



# The relationship between spatial configuration of urban parks and neighbourhood cooling in a humid subtropical city

Ravi Verma · Joanna Ewa Zawadzka ·  
Pradeep Kumar Garg · Ron Corstanje

Received: 24 April 2023 / Accepted: 26 December 2023 / Published online: 14 February 2024  
© The Author(s) 2024

## Abstract

**Context** Urban parks are essential for maintaining aesthetics within cities and keeping their its energy balance by helping mitigate the Urban Heat Island (UHI) effect through controlling ambient and land surface temperature (LST).

**Objectives** To investigate the impact of cooling in terms of distance by variously configured urban parks of a humid subtropical city, using landscape metrics and open-source data.

**Methods** Land use (LU) was obtained through maximum likelihood classification of 3 m resolution aerial RGB-NIR imagery supported by ground control points and park boundaries collected during

field survey. LST at matching resolution was obtained through downscaling of Landsat-8 LST at 30/100m resolution, calculated with the Radiative Transfer Equation (RTE). Landscape metrics for patches of parks were calculated using *landscapemetrics* R library and related to neighbourhood distances over built-up land use (LU).

**Results** Urban parks with homogenous cores and less complex shape provide distinctly higher cooling of neighbouring built-up LU of circa 2.55 °C over the distance of 18 m from park boundaries. Four metrics: contiguity index (CONTIG), core area index (CAI), fractal dimension index (FRAC) and perimeter-area ratio (PARA) represent significant relationship between spatial configuration of parks and their cooling distance. No cooling capacity of parks regardless of their shape and core was observed beyond the distance of 18 m, which remained constant with small fluctuations in the range of 0.5 °C up to the distance of 600 m.

**Conclusions** The study concludes that cooling distance of urban parks in their neighbourhood extends up to 18 m, which is shorter than suggested by other studies.

---

**Supplementary Information** The online version contains supplementary material available at <https://doi.org/10.1007/s10980-024-01818-y>.

---

R. Verma · P. K. Garg  
Department of Civil Engineering, Indian Institute of Technology Roorkee, Roorkee, Uttarakhand 247667, India  
e-mail: rverma2@ce.iitr.ac.in

P. K. Garg  
e-mail: p.garg@ce.iitr.ac.in

R. Verma · J. E. Zawadzka (✉) · R. Corstanje  
Cranfield Environment Centre, Cranfield University,  
Bedford MK43 0AL, UK  
e-mail: joanna.zawadzka@cranfield.ac.uk

R. Corstanje  
e-mail: roncorstanje@cranfield.ac.uk

**Keywords** Heat mitigation · Urban parks · Landscape metrics · Land use · Open-source data

## Introduction

In recent decades, urbanisation has become an important driver of climate change and a hot spot of urban growth (Scheuer et al. 2017) and irrespective of the findings that future urbanisation in cities will be of almost homogenous growth (Lemoine-Rodríguez et al. 2020), impacting albedo of the area (Ouyang et al. 2022) and contributing to the formation of the Urban Heat Island (UHI). The UHI can be used to describe the urban thermal environment in which urban centres and rural neighbourhoods of cities are facing a significant temperature difference (Zhou et al. 2014; Deilami et al. 2018; Yang et al. 2019). The UHI can be related to other issues occurring in the cities such as pollution (Li et al. 2018), health of city dwellers (Yuan et al. 2022), disturbance in energy balance (Hou et al. 2022) and unplanned urbanisation (Cui et al. 2016). Built-up and barren land being dominant factor for affecting urban thermal environment (Peng et al. 2016), in 44% of case studies concerning the UHI (Deilami et al. 2018), the driving factor behind its formation was vegetation loss (Cui et al. 2021; Hassan et al. 2021). Other influential factors include climate change (Zhao et al. 2014; Yang et al. 2021; Santis et al. 2021), seasonality (Peng et al. 2018; Guha and Govil 2022), diurnal temperature characteristics (Li et al. 2022), urbanisation patterns (Liu et al. 2018; Guo et al. 2019a; Stewart and Kremer 2022) and population density (Jaber 2020) among others. The UHI has implications on socio-economic factors of population such as monthly income (Buyantuyev and Wu 2010) as well as residential energy requirement (Imhoff et al. 2010).

Mitigation of the UHI can be achieved by greening specific parts of a city through introducing Urban Green Spaces (UGS) (Kotharkar et al. 2020), with the cooling effect being detectable at regional (Cui et al. 2021; Mohiuddin and Mund 2021), local (Yu et al. 2018; Guo et al. 2019a) and neighbourhood scales (Srivani & Hokao, 2013; Zawadzka et al. 2021). Cooling intensity of UGS in cities can be experienced up to a certain distance away from UGS, known as the inflation distance (Yu et al. 2017) or first turning point (Du et al. 2022), after which the cooling impact is no longer detectable. Literature points to a wide range of cooling distances of urban greenspaces that have been detected through land surface temperature (LST) analysis captured by medium resolution sensors, such

as Landsat OLI, which can range from 30 to 340 m in Changsha, Hunan Province, China (Qiu et al. 2023), up to 240 m in Addis Ababa, Ethiopia (Feyisa et al. 2014), and up to 347 m in Bengaluru, India (Shah et al. 2021). The differences in cooling distance were often attributed to the size and composition of the green spaces, with larger and greener parks contributing to more extensive cooling. Fewer studies used high resolution LST data. For example, Sun et al. (2023) obtained LST at 0.5 interval with a hand-held thermal infrared imager to determine that the cooling distance range of urban parks was 1.74–58.48 m in Xi'an City in Shaanxi Province, China.

Land surface temperature (LST), which is one of the factors in UHI formation (Voogt and Oke 2003) can be used for UHI magnitude studies (Tran et al. 2006; Zhou et al. 2018a) as well as quantification of the cooling effect of urban green spaces (UGS) (Sun and Chen 2017; Ekwe et al. 2021). LST can be derived from remotely sensed satellite images, capturing the thermal response of land surface at a variety of spatial resolutions. Deilami et al. (2018) reported that UHI studies have been predominantly carried out with medium- (Landsat, ASTER at 60 to 120 m) to low-resolution (MODIS, AVHRR at 1 km) thermal imagery. Whilst some authors argued that medium resolution LST may be sufficient for understanding the intra-urban heat variation (Kianmehr et al. 2023), others demonstrated that finer resolution LST can be important, especially when ascertaining the cooling distance of UGS (Zawadzka et al. 2021) at a neighbourhood scale. Moreover, micro-scale studies focusing on thermal comfort within buildings (Kandya and Mohan 2018; Alexander 2021; Tian et al. 2021) have brought out the importance of fine resolution imagery. Given that very fine (<5 m) spatial resolution open-source LST data is not currently available, LST downscaling can be used to sharpen the existing open-source medium to low resolution thermal satellite imagery through their proven relationship with high-resolution ancillary data (Zhan et al. 2013), including spectral indices such as the NDVI (Agam et al. 2007), NDBI and others (Zawadzka et al. 2020a).

Perception of open spaces' attributes can help in assessing thermal comfort objectively (Manavvi and Rajasekar 2023; Wei et al. 2022). Landscape configuration analysis of UGS can help in establishing a link between ecosystem services and UGS characteristics

(Grafius et al. 2018). Whilst the size of green spaces can directly affect LST patterns in cities (Srivani and Iamtrakul 2019; Gomez-Martinez et al. 2021), the impact of UGS on urban thermal environment can also be linked with their spatial patterns represented by landscape metrics (Yan et al. 2021, McGarigal & Marks, 1995), that add information on the shape of the UGS patches. Quantification of landscape metrics requires that a land cover map of sufficient spatial resolution is available. For example, the use of Landsat satellite images may not be helpful in detection of smaller green spaces (Qian et al. 2015), given that local scale climate effect of urban parks can be directly related to its size (Li et al. 2021b; Peng et al. 2021). Consequently, the spatial resolution of the imagery used to derive land cover maps is equally important (Li et al. 2013) as the spatial resolution of LST data. Since LST depends upon spatial configuration of a landscape as much as it depends upon landscape composition (Zhao et al. 2020), shape and size of UGS need to be accounted for to better understand their cooling capacity in their neighbourhoods (Xiao et al. 2021). Urban cooling distances can be more accurately analysed through use of higher resolution LST data as medium resolution data such as Landsat OLI captured at 100 m, may affect the results (Zhou et al. 2022).

In this study, our objective was to determine the cooling distance and cooling intensity of urban parks in relation to their spatial configuration characteristics determined by landscape metrics. Our focus was on relatively small urban parks with sizes rarely exceeding 1 ha, which differentiates our approach from other studies, where park sizes ranged from circa 1 to over 22 ha. We mitigated the possible adverse effect of medium resolution thermal imagery on accurate representation of UGS cooling distances by downscaling Landsat 8 derived LST to 3 m resolution using high-resolution RGB-NIR satellite imagery, which is particularly relevant for smaller parks. We hypothesised that the cooling effect of small parks is confined to their direct footprint only.

In our analysis, we used publicly available medium- and high-resolution satellite imagery to emphasise the importance of urban parks in understudied and less-populated cities of India, classified as Tier 2 on the road of smartification, and exemplified by Lucknow City. As such, we provided evidence for the extent of the cooling capacity of parks in

humid subtropical cities, for which data in literature is limited.

