33	31.76	23.35	14.18	37.87
BS	16.37	9.94	31.64	20.09	12.20	37.65
BU	1.73	1.05	30.42	12.57	7.63	37.65

Table 6 Difference in LST of greenbelt between VH and the other LULC classifications

LULC classification	LST difference in 2000 (°C)	LST difference in 2022 (°C)
CU	2.28	7.53
VL	2.15	7.30
BS	2.16	7.31

Variations in LULC area and LST from 2000 to 2022 are illustrated in Figure 4 [Figure 4: see original paper]. From 2000 to 2022, VL area declined by -8.72% while LST rose notably by 6.01°C. BU experienced the most substantial expansion among landscape types with 6.87% growth rate, concurrently encountering the greatest LST increase (7.23°C). Despite CU area' s modest 1.85% rise, LST increased substantially by 6.11°C. The correlation between LULC area percentage and LST in CU was greatest ($r=0.520$; $P<0.01$). BS increased by 2.26% and LST grew by 6.01°C, with significant positive connection between LULC area percentage and LST ($r=0.279$; $P<0.01$). VH decreased by -2.27%, and notably was the only land type where LST showed slight increase (0.83°C). VH exhibited strong negative relationship between LULC area percentage and LST ($r=-0.482$; $P<0.01$).

3.2 Landscape metrics of LULC and LST

Land use metric differences between 2000 and 2022 using variance analysis (t-test) are illustrated in Figure 5 [Figure 5: see original paper]. VL and VH, comprising the majority of study area, showed similar landscape metric changing trends. Parallel with total area reduction for both classes, metrics NP and PD increased significantly from 2000 to 2022. Likewise, DIVISION and LSI index rises provide further evidence of growing disaggregation. Although VL had the highest LPI value among land uses in 2000, it witnessed significant drop in 2022. VH LPI also experienced marginal fall with notable declining trend for both classes.

Regarding BU, NP increased parallel with area growth from 2000 to 2022, noticeable in total area intensification. This result was revealed by substantial LPI value increase during the period. Additionally, significant SHAPE_{MN} and LSI rises indicated BU consisted of more irregularly shaped patches. AI increased considerably, supported by DIVISION reduction from 2000 to 2022. Although CU landscape metric changes were not significant, it showed similar trend to BU. Observed rises occurred in NP, LPI, and PD values, while SHAPE_{MN} and LSI increases suggested shift toward more complex forms. Conversely, CU DIVISION values decreased. Regarding BS, significant LPI value growth was attributed to observed area rise. DIVISION decline provided further evidence that landscape type became more aggregated. In contrast, both AI and SHAPE_{MN} showed increasing trends throughout the study period.

Pearson' s correlation coefficients indicate LST-landscape metric connections differed among LULC classifications (Table 7). For VL, no significant relation existed between LST and any class metrics. Meanwhile, strong positive correlation was found between AI and LST in BU, though no other BU metrics showed significant LST relationship. In BS, LSI, PD, and NP had strong positive LST correlation at $P<0.01$ level, while AI showed positive relation at $P<0.05$ level. Among other BS metrics, DIVISION was negatively linked while SHAPE_{MN} was positively connected, though not significant. The majority of CU landscape indices were significant except NP and PD. LPI, AI, LSI, and SHAPE_{MN} all demonstrated high significant positive LST association, while DIVISION showed high significant negative relationship at $P<0.01$ level. VH metrics LPI, SHAPE_{MN}, and AI had strong significant negative LST correlation. Conversely, DIVISION was highly positively correlated with LST and PD showed positive relation at $P<0.05$ level. Examining landscape metric relevance to LST for LULC classification, results showed VH' s highest value in LPI, followed in descending order by SHAPE_{MN}, AI, DIVISION, and PD. For CU, order was LPI, AI, DIVISION, SHAPE_{MN}, and LSI. For BS, they were LSI, NP, PD, and AI. The only landscape metric revealing significant LST correlation in BU was AI, while VL metrics exhibited no significant association during the study period.

Table 7 Pearson' s correlation between changes of landscape metrics and LST of greenbelt

LULC classification	Change of landscape metrics in 2000 and 2022	Pearson' s correlation
VH	LPI	-0.488**
	SHAPE_{MN}	-0.475**
	AI	-0.319**
	DIVISION	0.374**
	PD	0.190*
CU	LPI	0.451**
	AI	0.258**
	DIVISION	-0.415**
	SHAPE_{MN}	0.181*
	LSI	0.199*
BS	LSI	0.325**
	NP	0.417**
	PD	0.320**
	AI	0.190*
	DIVISION	-0.381**
BU	AI	0.329**
VL	-	-

*Note: **, P<0.01 level; *, P<0.05 level.*

4.1 Relationship between LULC classification and LST

Results implied both LULC type and percentage related to LST, confirming landscape composition importance in minimizing surface temperature within semi-arid greenbelts.