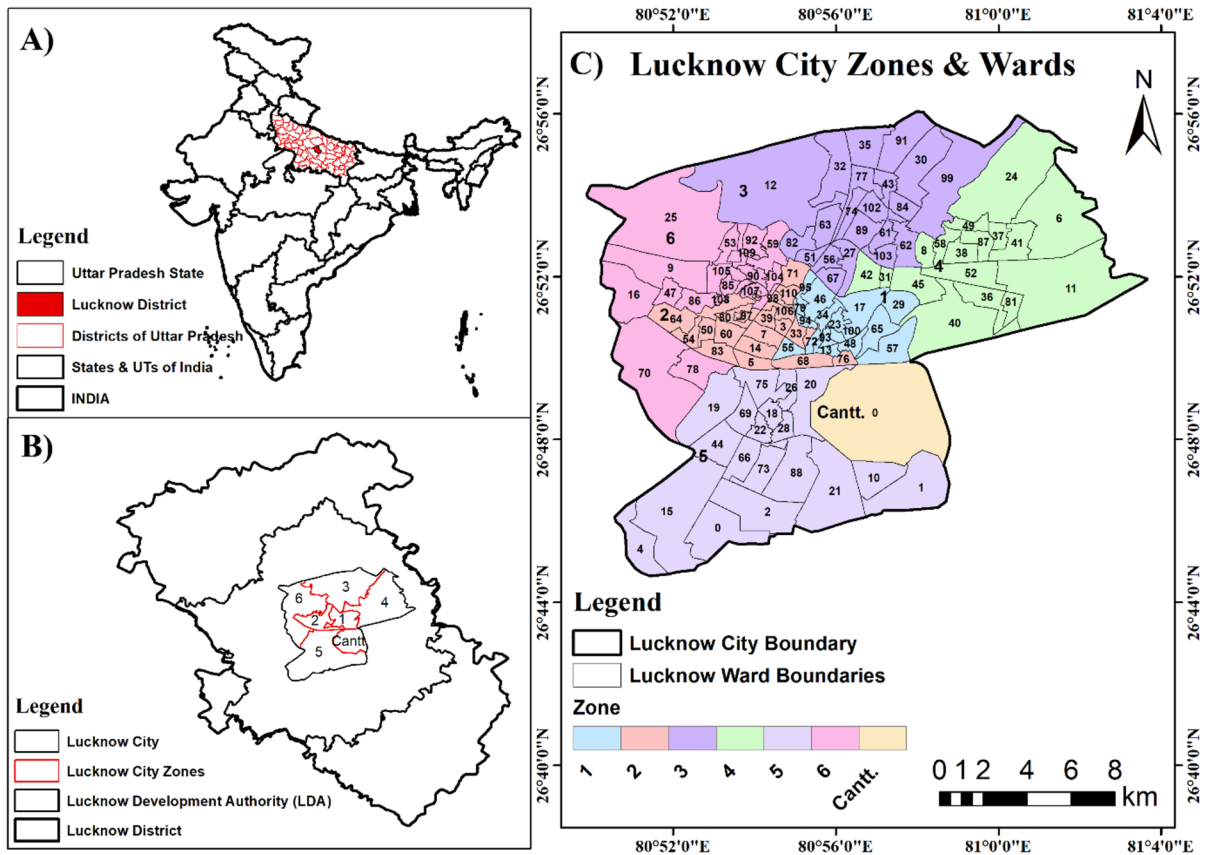
The secondary objective of this study was to provide a methodology for assessment of heat mitigation capacity of UGS with the use of open-source data, making such assessments feasible wherever financial resources are limited. Not only this study provided a direct qualitative perspective of UGS in terms of UHI mitigation in humid subtropical cities but also a quantitative perspective in achieving the Sustainable Development Goals set by World Health Organisation (WHO) (Egorov et al. 2016), related to Goal 11: sustainable cities and communities with focus on target 11.7 "...provide universal access to safe, inclusive and accessible, green and public spaces (...)" and target 11.b "...substantially increase the number of cities and human settlements adopting and implementing integrated policies and plans towards inclusion, resource efficiency, mitigation and adaptation to climate change (...)". Consequently, the results of this study are expected to equip spatial planners and decision makers with further insights to planning thermally comfortable and sustainable cities of the future.

## Materials and methods

### Study area

Lucknow city was selected as the study area as it is one of the fastest developing Tier-2 cities in India and one of the 100 cities to be developed as a smart city in the future by the Government of India under SMART CITY MISSION. Lucknow has flourished economically and socially with the help of infrastructure growth in the last 20 years. Being in the centre of the capital district of the largest state of India (Fig. 1A), Uttar Pradesh (Fig. 1B), Lucknow city has seen much more immobilisation of population from neighbouring towns and districts than any other of the eleven smart cities in Uttar Pradesh.

Lucknow is situated in the humid subtropical climate (Cwa in the Köppen climate classification system) with hot, dry summers from March to May and dry winters from November to February. It receives the southwest monsoon rain (828 mm) near about 20th June every year and also a significant amount of rain during the retreat of monsoon. Maximum temperature can reach up to 48 °C and minimum down to



**Fig. 1** Location of the study area within India (A), the Uttar Pradesh State (B) and the Lucknow City (C)

1.67 °C. Water level stands generally at 18 m below the ground. Population of the city was at 2.81 million as per 2011 census of India, and which is estimated to increase to up to 4.6 million by 2031. This large stratum of population has put pressure on ecological balance of the city. Continuing development to accommodate population and new industrial growth has put constraints on local population to depend upon existing parks for health and wellbeing benefits. To counteract this imbalance, local authorities introduced large parks of varied sizes within the boundary of the city. The city also comprises a portion of the Kukrail Ghariyal Reserve Forest, which was planted in 1950 as an urban forest and is being used as part of Ghariyal Rejuvenation scheme since year 1973.

Lucknow city consists of 7 Zones and the total of 112 wards (Fig. 1C). It is part of the Lucknow Development Authority Area (LDA) with most of urbanisation occurring within the city limits. Inside the Lucknow city boundary, except for the Cantonment Zone

(Cantt.), which is a defence area reserved by Indian Military, urbanisation is most dense near the centre and increasingly dispersed towards the outskirts. Zones 1 & 2 comprise most of the administrative buildings of Lucknow city and Uttar Pradesh state as well as other commercial and business areas. These zones also contain the largest parks. Zones 3, 4, 5 & 6 are mostly urbanised towards the centre of Lucknow city, with the outer boundaries of these zones still in the development phase. The parks here are smaller and dispersed across the zones. Zones 3, 4 & 6 contain some areas of reserve forests within their boundaries, with the cantonment zone being the richest in vegetation.

#### Data

In this study, two types of data, namely, satellite and inventory, were used. PlanetScope satellite images were used to generate a land use map of the area.

Data provided by local authorities in the form of inventories of parks or development masterplans of Lucknow, were used to generate vector files such as boundaries of zones, wards, and parks (Table 1). A Landsat-8 OLI/TIRS image was used to generate an LST map of the city and a PlanetScope image comprising of blue, red, green and NIR bands at 3 m resolution was used for land use classification. PlanetScope data, which are captured by the SkySat satellite constellation, is an open-source data downloaded through institutional or departmental access of Planet Explorer. The high spatial and spectral resolution makes this data especially useful for urban studies. Zone and ward boundaries of Lucknow city are open access material which can be found in the masterplan of Lucknow City for Smart City Mission. Digitisation of parks was done through field survey and Google Earth Engine vectorisation based on the lists of parks provided by the Lucknow Nagar Nigam local authority.

## Methods

### *Overview of the methodology*

The methodology for the determination of the relationship between spatial configuration of urban parks and their cooling in this study comprised of several steps (Fig. 2). Firstly, vectorisation of parks was carried out and this file was in part used to classify land use of Lucknow city at 3 m resolution using PlanetScope data. Secondly, LST was derived from Landsat-8 TIRS images and then downscaled to 3 m resolution with NDVI products of both Landsat and PlanetScope data. Thirdly, land use and downscaled LST at 3 m resolution were used to establish the relationship between spatial arrangements of urban parks

and their cooling effect over LST within multiple sets of concentric neighbourhoods.

### *Digitisation of parks*

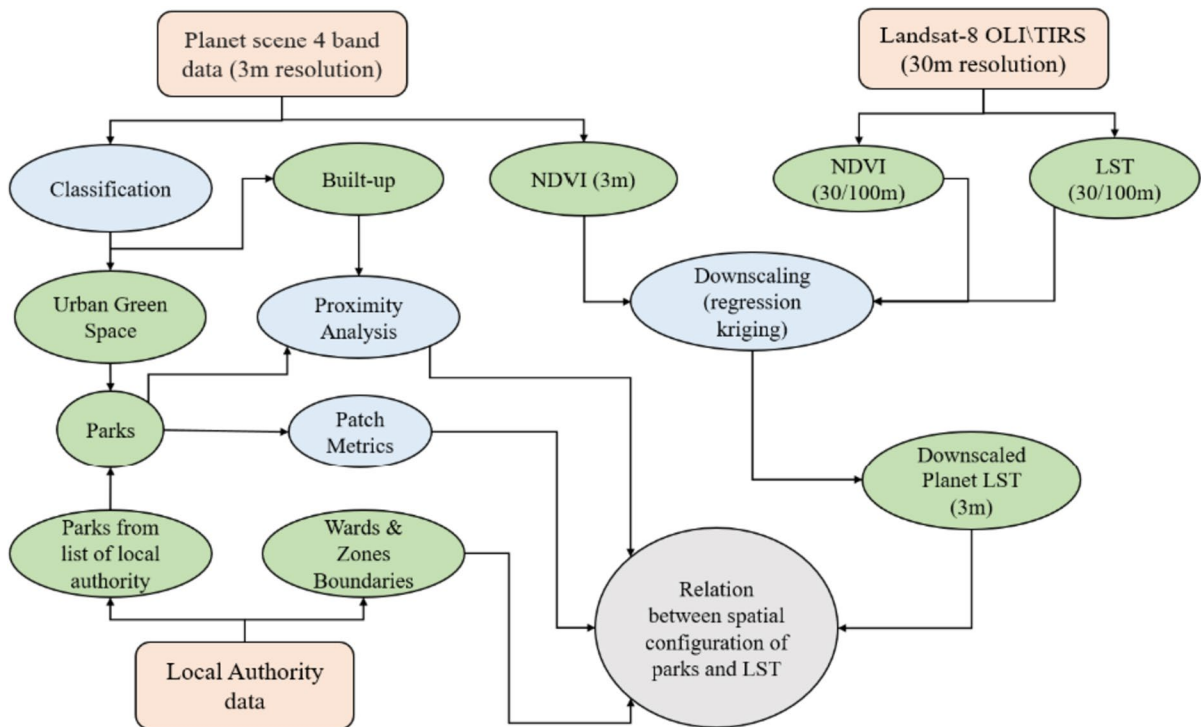
Zone and ward boundaries obtained through the master plan were topologically corrected through GIS software programmes. A list of 1684 parks containing information about the location (nearby house/building address), ward no. and corresponding zone no., was obtained from Lucknow Nagar Nigam website and used for digitisation of 1540 parks in GIS environment. This digitisation took place through both field survey and Google Earth maps. Additional 209 parks were found through the Open Street Map (Table 2). In total, 1893 parks were digitised through different sources (Fig. 3) across all Zones except for the Cantonment (Cantt.), as the zone is a part of the defence establishment with limited data access. These 1893 digitised parks helped in extracting patches of parks from classified PlanetScope data and subsequently related to LST maps for determining the impact of parks' spatial attributes on LST in their neighbourhoods.

### *Land Use classification*

Four scenes of PlanetScope RGB+NIR data were used to create a mosaic covering the Lucknow city area. LU map was obtained from a false colour composite (FCC) of all the bands of the mosaicked image classified using Ground Control Points (GCPs) collected through field survey and Google Earth Engine (GEE). 192 points in total were used for sampling and 96 for accuracy assessment.(Fig. 4A). Maximum likelihood algorithm was used to classify the FCC into 7 main classes: Roads, Built-up, Barren, Bare soil, Water, Shrubs and Vegetation (Fig. 4B). Bare soil LU

**Table 1** Data used in this study

Name	Date	Data agency
Landsat-8 OLI & TIRS (30/100m resolution)	16/04/2020	USGS Earth explorer ( <a href="https://earthexplorer.usgs.gov/">https://earthexplorer.usgs.gov/</a> )
PlanetScope scene_4 Band (3 m)	17/04/2020	Planet explorer ( <a href="https://www.planet.com/">https://www.planet.com/</a> )
Zone/ward boundaries	January, 2020	Master Development Plan, Lucknow ( <a href="https://lmc.up.nic.in/">https://lmc.up.nic.in/</a> )
List of parks	January, 2020	Lucknow Nagar Nigam ( <a href="https://lmc.up.nic.in/">https://lmc.up.nic.in/</a> )



**Fig. 2** Overview of the methodology for quantification of the cooling effect of spatial pattern of urban parks in their neighbourhoods

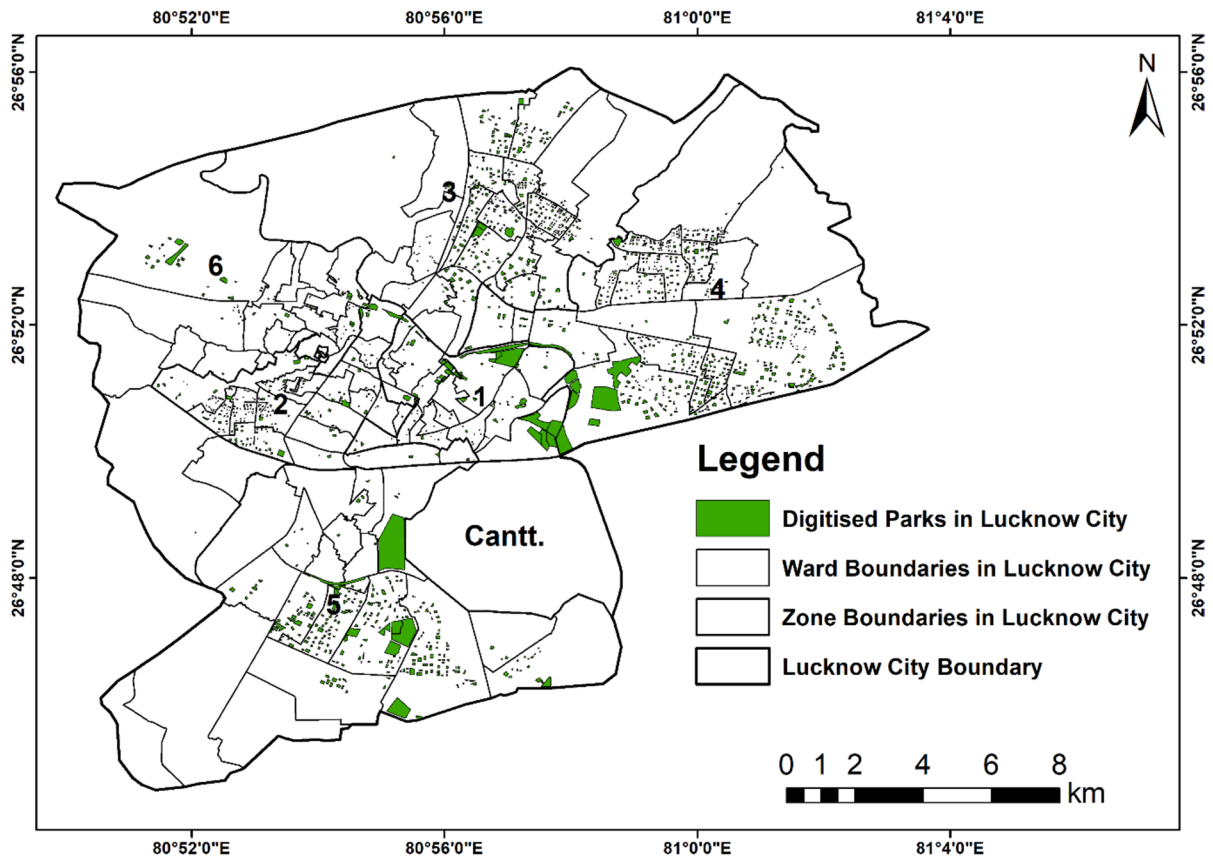
is part of agricultural land left in prospect of urbanisation. Overall classification accuracy of Planet data was 90.63% with kappa statistics of 0.88 (Supplementary Materials 1). Shrub and vegetation LU classes in were merged for to depict urban green space distribution within the study area. Digitised parks were then used to extract UGS that corresponded to patches of urban parks only.

### *LST mapping and downscaling*

In this study, LST data was sourced from the Landsat 8 TIR bands 10 and 11, which are captured at 100 m resolution and subsequently resampled by the data provider (United States Geological Survey) to 30 m resolution to match the spatial resolution of the OLI bands – a process that places the actual spatial resolution of the Landsat 8 - derived LST maps somewhere between 30 and 100 m. The LST maps were generated with the application of two algorithms: radiative transfer equation (RTE) (Sobrino et al. 2008) and at-surface brightness temperature (ASBT) (Stathopoulos and Cartalis 2007) with the split-window method

(Jiménez-Munoz et al. 2014), described in detail in Supplementary Materials 2. We considered the spatial resolution of Landsat 8 LST maps to be too coarse for the purpose of this study as the cooling distances of parks may be capped at below 30 m, and therefore applied an LST downscaling method to match the 3 m spatial resolution of the PlanetScope data.

Downscaling of Landsat-8 LST of 30/100m resolution to 3 m resolution was achieved through the process of regression, prediction, residual calculation, kriging of residuals and addition of residuals. The LST downscaling method used here was based on the method by Zawadzka et al. (2020a) whereby Landsat 8-derived LST data was downscaled to 2m resolution using high-resolution spectral indices derived from hyperspectral imagery and other ancillary data. In our study, we could only use the normalised difference vegetation index (NDVI), calculated from red and near-infrared bands, as the sole scaling factor of LST due to the limited spectral resolution of the Planet data. In the downscaling process, LST at 30/100m resolution was related to Landsat-derived NDVI, which was resampled to 100 m and then back



**Fig. 3** Parks digitised in Lucknow city boundary

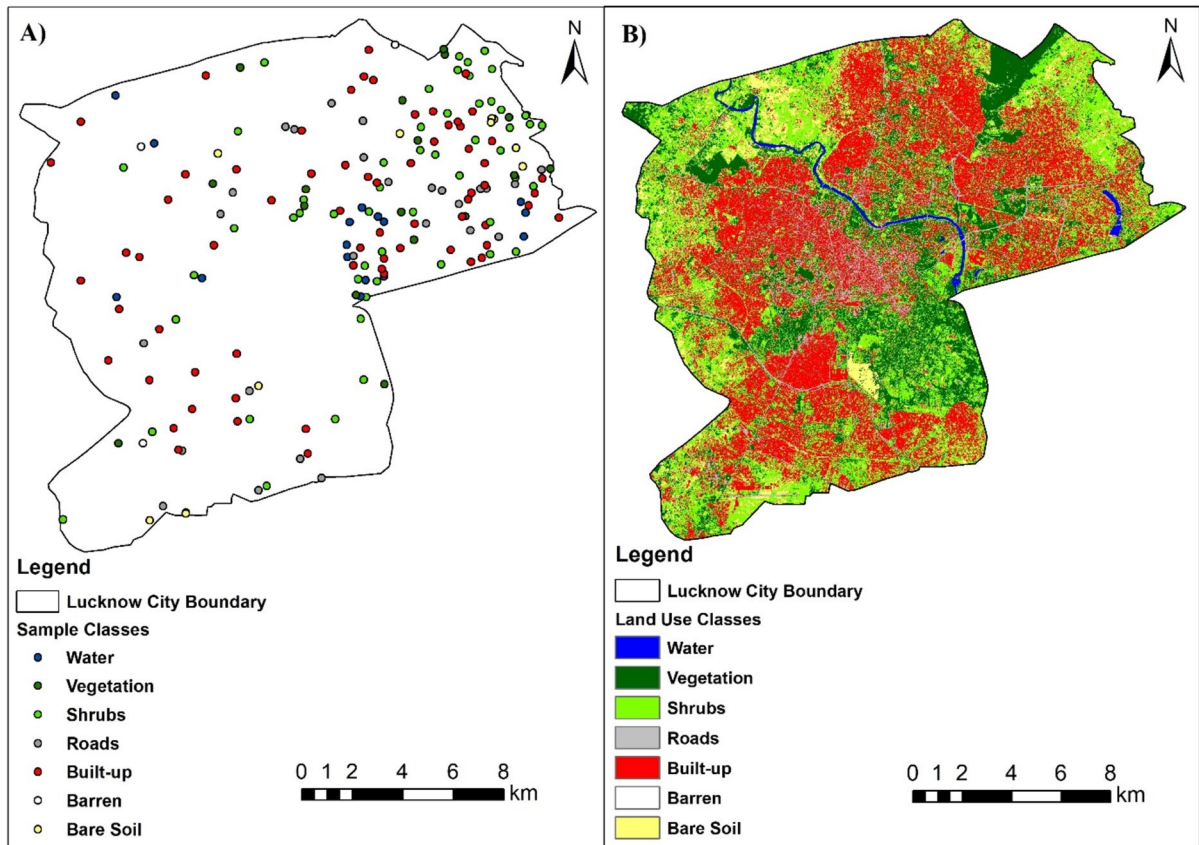
**Table 2** Different sources/lists of parks

Zone no.	No. of wards	As per in list of Local Govt. Body (Nagar Nigam)	Digitised as located in field survey and GEE	Open street maps (OSM)	Total no. of Parks
1	16	57	71	20	91
2	20	297	239	21	260
3	21	389	360	112	472
4	17	597	529	155	684
5	19	273	273	24	297
6	18	71	67	22	89
Total	111	1684	1539	354	1893

to 30 m to match the mixed spatial resolution of the LST. Two methods, the ordinary least squares (OLS) regression and multiple adaptive regression splines (MARSplines), were used to find the relationship between NDVI and LST. The strength of the relationship was assessed via the coefficient of determination  $R^2$  (Table 3), which indicated that a portion of the

variation in Landsat8-LST (30/100m) remained unexplained by NDVI.