First, the study found that between 2000 and 2022, green spaces including VH and VL declined, replaced by non-green types comprising BU, BS, and CU. This result is attributed to village expansion and roadway extension affecting VH within them, including crops and trees. Additionally, increased private summer houses due to 2003 economic growth affected VL transition to BU, regardless of small green area presence on these farms. This aligns with Rash et al. (2023), who highlighted grassland encroachment by villagers and suburban people, transforming green spaces to BU. Climate change and drought affected VL transition to BS (Chavez Rodriguez et al., 2024), while CU expansion also affected VL due to economic growth and farmer shift to mechanical irrigation systems. Hamad et al. (2018) highlighted economic development effects on LULC change in Iraq' s Kurdistan Region, examining human activity impacts—namely agricultural practices—on landscape due to improved economic circumstances and political stability during recent decades.

Moreover, results showed LST variations among LULC classifications within these two years. VH was linked to lowest LST, aligning with other studies (Song et al., 2020; Bhagat and Prasad, 2023). However, LST difference between VH and other LULC classifications was not high, ranging from 2.00°C to 7.00°C in 2000 and 2022. Reasons include VH consisting mostly of crops, vegetables, and shrubs, while limited tree availability affected cooling consequences (Kong et al., 2014). Notably, VL LST in 2000 and 2022 increase trend were similar to BS, with LST differences existing between VH and VL. Results may be explained by grass' s minimal LST reduction effect, particularly in semi-arid areas where grass experiences water stress due to shallow roots, potentially losing evapotranspiration function sooner (Myint et al., 2015). This is consistent with Yang et al. (2017), who detected grass' s low cooling effect, while trees had greatest effects on decreasing LST compared to shrubs and crops (Bao et al., 2016; Liu et al., 2022b). Thus, planning greenbelts in semi-arid climates requires emphasizing green space types comprising mostly trees, followed by shrubs, crops, and vegetables. Conversely, VL consisting of grass should be less considered by urban and landscape planners.

CU had highest LST within these two years and highest LST difference with VH. The same trend was observed for BS but with slight LST difference from CU. Reasons can be attributed to BS and CU characteristics, wherein vegetation absence and reduced moisture content eventually increase surface temperatures. Rasul et al. (2017) and Azhdari et al. (2018) confirmed BS heating effects in semi-arid areas, though previous studies have not investigated CU heating effects in semi-arid regions.

LST was lower in BU than BS and CU, and even lower than VL in 2000. This result is explained by two reasons: first, most village building material was mud in 2000, which has low surface temperature (Madhumathi et al., 2014); second, green spaces including trees and shrubs in BU played important cooling roles. However, the 2022 BU trend differed as LST was high. Reasons relate to building material change to concrete in 2022, critically impacting LST elevation (Connors et al., 2013). Materials such as cement and tiles, commonly used in buildings, squares, housing developments, roads, and bridges, release considerable heat, causing elevated temperatures (Wang et al., 2017). Results revealed that BU temperature in semi-arid areas mostly correlated with urban areas, and BU LST was lower than BS LST (Rasul et al., 2015).

Additionally, not only landscape type but also LULC classification changes affect LST. Pearson' s correlation results revealed variations in LULC classification change impacts on LST. VH had significantly negative effect, while VL had no effect. This result parallels Naeem et al. (2018), who found that increasing green space proportion with trees or reducing impermeable surface percentage can enhance cooling impact more efficiently. Findings revealed CU and BS had significantly positive effects, while BU had no effect. Similar results were found in other studies (Lai et al., 2012; Li et al., 2013a; Myint et al., 2015; Naeem et al., 2018; Amani-Beni et al., 2019).

4.2 Relationship between landscape metrics and LST

In this study, LULC classification exhibited landscape spatial distribution changes that substantially impacted LST from 2000 to 2022. Specifically, VH patches became more fragmented, heterogeneous, and dispersed due to NP, LSI, DIVISION, and PD increases. Nevertheless, only DIVISION and PD showed significantly positive relations. LPI, SHAPE_{MN}, and AI value reductions resulted in smaller, fragmented, disaggregated patches, showing significantly negative LST connections. Consequently, VH spatial configuration metrics impacted LST. However, VL had similar spatial characteristics to VH, but VL metric correlations with LST were not significant, thus VL spatial configuration had no LST effect. These findings align with Hou and Estoque (2020), who found negative LPI, SHAPE_{MN}, and AI correlations with LST for VH, while VL metrics had no significant relation. Previous studies by Maimaitiyiming et al. (2014) and Masoudi and Tan (2019) verified these results.