These regression equations were then used to downscale the Landsat-8 LST to 3 m using Planet-Scope-derived NDVI. To take account of the unexplained portion of variation in LST by NDVI, residuals calculated between Landsat-8 LST (30/100m)



**Fig. 4** Classified map of Lucknow city at 3 m resolution from Planet FCC. (A) Ground control points, (B) resulting classified map of land use

**Table 3** Linear and MARSpline regression between Landsat-8 LST (30/100m) and Landsat-8 NDVI (30/100m)

S.No.	LST calculation technique	Regression method	Best Fit regression equation	R <sup>2</sup>
1	At surface brightness temperature (ASBT)	Linear	$y = 35.3 - 1.65x - 11.7 \times 2$	0.49
2		MARSpline	$y = 34.5 - 0.969x - 0.134 \times 2 - 0.798 \times 3 - 2.23 \times 4 - 2.46 \times 5 - 5.79 \times 6$	0.52
3	Radiative transfer equation (RTE)	Linear	$y = 35.5 - 6.43x$	0.34
4		MARSpline	$y = 34.2 - 0.589x - 2.54 \times 2 - 4.51 \times 3$	0.42

and Planet LST (3 m) were distributed across the study area at 3 m resolution using the ordinary kriging method and subsequently added to the Planet LST (3 m). Accuracy assessment (Table 4) of downscaling process shows that the downscaled map generated through OLS regression on Radiative Transfer Equation Landsat-8 LST (30/100m) had a stronger relationship as determined by R<sup>2</sup> to Planet

NDVI (3 m) than the ASBT method. All methods resulted in downscaled LST exhibiting overall LST patterns similar to the original LST as well as to each other as measured by R<sup>2</sup> and root mean square error (RMSE) and Pearson correlation coefficient *r*. Upon visual inspection of the downscaled maps, the OLS RTE map was chosen for further analysis due to the greater sharpness of the LST values.



**Table 4** Accuracy assessment of the LST downscaling process using coefficient of determination ( $R^2$ ), Pearson correlation coefficient  $r$ , and root mean square error (RMSE)

	At surface brightness temperature (ASBT)		Radiative transfer equation (RTE)	
	Linear	MARSpline	Linear	MARSpline
Downscaled planet LST (3 m) and planet NDVI (3 m)	$R^2=0.89$	$R^2=0.81$	$R^2=0.94$	$R^2=0.88$
Planet LST downscaled at 3 m and Landsat-8 LST resampled at 3 m	$r=0.35$ $R^2=0.12$ RMSE=1.77 $p<2.2e-16$	$r=0.35$ $R^2=0.12$ RMSE=0.52 $p<2.2e-16$	$r=0.3$ $R^2=0.09$ RMSE=1.45 $p<2.2e-16$	$r=0.32$ $R^2=0.1$ RMSE=0.86 $p<2.2e-16$
Planet LST resampled at 30 m and Landsat-8 LST at 30 m	$r=0.36$ $R^2=0.13$ RMSE=1.77 $p<2.2e-16$	$r=0.37$ $R^2=0.13$ RMSE=0.52 $p<2.2e-16$	$r=0.29$ $R^2=0.086$ RMSE=1.47 $p<2.2e-16$	$r=0.32$ $R^2=0.1$ RMSE=0.87 $p<2.2e-16$

*Cooling capacity of urban parks on their neighbourhoods*

The determination of the cooling capacity of urban parks on their neighbourhoods involved identification of the distance away from park boundaries over which cooling occurred as well as the magnitude of temperature difference between parks and their surroundings, focussing solely on the built-up land cover class. This process involved extracting park patches from the 3 m resolution classified LU map using digitised park boundaries, which excluded non-park greenspace patches from the analysis.

The cooling extent of parks was determined through buffer analysis. Concentric buffers up to the distance of 600 m every 3 m (only up to 30 m distance), 6 m (only up to 60 m distance), 30 m (up to 300 m) and 60 m (up to 600 m) were generated via the proximity analysis in GIS environment. Buffers for each park patch were matched through their unique ID and merged to create a vector file containing park patches and their neighbourhoods represented by concentric rings of all buffers. Both the park patches and built-up spaces within the concentric buffers were attributed with means of the downscaled LST. Next, scatterplots representing the mean LST within parks and the concentric buffers for each zone of the city separately as well as for the entire city were constructed to identify the inflation point (Yu et al. 2017) or the first turning point (Du et al. 2022) and consequently the maximum cooling distance of parks. Additionally, regression analysis and coefficients of determination  $R^2$  were used to determine the strength

of the relationship between LST of the parks and the LST of the surrounding built-up spaces, which provided a measure of the contribution of the urban parks to cooling of their neighbourhoods. Cooling magnitude was calculated as the difference between the mean LST of built-up spaces within the concentric rings drawn around the parks and the mean LST of the parks.

*Impact of spatial configuration of urban parks on their cooling capacity*

Patch-level landscape metrics were used to describe the spatial configuration of park patches in our study area. We used an open-source R tool and the *landscapemetrics* (Hesselbarth et al. 2019) library to derive all twelve patch-level metrics available that collectively described the area, shape, complexity, compactness and isolation of the parks (Table 5). These twelve metrics cover all the aspects of spatial attributes of urban parks defined in previous studies, where only four metrics having been found to be the most effective for relation with various ecosystem services inside a city (Grafius et al. 2018; Sathyakumar & Ramsankaran, 2019). Effect of spatial attributes of parks on their neighbourhood is evident through several studies. Size and shape of parks not only can provide information about accessibility of UGS to population centres (Sathyakumar & Ramsankaran, 2019) but also help in Urban Heat Island mitigation (Bao et al. 2016; Masoudi et al. 2021). Ecosystem services in the city can also be affected by spatial attributes of UGS such as contiguity index,

**Table 5** Patch-level metrics used to describe spatial configuration of urban parks

S.No.	Metric	Name	Type	Information about patch
1	AREA	Patch area	Area and edge metric	Patch area
2	CAI	Core area index	Core area metric	Patch area and shape
3	CIRCLE	Related circumscribing circle	Shape metric	Compactness
4	CONTIG	Contiguity index	Shape metric	Connections between patch cells
5	CORE	Core area	Core area metric	Patch area and shape
6	ENN	Euclidean nearest neighbour distance	Aggregation metric	Patch isolation
7	FRAC	Fractal dimension index	Shape metric	Standardised Complexity
8	GYRATE	Radius of gyration	Area and edge metric	Patch area and compactness
9	NCORE	Number of core areas	Core area metric	Patch area and shape
10	PARA	Perimeter-area ratio	Shape metric	Complexity
11	PERIM	Patch perimeter	Area and edge metric	Patch area and shape
12	SHAPE	Shape index	Shape metric	Hypothetical Ratio for patch at maximum compactness

fractal dimension index, core area index and perimeter-area ratio (Grafius et al. 2018).

The relationship between spatial configuration of parks, described by landscape metrics listed in Table 5, and LST of the parks and built-up land use within concentric rings surrounding the parks was established through linear regression analysis and  $R^2$  coefficient. Pre-screening of the strength of the relationship between spatial configuration of parks and LST values within the parks as well as built-up LU within the concentric rings determined that the relationships were the strongest for buffers spaced every 3 m, and these were reported on in the results section. Additionally, the strength of the relationships was analysed for parks of different sizes represented by 1st quartile, median, 3rd quartile and maximum area values, referred to throughout this manuscript as Q1, Q2, Q3 and Q4 parks, to develop further insights on the impact of the size of the parks on their cooling capacity.

## Results

### Impact of parks on cooling within their footprint

LST values were found to be the lowest inside parks and variable within their boundaries (Fig. 5). As the distance progressed away from park boundaries, LST kept increasing up to the distance of 18 m away from the parks and became fairly constant over the distance

of as far away as 600 m (Figures in Appendix). The average LST was approximately 32.58 °C inside the parks and 35.43 °C within the 18 m away from the parks. Beyond 18 m up to 600 m, LST ranged from 35.13 to 35.42 °C, indicating a 2.55 – 2.84 °C cooling capacity of parks. The levelling off of LST at the 18 m distance was observed in all zones of the city (Fig. 6) despite the different numbers of parks present in each zone as well as differing thermal properties thereof, suggesting a degree of similarity in LST behaviour across the entire city.

The range of coefficient of determination  $R^2$  between distances and LST for built-up around parks was analysed for concentric 3 m buffers up to the distance of 30 m and for concentric 6 m buffers up to the distance of 60 m after the distance of 30 m. The analysis was focussed on the distance up to 60 m given the short range of major changes in LST values away from the parks. The coefficient of determination  $R^2$  between LST values and distance from the parks ranged from 0.45 to 0.60 for the 6 individual zones of Lucknow city with a mean of 0.42 for all (Fig. 6), indicating that proximity of built-up spaces to parks had a considerable impact on their LST. The fact that the mean  $R^2$  value for all zones is lower than the means of individual zones suggests that each zone had specific properties that strengthened the relationship between the LST of built-up spaces and distance away from parks.

This study shows that Zones no. 2 & 3 were the most consistent in variations of LST at built-up LU