Nevertheless, BU LPI, NP, SHAPE_{MN}, LSI, and AI increases suggest transition to more dominant, aggregated, complex, and irregular patches, while DIVISION reduction showed aggregation and homogeneity. However, only AI showed substantially positive LST correlation. Li et al. (2011) demonstrated similar findings, affirming BU effects on elevating LST. Results showed CU patches became more homogenous, irregular, aggregated, and larger as AI, LPI, SHAPE_{MN}, and LSI increased. DIVISION reduction indicated defragmentation with significantly negative association. Madanian et al. (2018) found similar results regarding AI and LPI effects of harvested agricultural land on rising LST. Findings revealed BS became more irregular and complex with SHAPE_{MN} and LSI increases in 2022. Additionally, patches became more contiguous due to AI rise, with significantly positive correlation. Li et al. (2020) observed that BS scattered arrangement and limited connectivity contributed to efficient warming effect mitigation.

These results led to the conclusion that VH metrics had greatest impact, with the highest number significantly correlated with LST, as recognized in previous studies (Li et al., 2011; Liu et al., 2022b). Conversely, VL metrics had no LST effect. Consistent with Azhdari et al. (2018), this study found CU and BS metrics had high influence on increasing LST. Findings showed BU metrics did not have consequential LST effects. Results are comparable to Zheng et al. (2014) but differ from other research (Liu and Weng, 2008; Effati et al., 2021), suggesting BU metrics effectively raised LST. Results proved AI metrics were most impactful due to significant LST correlations in all LULC classifications except VL. These results are similar to prior studies by Li et al. (2012) and Estoque et al. (2017), revealing that green and impervious patch defragmentation and aggregation had the most consistently significant LST relations.

Ultimately, LULC spatial characteristic variations and their LST relations were observed. As VH patches became disaggregated, fragmented, smaller, and regularly shaped, LST increased. Conversely, elevated BS and CU surface temperatures were associated with contiguous, aggregated, defragmented, larger, and complex patches. BU LST increased as patch layout became more concentrated and aggregated. Thus, landscape designers and planners must consider LULC spatial configuration to enhance VH cooling impact and reduce CU, BS, and BU warming effects within semi-arid greenbelts.

4.3 Implications and limitations

Findings provide guidelines for urban planning and landscape design. First, it is essential to increase VH by focusing on denser tree availability through afforestation to decrease BS and VL. Additionally, CU should be converted to agricultural lands utilizing specific vegetation types that can grow within greenbelts year-round, reducing dry CU effects on LST elevation. Second, urban planners and policymakers should optimize specific LULC spatial patterns to mitigate LST by connecting small VH patches to produce larger aggregated green corridors and planning irregularly shaped VH within CU and BS to divide them into smaller fragmented patches. Similarly, gardens and green spaces with dense trees should be included in villages and main roads to scatter BU layout.

Overall, the study provides valuable insights and expands limited knowledge on landscape composition and configuration effects on LST within semi-arid greenbelts, promoting sustainable development.

As the study examined spatial and temporal landscape metric changes within a two-year period, several limitations exist. Freely available remote sensing data with enhanced spatial resolution had accessibility constraints throughout the study period, affecting precise quantitative outcome acquisition. Furthermore, data limitations influenced LULC classification without characteristic consideration. For instance, restrictions prevented consideration of tree species within VH, and evaluation of greenness, leaf pigments, chlorophyll levels, and vegetation water content. Additionally, BU had data constraints regarding village block types and building features. Moreover, the study depended solely on spring daytime remote sensing data. Future research could consider seasonal and nighttime data for landscape pattern-LST relationship analysis. The study was conducted in Erbil City, Iraq, with semi-arid climate, and findings may not generalize to dissimilar climate areas. Further research employing higher-resolution remote sensing data regarding detailed LULC classification parameters is recommended. Additional studies might expand present understanding of spatiotemporal landscape pattern-LST relationships within greenbelts of other semi-arid climate cities.

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5 Conclusions

The study examined spatial and temporal LULC changes and their LST relationships from 2000 to 2022 within an inner greenbelt in semi-arid Erbil, northern Iraq. Results indicate LST may be alleviated by specific LULC types throughout planning processes. Raising VH and improving it by adding more dense trees is recommended. This aligns with previous strategies emphasizing green space expansion in greenbelts. Within LULC, reducing BS and CU areas would be beneficial. However, in semi-arid areas, raising VL or lowering BU does not substantially contribute to greater surface temperature reduction. The most efficient cooling landscape type among all LULC classifications was VH, consisting of crops, grains, shrubs, and dispersed trees. Urban planners must prioritize optimizing effective LULC spatial configuration to reduce LST within semi-arid greenbelts. VH patches should be larger, aggregated, concentrated, and complex-shaped. Additionally, scattered BU patches and small, fragmented, dispersed, regular-shaped BS and CU patches can contribute to LST reduction. Therefore, LST in semi-arid greenbelts can be altered not only by landscape composition but also by spatial configuration improvement.

Conflict of interest

The authors declare no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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