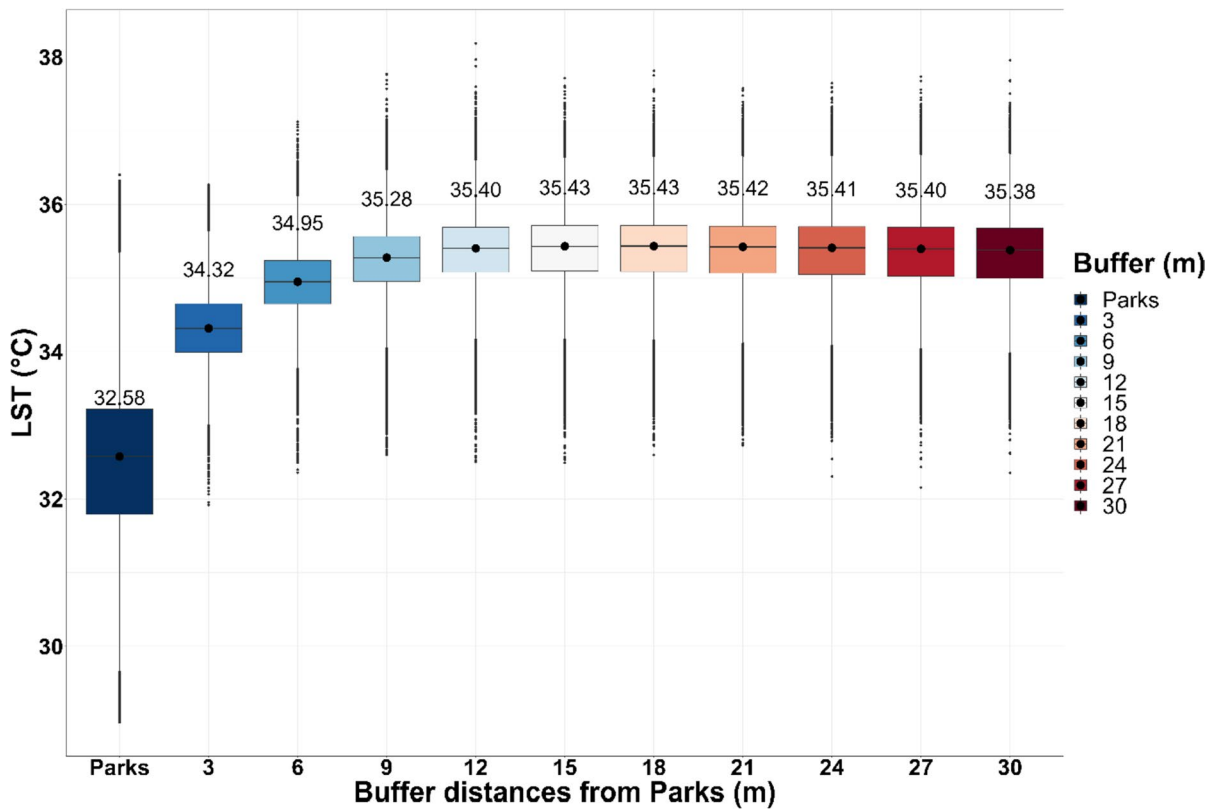
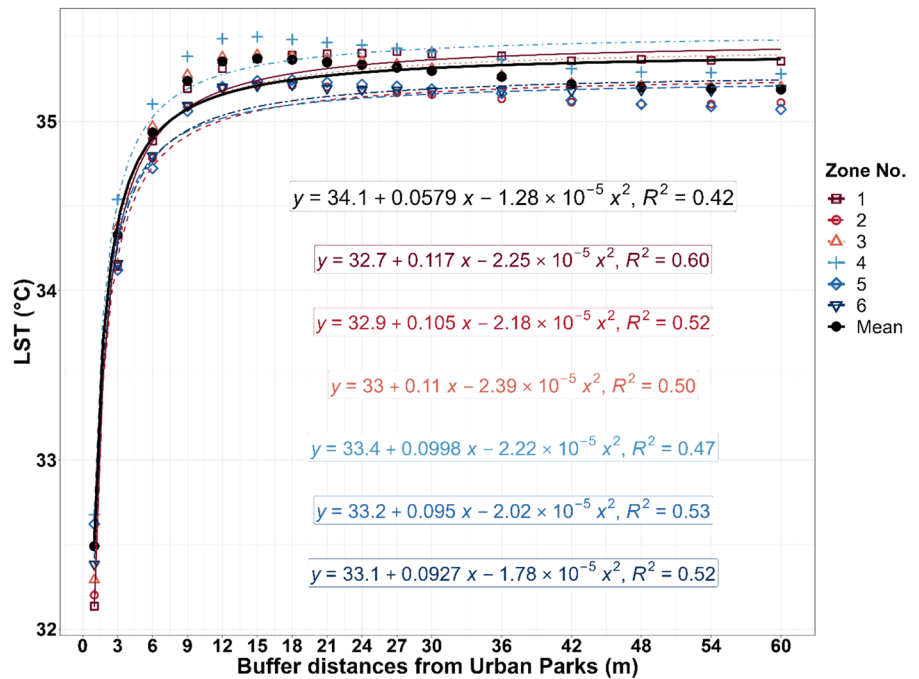


Fig. 5 Range of LST values within parks and at different distances away from the parks in all zones of the Lucknow city

Fig. 6 Downscaled LST variations through means and lines representing fitted functions within different zones (except Cantonment zone) up to 60 m distance from parks in 3 to 6 m buffers



pixels over the various buffer distances from parks, meaning very little deviation from the mean LST value of these zones (Fig. 6). However, Zone 3 appeared to be warmer than Zone 2. Parks in Zones 4 & 5 were the warmest, with LST more than 32.5 °C (32.72 °C & 32.74 °C). There was a lot of variation in LST values of the built-up LU outside of the parks in these Zones. Zones 1 & 2 had the lowest LST values of 32.1 and 32.26 °C respectively inside parks, however, Zone 1 had higher LST outside of parks than Zone 2.

From the above results, it transpires that the built-up land use within 18 m away from park boundaries can be cooled down effectively by the presence of parks. After the distance of 18 m and up to the distance of 600 m studied here, the cooling effect of parks dissipates as LST becomes fairly constant with some minor fluctuations observed in all zones of the city. These fluctuations likely indicate interactions between the neighbourhood cooling of parks and the presence of other cooling features such as greenspaces or water within the heterogeneous urban fabric that operate at various spatial scales.

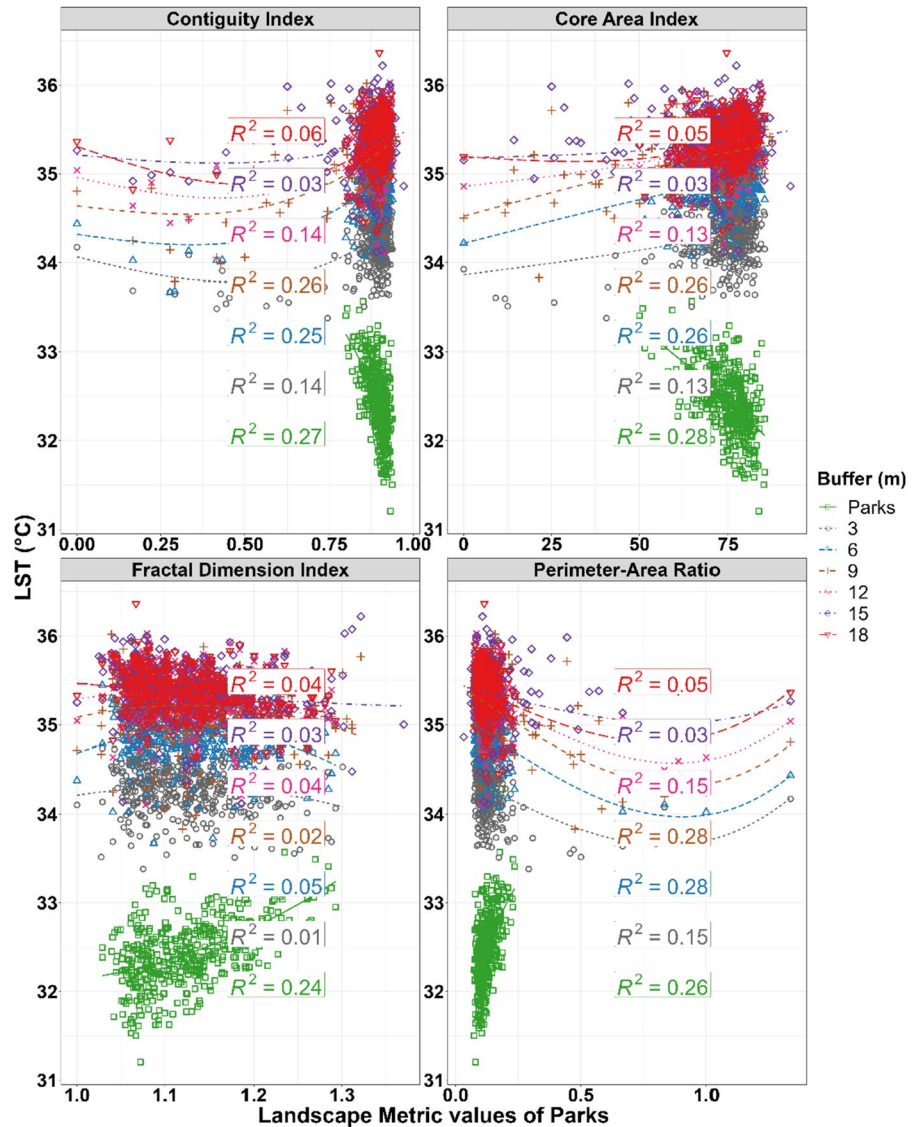
#### Impact of spatial configuration of parks on cooling of their neighbourhoods

In this study, patch level landscape metrics defined in Table 5 were used to define spatial configuration parameters of parks and then relate them to LST variations over different distances from parks. Firstly, an association was determined between all 12 landscape metrics and all the 6 land use classes present in classified map of PlanetScope data at 3 m resolution, which showed that contiguity index (CONTIG), core area index (CAI) and perimeter-area ratio (PARA) were the only three metrics which exhibited a significant relationship with LST values of all LU classes in the neighbourhood of parks (Figure S4.1) with  $R^2$  above 0.5. Radius of gyration (GYRATE) was the only other landscape metric of urban parks which showed a relationship, however, its effect was only evident inside parks with  $R^2$  value of 0.1, which instantly became  $R^2 < 0.01$  outside of parks. However, after filtering for built-up LU class only, Fractal Dimension index (FRAC) value showed some small  $R^2$  values at different buffer distances from park boundaries apart from Q3 parks.

The relationships between all spatial configuration metrics considered here with LST were the strongest for LST of the parks, with CONTIG, CAI and PARA having the highest  $R^2$  of 0.52–0.53 for parks of all sizes and FRAC of 0.24 for Q3 parks (Fig. 7 and Figure S4.5 for FRAC values in Q3), with size ranging between 1961.76 m<sup>2</sup> (median) and 5381.34 m<sup>2</sup> (3rd quartile). The relationships between the spatial configuration of parks of all sizes and LST of the neighbouring built-up LU were weaker and ranged from  $R^2 < 0.01$  for the 3 m buffer, increasing to circa 0.28 for CONTIG, CAI and PARA at 9 m buffer, and dropping to below 0.04 at 18 m buffer. For all Q1, Q2 and Q4 parks, the  $R^2$  values were almost the same and ranged from 0.1 to 0.15 and were the highest at the 12 m buffer. The strength of the relationship continued dropping for farther distances, confirming the 18 m cooling cut-off value of urban parks. The sudden drop for the 3 m buffer can be explained by the presence of the roads in the immediate proximity to the parks whose LSTs were not included in the analysis, resulting in a lower number of pixels classed as built-up present in this buffer. It also needs to be noted that we did not find a strong relationship between area of parks and LST within them. The highest  $R^2$  values of 0.18 were observed for Q3 parks, with  $R^2$  of 0.08 for Q1 and Q2 and 0.01 for Q4 parks. This implies that the park area itself is not sufficient to effectively describe their cooling impact and information on their shape is required.

The four landscape metrics provide insights into the spatial configuration of urban parks and how it relates to LST within and outside of them (Fig. 7). Values of CONTIG approximating 1 suggest high contiguity or connectedness of cells of land use inside patches of parks, which in turn translates into the lowest within-park LST. High values of CAI for parks indicate prevalence of parks in a square or rectangular form than any other shapes and the presence of large core areas inside parks. The more the shape of the parks approximates a square, the lower the LST within them. There is also a weak association between the square shape of parks and lower LST within the built-up area up to 18 m away from park boundaries. PARA, on the other hand, exhibits grouping of values at the lower side of the scale indicating prevalence of least complex shapes of park patches within the study area, which again confirms that a lower complexity of parks' shape yields lower LST within the parks and

**Fig. 7** The relationship between downscaled LST inside parks and built-up LU within distance up to 18 m in 3 m concentric buffers and selected four patch-level landscape metrics



greater cooling capacity of neighbouring land cover. FRAC values are more dispersed, however, grouping at the lower side of the scale, confirms less complex structures of parks in study area. Although FRAC may depict subtle changes in the shape of the parks' complexity, these do not translate into their cooling capacity of the neighbouring LU, making this metric less suitable for urban LST studies.

Results of this study indicate that landscape metrics describing shape of parks are more useful than other metrics (area, edge, and aggregation) in defining the relation with temperature in surroundings of parks. Core metrics can also play an important role.

Results of study indicate that four metrics: CONTIG, CAI, FRAC and PARA best represent the relationship between parks and temperature in their neighbourhoods, although LST inside parks is much better related with higher value of coefficient of determination ( $R^2$ ). These four metrics suggest that patches present in form of square with less complex shape and distinct core of green space will have much more cooling effect on the LST within and in the neighbourhood of those parks than parks with much more complex shape and diversified core of green space.

## Discussion

The aim of our study was to determine the cooling capacity within urban parks as well as their neighbourhoods taking into account their spatial configuration properties expressed by patch-level landscape metrics, which is relatively scarce in literature often focussing on the relationships between LST and spatial configuration of greenspaces at a class-level within arbitrary units of assessment (Li et al. 2023). This study made use of remotely sensed imagery to establish the relationship between UGS' attributes and LST behaviour in its neighbourhood, which constitutes one of the possible methods for quantification of UHI mitigation capacity of urban greenspaces (Bartesaghi Koc et al. 2018).

We observed a relatively strong relationship between mean LST within the parks' footprint and their spatial configuration properties expressed by patch-level landscape metrics used in other UHI mitigation studies (Li et al. 2023): CI, CAI, PARA ( $R^2$  of circa 0.5) and, to lesser extent, FRAC ( $R^2$  of 0.24), suggesting that parks with a better defined core and a less complex shape have a lower LST. This finding confirms results of previous studies carried out in a variety of urban and climatic contexts (Ren et al. 2013; Chen et al. 2014; Bao et al. 2016), which conclude that urban green spaces with a more aggregated shape mitigate heat more effectively than the ones characterised with a more complex shape. However, contrary to studies carried out with class-level landscape metrics (Maimaitiyiming et al. 2014; Kong et al. 2014a; Masoudi et al. 2021; Wang et al., 2022) and many others, who determined that the area of urban parks and not their shape as the primary factor contributing to their heat mitigation capacity, we did not find a relationship between LST of the parks and their size. We attribute this lack of a relationship to the relatively small sizes of parks in the Lucknow city, rarely exceeding 1 ha. Only when parks with sizes located in the third quartile (Q3) were considered, a weak relationship with LST was found. The implication of this finding is that for relatively small parks, their shape matters more in terms of cooling capacity than their size. We theorize that smaller parks with a complex shape could become negatively affected by the heat radiated from the hotter built-up areas in their vicinity, however, this effect could depend also on their composition as well as season (Xiang et al.

2022) and the related condition of the vegetation. The association between the spatial properties of parks and LST in their surroundings was much weaker (maximum  $R^2$  of circa 0.28), which can be referenced back to studies where other patch-level landscape metrics have also shown similar trends in  $R^2$  (Bao et al. 2016; Shah et al. 2021). Nevertheless, our findings indicated that parks with distinct cores and less complex shape, much in the shape of a square, can also offer a better cooling of their surroundings.

The maximum cooling distance of parks in Lucknow was found to be 18 m. The same pattern was observed over all 6 zones separately and in a combined form for the entire city. This particular cut-off of 18 m could be attributed to the typical house width of 10-15 m present in residential areas of the city and a lack of optimised placement of the parks for cooling (Masoudi et al. 2019). Given that the average LST value inside the parks was 32.58 °C and in the 18 m buffer 35.43 °C, the magnitude of cooling was 2.55 °C on average. Both the cooling intensity and cooling distance within the neighbourhoods was lower than in other studies. For example, Feyisa et al. (2014) observed a cooling magnitude of 3.93 °C on average, however, extending over the distance of 224 m away from the parks in Addis Ababa, depending on the park size and NDVI value, as read from Landsat ETM+ derived LST data with the thermal band captured at 60 m resolution. The cooling distance of urban parks was found to be between 31 and 370 m and 179 m on average in Zhengzhou city, Henan Province, China, with maximum cooling of 4.61 °C (Gao et al. 2023), or as much as 700 m in Shanghai, China (Wang et al. 2022) depending on park type, perimeter, and presence of water, as detected from Landsat 8- derived LST. The lower cooling distance observed in our study could stem from the intrinsic characteristics of the study area such as its location (latitude, longitude) and local background climate (Zhou et al. 2023; Geng et al. 2022; Yu et al. 2018) as well as high resolution of our LST data.

Since urban cooling capacity is dependent on composition of the cool island and its neighbouring thermal environment (Kong et al. 2014b), further studies need to focus on ascertaining the cooling effect of different park designs on different types of urban form. It is also of note that the use of high-resolution imagery for land use classification can not only help in finding

exact composition of parks as different trees with variety of heights and crown thickness can be important factor affecting cooling intensity of UGS (Wang et al. 2023). This can help in better understanding of the association between UGS and LST as recommended by other studies (Qian et al. 2015; Zhou et al. 2018b). The role of background climate on UGS's cooling intensity also needs to be considered (Zhou et al. 2023).

A strength of our study is that we used 3 m resolution PlanetScope data to map land use as well as land surface temperature across Lucknow, which facilitated much more accurate detection of urban parks as well as more precise determination of their capacity to cool their surroundings (Li et al. 2013). Whilst the use of easily accessible Landsat satellite images may be helpful in UHI mitigation studies to some extent, their 30 m spatial resolution is insufficient for detection of smaller green spaces (Qian et al. 2015). Moreover, Zhou et al. (2022) found that it was infeasible to determine a particular cooling distance from urban parks using Landsat OLI data. In order to remove this limitation, we downscaled Landsat-8 LST captured at 100 m to match the 3 m spatial resolution of the LU map classified from PlanetScope data. In our RTE-linear regression approach, following authors such as Bonafoni et al. (2016) and Agam et al. (2007), we used NDVI as the sole LST downscaling factor, which showed a strong association with the LST as determined by  $R^2$  of 0.94 in our study area. Whilst there is a trend in literature to use multiple downscaling factors to improve the accuracy of the sharpened LST images (Bala et al. 2019; Bonafoni and Tosi, 2016; Deng and Wu 2013) in addition to NDVI, our method resulted in RMSE in the range of 0.52 to 1.77 °C, comparable to or lower than downscaling accuracies observed in these studies. Nevertheless, improvements in LST downscaling accuracy over urban areas due to the use of multiple spectral indices (Zawadzka et al. 2020a), or normalised difference built-up index (NDBI) (Bala et al. 2019) are possible. This, however, would require the availability of shortwave infrared bands in the high spatial resolution imagery, which is not the case in the PlanetScope data. The specific downscaled LST image used here had the RMSE of 1.45 °C after correction for residuals, which compared to LST range in the study area of circa 30 to 42 °C, still allows for identification of temperature gradients within the city with a high level

of certainty. Given that LST extremes are usually misrepresented during LST downscaling, the cooling magnitude of urban parks observed in this study could have been affected. The use of downscaled, rather than directly observed LST values, constitutes the main limitation of our study. Future approaches could benefit from emerging high-resolution LST products, such as HotSat-1 satellite thermal imagery at 3.5 m spatial resolution, however, these are currently not available in the open domain.

With regards to LST distribution within and around the urban parks in different administrative zones of the Lucknow city, we have determined that means of LST values inside the parks varied somewhat between the six different zones, with the maximum difference of 0.5 °C observed for parks in zone 1 and 4. However, the means of LST within the concentric rings around the parks are quite similar regardless of the zone, and especially in the 12 m buffer onwards. We attribute this finding to differences in spatial configuration of urban parks in different zones of the city and a relatively homogenous thermal response of the surrounding areas across the entire city. A higher variation in mean LST in the 3–6 m buffer could be explained by the fact that this buffer likely contains roads that tend to be 6 to 7 m wide and adjacent to the parks. These road pixels in the satellite image used for LU classification may be partially overshadowed by trees and buildings or be subject to misclassification with buildings, resulting in inconsistent LST values.

Our study provides evidence that the cooling distance of urban parks less than a hectare in size is substantially lower than that of larger parks. Consequently, our findings suggest that to maximise heat mitigation, parks should be arranged such that any built-up land use is situated within 18 m at the most from the boundary of the nearest park, and the design of parks should be of less complex shape with presence of distinct green space in their core. Given that these guidelines may prove unrealistic to implement, it is necessary to consider other forms of urban greenspaces, such as street trees, green walls, and green roofs, for cooling benefits or introducing different forms of parks having a better capacity to cool down larger neighbourhoods. Conversely, further studies should focus on the determination of the cooling capacity of variously configured parks in differing urban contexts.

This study provides further insights to the understanding of the thermal environment of the Lucknow city, with previous studies relating it to the increasing urbanisation (Singh et al. 2017), vegetation indices (Verma and Garg 2021) and green space density (Shukla and Jain 2021; Verma and Kundapura 2020), all of which were established using Landsat imagery. It also provides further evidence on cooling capacity of urban parks in Indian cities, which previously have been studied without reference to spatial configuration of urban parks except for Raiganj city and to some extent Bengaluru (Shah et al. 2021; Basu and Das 2023). Our results also extend previous analyses by adding the focus on spatial attributes of small urban parks described by landscape metrics and thus provides an advancement in existing literature about the cooling impact and spatial configuration effects of smaller urban greenspaces, which are understudied globally.

Although the use of PlanetScope and Landsat 8 data proved successful in identifying trends in cooling capacity of urban parks, similar studies could be further extended towards the use of even higher resolution imagery for detailing the composition of urban parks as well as describing the character of neighbouring urban form. As PlanetScope data used in the study only contains four bands, use of only one vegetation index, NDVI, was possible for downscaling of LST from Landsat imagery. This limitation can be improved by enhancing spectral resolution of the imagery and hence enhancing the land use classification as well as LST downscaling, with bands in the short-wave infrared spectrum enabling the inclusion of further spectral indices into the analysis. Furthermore, our study is based on data captured on a single day representative of a hot summer day. Subsequent studies should focus on gaining understanding of the cooling capacity of parks in different seasons and weather conditions as well as the impact of the parks on the UHI formation at night. This can further lead to association with population data for socio-economic impact of UGS in different administrative boundaries. Studies of urban parks based primarily on classified raster images can greatly benefit from pre-digitised park boundaries that can be used to extract pixels belonging to parks, which, otherwise, could be difficult to separate from adjacent urban greenspaces due to the raster data structure (Zawadzka et al. 2020b). This could be further facilitated by

repositories of parks held by town authorities, as reliable determination of urban parks from existing datasets and field survey can prove challenging, especially city-wide, as was the case in this study. Finally, our study area – the Lucknow city – was found to contain urban parks of fairly homogenous morphology, and therefore studies considering a wider variety of parks are needed.

## Conclusions

This study set out to determine the impact of spatial configuration of urban parks on their cooling capacity within their footprint as well as in their neighbourhoods using publicly available PlanetScope and Landsat 8 data. Four patch-level landscape metrics, CONTIG, CAI, PARA, and to a lesser extent FRAC, have proved useful in describing the relationship between urban parks and LST. Area of the parks, on the other hand, did not have a large impact on the cooling capacity of the parks, which we explain by their relatively small size. Consideration of patch-level landscape metrics was made possible through extraction of the pixels occupied by urban parks only by a set of digitised park boundaries, making them distinct from other green spaces in the city. We found evidence for parks with low shape complexity to have the lowest LST, and the cooling distance to be discernible up to 18 m away from the parks, ascertaining circa 2.55 °C cooling capacity. As such, our study presents evidence that the cooling distance of parks may be significantly lower than indicated in other studies, and that less complex shape is important to achieve a better cooling capacity for relatively small parks. Our findings equip urban planners with parameters of spatial arrangement of urban parks that could help mitigate the urban heat island effect. Whilst our study focussed on the heat mitigation capacity of urban green infrastructure, design of urban parks and greenspaces should take into account other ecological and cultural functions they can provide, such as habitat for biodiversity and ecological corridors, water retention and flood prevention or recreation to ensure that the cities are a place where both humans and nature can thrive in changing climates.

**Acknowledgements** Authors are thankful to the Commonwealth Scholarship Commission for providing financial



support, and IIT Roorkee, India, and Cranfield University, United Kingdom, for providing infrastructure to conduct the study. Authors also acknowledge the use of the PlanetScope data for the completion of this study.

**Author contributions** RV conducted the analysis, prepared the figures and wrote the manuscript, JZ provided technical advice and supervisory support to RV and contributed to writing the manuscript; RC and PKG provided the scientific overview of the work. All authors reviewed the manuscript.

**Funding** The authors thank the Commonwealth Scholarship Commission for funding the 1-year research visit of Ravi Verma at Cranfield University, United Kingdom, through the Commonwealth Split-Site Scholarship, which helped in the completion of the study.

**Data availability** The raw data used in the study is available in the public domain for free use.

#### Declarations

**Competing interests** The authors declare no competing interests.

**Ethical approval** Not Applicable.

**Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

#### References

- Agam N, Kustas WP, Anderson MC, Li F, Neale CM (2007) A vegetation index based technique for spatial sharpening of thermal imagery. *Remote Sens Environ* 107(4):545–558
- Alexander C (2021) Influence of the proportion, height and proximity of vegetation and buildings on urban land surface temperature. *Int J Appl Earth Obs Geoinf* 95:102265
- Bala R, Prasad R, Yadav VP (2019) Disaggregation of Modis land surface temperature in urban areas using improved thermal sharpening techniques. *Adv Space Res* 64(3):591–602
- Bao T, Li X, Zhang J, Zhang Y, Tian S (2016) Assessing the distribution of urban green spaces and its anisotropic cooling distance on urban heat island pattern in Baotou, China. *ISPRS Int J Geo-Information* 5(2):12
- Bartasaghi Koc C, Osmond P, Peters A (2018) Evaluating the cooling effects of green infrastructure: a systematic review of methods, indicators and data sources. *Sol Energy* 166:486–508
- Basu T, Das A (2023) Urbanization induced degradation of urban green space and its association to the land surface temperature in a medium-class city in India. *Sustainable Cities and Society* 90:104373
- Bonafoni S, Tosi G (2016) Downscaling of land surface temperature using airborne high-resolution data: a case study on Apulia, Italy. *IEEE Geosci Remote Sens Lett* 14(1):107–111
- Bonafoni S, Anniballe R, Gioli B, Toscano P (2016) Downscaling Landsat land surface temperature over the urban area of Florence. *Eur J Remote Sens* 49(1):553–569
- Buyantuyev A, Wu J (2010) Urban heat islands and landscape heterogeneity: linking spatiotemporal variations in surface temperatures to land-cover and socioeconomic patterns. *Landscape Ecol* 25(1):17–33
- Chen A, Yao XA, Sun R, Chen L (2014) Effect of urban green patterns on surface urban cool islands and its seasonal variations. *Urban for Urban Green* 13:646–654. <https://doi.org/10.1016/J.UFUG.2014.07.006>
- Cui Y, Xu X, Dong J, Qin Y (2016) Influence of urbanization factors on surface urban heat island intensity: a comparison of countries at different developmental phases. *Sustainability* 8(8):706
- Cui F, Hamdi R, Yuan X, He H, Yang T, Kuang W, De Maeyer P (2021) Quantifying the response of surface urban heat island to urban greening in global north megacities. *Sci Total Environ* 801:149553
- De Santis D, Del Frate F, Schiavon G (2021) Analysis of climate change effects on surface temperature in central-Italy lakes using satellite data time-series. *Remote Sens* 14(1):117
- Deilami K, Kamruzzaman M, Liu Y (2018) Urban heat island effect: a systematic review of spatio-temporal factors, data, methods, and mitigation measures. *Int J Appl Earth Obs Geoinf* 67:30–42
- Deng C, Wu C (2013) Estimating very high resolution urban surface temperature using a spectral unmixing and thermal mixing approach. *Int J Appl Earth Obs Geoinf* 23:155–164
- Du C, Jia W, Chen M, Yan L, Wang K (2022) How can urban parks be planned to maximize cooling effect in hot extremes? Linking maximum and accumulative perspectives. *J Environ Manage* 317:115346
- Egorov AI, Mudu P, Braubach M, Martuzzi M (2016) Urban Green Spaces and Health. WHO Regional Office for Europe, Copenhagen
- Ekwe MC, Adamu F, Gana J, Nwafor GC, Usman R, Nom J, Aderoju OM (2021) The effect of green spaces on the urban thermal environment during a hot-dry season: a case study of Port Harcourt, Nigeria. *Environ Dev Sustain* 23:10056–10079
- Feyisa GL, Dons K, Meilby H (2014) Efficiency of parks in mitigating urban heat island effect: an example from Addis Ababa. *Landscape Urban Plann* 123:87–95

- Gao Y, Pan H, Tian L (2023) Analysis of the spillover characteristics of cooling effect in an urban park: a case study in Zhengzhou city. *Front Earth Sci* 11:1133901
- Geng X, Yu Z, Zhang D, Li C, Yuan Y, Wang X (2022) The influence of local background climate on the dominant factors and threshold-size of the cooling effect of urban parks. *Sci Total Environ* 823:153806
- Gomez-Martinez F, de Beurs KM, Koch J, Widener J (2021) Multi-temporal land surface temperature and vegetation greenness in urban green spaces of Puebla. *Mexico Land* 10(2):155
- Grafius DR, Corstanje R, Harris JA (2018) Linking ecosystem services, urban form and green space configuration using multivariate landscape metric analysis. *Landscape Ecol* 33(4):557–573
- Guha S, Govil H (2022) Seasonal impact on the relationship between land surface temperature and normalized difference vegetation index in an urban landscape. *Geocarto Int* 37(8):2252–2272
- Guo L, Liu R, Men C, Wang Q, Miao Y, Zhang Y (2019a) Quantifying and simulating landscape composition and pattern impacts on land surface temperature: a decadal study of the rapidly urbanizing city of Beijing, China. *Sci Total Environ* 654:430–440
- Hassan T, Zhang J, Prodhon FA, Sharma P, T. P., Bashir B (2021) Surface urban heat islands dynamics in response to land use and vegetation across south asia (2000–2019). *Remote Sens* 13(16):3177
- Hesselbarth MH, Sciaini M, With KA, Wiegand K, Nowosad J (2019) Landscapemetrics: an open-source R tool to calculate landscape metrics. *Ecography* 42(10):1648–1657
- Hou H, Su H, Liu K, Li X, Chen S, Wang W, Lin J (2022) Driving forces of UHI changes in China's major cities from the perspective of land surface energy balance. *Sci Total Environ* 829:154710
- Imhoff ML, Zhang P, Wolfe RE, Bounoua L (2010) Remote sensing of the urban heat island effect across biomes in the continental USA. *Remote Sens Environ* 114(3):504–513
- Jaber SM (2020) Is there a relationship between human population distribution and land surface temperature? Global perspective in areas with different climatic classifications. *Remote Sens Applications: Soc Environ* 20:100435
- Jiménez-Muñoz JC, Sobrino JA, Skoković D, Mattar C, Cristóbal J (2014) Land surface temperature retrieval methods from Landsat-8 thermal infrared sensor data. *IEEE Geosci Remote Sens Lett* 11(10):1840–1843
- Kandya A, Mohan M (2018) Mitigating the Urban Heat Island effect through building envelope modifications. *Energy Build* 164:266–277
- Kianmehr A, Lim TC, Li X (2023) Comparison of different spatial temperature data sources and resolutions for use in understanding intra-urban heat variation. *Sustainable Cities and Society* 96:104619
- Kong F, Yin H, James P, Hutrya LR, He HS (2014a) Effects of spatial pattern of greenspace on urban cooling in a large metropolitan area of eastern China. *Landscape Urban Plann* 128:35–47
- Kong F, Yin H, Wang C, Cavan G, James P (2014b) A satellite-image-based analysis of factors contributing to the green-space cool island intensity on a city scale. *Urban For Urban Green* 13(4):846–853
- Kotharkar R, Bagade A, Singh PR (2020) A systematic approach for urban heat island mitigation strategies in critical local climate zones of an Indian city. *Urban Clim* 34:100701
- Lemoine-Rodríguez R, Inostroza L, Zepp H (2020) The global homogenization of urban form. An assessment of 194 cities across time. *Landscape Urban Plann* 204:103949
- Li X, Zhou W, Ouyang Z (2013) Relationship between land surface temperature and spatial pattern of greenspace: what are the effects of spatial resolution? *Landscape Urban Plann* 114:1–8
- Li H, Meier F, Lee X, Chakraborty T, Liu J, Schaap M, Sodoudi S (2018) Interaction between urban heat island and urban pollution island during summer in Berlin. *Sci Total Environ* 636:818–828
- Li Y, Fan S, Li K, Zhang Y, Kong L, Xie Y, Dong L (2021b) Large urban parks summertime cool and wet island intensity and its influencing factors in Beijing, China. *Urban For Urban Green* 65:127375
- Li Y, Zhao Z, Xin Y, Xu A, Xie S, Yan Y, Wang L (2022) How are Land-Use/Land-Cover indices and daytime and Nighttime Land Surface temperatures Related in Eleven Urban centres in different global climatic zones? *Land* 11(8):1312
- Liu Y, Peng J, Wang Y (2018) Efficiency of landscape metrics characterizing urban land surface temperature. *Landscape Urban Plann* 180:36–53
- Maimaitiyiming M, Ghulam A, Tiyyip T, Pla F, Latorre-Carmona P, Halik Ü, Caetano M (2014) Effects of green space spatial pattern on land surface temperature: implications for sustainable urban planning and climate change adaptation. *ISPRS J Photogrammetry Remote Sens* 89:59–66
- Manavvi S, Rajasekar E (2023) Assessing thermal comfort in urban squares in humid subtropical climate: a structural equation modelling approach. *Build Environ* 229:109931
- Masoudi M, Tan PY, Liew SC (2019) Multi-city comparison of the relationships between spatial pattern and cooling effect of urban green spaces in four major Asian cities. *Ecol Ind* 98:200–213
- Masoudi M, Tan PY, Fadaei M (2021) The effects of land use on spatial pattern of urban green spaces and their cooling ability. *Urban Clim* 35:100743
- McGarigal K, Marks BJ (1995) FRAGSTATS: spatial pattern analysis program for quantifying landscape structure (Gen. Tech. Rep. PNW-GTR-351. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, 122 p.) <https://www.fs.usda.gov/treesearch/pubs/3064> Accessed 20 December 2019
- Mohiuddin G, Mund JP (2021) Application of Land Surface Temperature Analysis in Urban Green spaces: Case studies from South Asia. *GI\_Forum* 9:202–214
- Ouyang Z, Sciusco P, Jiao T, Feron S, Lei C, Li F, Chen J (2022) Albedo changes caused by future urbanization contribute to global warming. *Nat Commun* 13(1):1–9
- Peng J, Xie P, Liu Y, Ma J (2016) Urban thermal environment dynamics and associated landscape pattern factors: a case study in the Beijing metropolitan region. *Remote Sens Environ* 173:145–155
- Peng J, Jia J, Liu Y, Li H, Wu J (2018) Seasonal contrast of the dominant factors for spatial distribution of land

- surface temperature in urban areas. *Remote Sens Environ* 215:255–267
- Peng J, Dan Y, Qiao R, Liu Y, Dong J, Wu J (2021) How to quantify the cooling effect of urban parks? Linking maximum and accumulation perspectives. *Remote Sens Environ* 252:112135
- Qian Y, Zhou W, Yu W, Pickett ST (2015) Quantifying spatiotemporal pattern of urban greenspace: new insights from high resolution data. *Landscape Ecol* 30:1165–1173
- Qiu X, Kil SH, Jo HK et al (2023) Cooling Effect of Urban Blue and Green spaces: a case study of Changsha, China. *Int J Environ Res Public Health* 2023 20:202613. <https://doi.org/10.3390/IJERPH20032613>
- Ren Z, He X, Zheng H, Zhang D, Yu X, Shen G, Guo R (2013) Estimation of the relationship between urban park characteristics and park cool island intensity by remote sensing data and field measurement. *Forests* 4(4):868–886
- Sathyakumar V, Ramsankaran RAAJ, Bardhan R (2019) Linking remotely sensed Urban Green Space (UGS) distribution patterns and Socio-Economic Status (SES)-A multi-scale probabilistic analysis based in Mumbai, India. *GIScience & Remote Sensing* 56(5):645–669
- Scheuer S, Haase D, Volk M (2017) Integrative assessment of climate change for fast-growing urban areas: measurement and recommendations for future research. *PLOS ONE* 12(12):e0189451
- Shah A, Garg A, Mishra V (2021) Quantifying the local cooling effects of urban green spaces: evidence from Bengaluru, India. *Landsc Urban Plann* 209:104043
- Shukla A, Jain K (2021) Analyzing the impact of changing landscape pattern and dynamics on land surface temperature in Lucknow city, India. *Urban For Urban Green* 58:126877
- Singh P, Kikon N, Verma P (2017) Impact of land use change and urbanization on urban heat island in Lucknow city, Central India. A remote sensing based estimate. *Sustainable Cities and Society* 32:100–114
- Sobrino JA, Jiménez-Muñoz JC, Soria G, Romaguera M, Guanter L, Moreno J, Martínez P (2008) Land surface emissivity retrieval from different VNIR and TIR sensors. *IEEE Trans Geosci Remote Sens* 46(2):316–327
- Srivanit M, Hokao K (2013) Evaluating the cooling effects of greening for improving the outdoor thermal environment at an institutional campus in the summer. *Build Environ* 66:158–172
- Srivanit M, Iamtrakul P (2019) Spatial patterns of greenspace cool islands and their relationship to cooling effectiveness in the tropical city of Chiang Mai, Thailand. *Environ Monit Assess* 191(9):1–16
- Stathopoulou M, Cartalis C (2007) Daytime urban heat islands from Landsat ETM+ and Corine land cover data: an application to major cities in Greece. *Sol Energy* 81(3):358–368
- Stewart JD, Kremer P (2022) Temporal change in relationships between urban structure and surface temperature. *Environ Plan B* 49:2297
- Sun R, Chen L (2017) Effects of green space dynamics on urban heat islands: Mitigation and diversification. *Ecosyst Serv* 23:38–46
- Sun M, Zhao X, Wang Y et al (2023) Factors affecting the high-intensity cooling Distance of Urban Green spaces: a Case Study of Xi'an. *China Sustain* 2023 15:6735. <https://doi.org/10.3390/SU15086735>
- Tian L, Li Y, Lu J, Wang J (2021) Review on urban heat island in China: methods, its impact on buildings energy demand and mitigation strategies. *Sustainability* 13(2):762
- Tran H, Uchiyama D, Ochi S, Yasuoka Y (2006) Assessment with satellite data of the urban heat island effects in Asian mega cities. *Int J Appl Earth Obs Geoinf* 8(1):34–48
- Verma R, Garg PK (2021) Mapping the spatiotemporal changes of land use/land cover on the urban heat island effect by open source data: a case study of Lucknow, India. *J Indian Soc Remote Sens* 49(11):2655–2671
- Verma R, Kundapura S (2020) Urban Weighted Green Index-A study of urban green space in relation to Land Surface temperature for Lucknow city, India, vol 20. *Society and Environment, Remote Sensing Applications*, p 100429
- Voogt JA, Oke TR (2003) Thermal remote sensing of urban climates. *Remote Sens Environ* 86(3):370–384
- Wang T, Tu H, Min B, Li Z, Li X, You Q (2022) The Mitigation Effect of Park Landscape on Thermal Environment in Shanghai City Based on remote sensing Retrieval Method. *Int J Environ Res Public Health* 19(5):2949
- Wang C, Ren Z, Chang X, Wang G, Hong X, Dong Y, Wang W (2023) Understanding the cooling capacity and its potential drivers in urban forests at the single tree and cluster scales. *Sustainable Cities and Society* 93:104531
- Wei D, Yang L, Bao Z, Lu Y, Yang H (2022) Variations in outdoor thermal comfort in an urban park in the hot-summer and cold-winter region of China. *Sustainable Cities and Society* 77:103535
- Xiang Y, Ye Y, Peng C, Teng M, Zhou Z (2022) Seasonal variations for combined effects of landscape metrics on land surface temperature (LST) and aerosol optical depth (AOD). *Ecol Ind* 138:108810
- Xiao L, Wang W, Ren Z, Fu Y, Lv H, He X (2021) Two-city street-view greenery variations and association with forest attributes and landscape metrics in NE China. *Landscape Ecol* 36(4):1261–1280
- Yan L, Jia W, Zhao S (2021) The cooling effect of urban green spaces in metacities: a case study of Beijing, China's capital. *Remote Sens* 13(22):4601
- Yang Q, Huang X, Tang Q (2019) The footprint of urban heat island effect in 302 Chinese cities: temporal trends and associated factors. *Sci Total Environ* 655:652–662
- Yang J, Ren J, Sun D, Xiao X, Xia JC, Jin C, Li X (2021) Understanding land surface temperature impact factors based on local climate zones. *Sustainable Cities and Society* 69:102818
- Yu Z, Guo X, Jørgensen G, Vejre H (2017) How can urban green spaces be planned for climate adaptation in subtropical cities? *Ecol Ind* 82:152–162
- Yu Z, Xu S, Zhang Y, Jørgensen G, Vejre H (2018) Strong contributions of local background climate to the cooling effect of urban green vegetation. *Sci Rep* 8(1):1–9
- Yuan W, He BJ, Yang L, Liu X, Yan L (2022) Heat-induced healthimpacts and the drivers: implications on accurate heat-health plans andguidelines. *Environ Sci Pollut Res* 29:1–20
- Zawadzka J, Corstanje R, Harris J, Truckell I (2020a) Downscaling Landsat-8 land surface temperature maps in diverse urban landscapes using multivariate adaptive regression

- splines and very high-resolution auxiliary data. *Int J Digit Earth* 13(8):899–914
- Zawadzka JE, Harris JA, Corstanje R (2020b) A simple method for determination of fine resolution urban form patterns with distinct thermal properties using class-level landscape metrics. *Landscape Ecol* 36(7):1863–1876. <https://doi.org/10.1007/s10980-020-01156-9>
- Zawadzka JE, Harris JA, Corstanje R (2021) The importance of spatial configuration of neighbouring land cover for explanation of surface temperature of individual patches in urban landscapes. *Landscape Ecol* 36(11):3117–3136
- Zhan W, Chen Y, Zhou J, Wang J, Liu W, Voogt J, Li J (2013) Disaggregation of remotely sensed land surface temperature: literature survey, taxonomy, issues, and caveats. *Remote Sens Environ* 131:119–139
- Zhao L, Lee X, Smith RB, Oleson K (2014) Strong contributions of local background climate to urban heat islands. *Nature* 511(7508):216–219
- Zhao H, Tan J, Ren Z, Wang Z (2020) Spatiotemporal characteristics of urban surface temperature and its relationship with landscape metrics and vegetation cover in rapid urbanization region. *Complexity*. <https://doi.org/10.1155/2020/7892362>
- Zhou D, Zhao S, Liu S, Zhang L, Zhu C (2014) Surface urban heat island in China's 32 major cities: spatial patterns and drivers. *Remote Sens Environ* 152:51–61
- Zhou D, Xiao J, Bonafoni S, Berger C, Deilami K, Zhou Y, Sobrino JA (2018a) Satellite remote sensing of surface urban heat islands: Progress, challenges, and perspectives. *Remote Sens* 11(1):48
- Zhou W, Wang J, Qian Y, Pickett ST, Li W, Han L (2018b) The rapid but invisible changes in urban greenspace: a comparative study of nine Chinese cities. *Sci Total Environ* 627:1572–1584
- Zhou Y, Zhao H, Mao S, Zhang G, Jin Y, Luo Y, Lun F (2022) Studies on urban park cooling effects and their driving factors in China: considering 276 cities under different climate zones. *Build Environ* 222:109441
- Zhou W, Yu W, Zhang Z, Cao W, Wu T (2023) How can urban green spaces be planned to mitigate urban heat island effect under different climatic backgrounds? A threshold-based perspective. *Sci Total Environ* 890:164422

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.