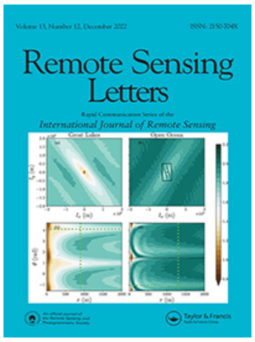

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Impacts of the spatial configuration of built-up areas and urban vegetation on land surface temperature using spectral and local spatial autocorrelation indices

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ABSTRACT

Understanding how the spatial configuration of land cover patterns of built-up areas and urban vegetation affect urban surface temperatures is crucial for improving the sustainability of cities as well as optimizing urban design and landscape planning. Because of their capability to detect distinct surface thermal features, satellite data have proved useful in exploring the impacts of spatial configuration of land cover on land surface temperature (LST). In this study, we examine how the spatial configuration of built-up and urban vegetation affects the LST in the Harare metropolitan city, Zimbabwe. In order to achieve this objective, we combined the LST, local spatial statistics of Getis-Ord *Gi** and local Moran's *I* statistic, Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Built-Up Index (NDBI) derived from multi-date Landsat satellite data (1994, 2001 and 2017). The results of local Moran's *I* statistic showed moderate and negative correlations between LST and Landsat derived NDVI. Overall, these results of local Moran's *I* statistic demonstrate that clustered vegetation tend to lower LST, providing thermal comfort conditions. In contrast, clustered spatial arrangements of NDBI based on the Getis-Ord *Gi** elevate LST, implying that continued clustered built-up expansion has the potential to increase urban surface temperatures.

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1. Introduction

Worldwide, the increasing urbanization inevitably generates urban heat islands (UHI) effects, which is largely induced by the expansion of built-up areas and loss of vegetation. In urban areas, the UHI phenomenon is associated with higher atmospheric and surface temperatures and warmer nights in urban areas than in the less developed, surrounding and rural areas (Oke 1982; Voogt and Oke 2003; Buyantuyev and Wu 2010). The UHI effects negatively affect the human health and welfare of urban dwellers by inducing cardiovascular and respiratory disorders and strokes (Lafortezza et al. 2009; Song and Park 2014). Generally, the UHI effects increase the urban energy and electricity consumption needed for cooling buildings (Kumari et al. 2021). Conventionally, UHI is derived from air temperature measurements (Schwarz et al. 2012) and land surface temperature (LST) (Voogt and Oke 2003; Buyantuyev and Wu 2012) derived from remotely sensed data (Sobrino, Jimenez-Munoz, and Paolini 2004; Weng, Lu, and Schubring 2004; Buyantuyev and Wu 2010).

Over the years, many studies have established that the spatial configuration (e.g., shape complexity, size, edge density, diversity, connectivity, proximity, aggregation and fragmentation) of land cover features have significant impacts on LST by optimizing, increasing, or mitigating the UHI effects (Fan, Myint, and Zheng 2015; Fan and Wang 2020; Kong et al. 2014; Maimaitiyiming et al. 2014; Zhang, Odeh, and Han 2009; Zhou, Huang, and Cadenasso 2011). Spatial configuration refers to the spatial arrangement and pattern of land cover types or patches in a landscape (Zhou, Huang, and Cadenasso 2011; Zheng, Myint, and Fan 2014). Landscape metrics are widely used to characterize the spatial configuration and land cover fragmentation (McGarigal et al. 2002). However, not all the widely used landscape metrics of spatial configuration are responsible for thermal heat transfers and exchange processes in urban areas (Chen et al. 2016). Furthermore, most previous studies did not consider spatial configurations based on the computed landscape metrics as continuous surfaces, resulting in a loss of vital ecological information (Fan and Myint 2014; Fan, Myint, and Zheng 2015).

However, these limitations can be addressed through the use of continuous methods called Local Indicators of Spatial Association or Spatial Autocorrelation (LISA) indices or local spatial statistics including the Getis-Ord *Gi**(Getis and Ord 1992) and the local Moran's *I* (Anselin 1995). LISA statistics are useful in identifying the presence of significant spatial clustering of similar values around an observation, stationarity and distances beyond which no discernible spatial association remains (Getis 1996). However, until now, the relationship between spatial configuration of land cover features and LST have been conducted mainly in major cities of the United States of America (Buyantuyev and Wu 2010; Fan and Wang 2020; Maimaitiyiming et al. 2014; Wang et al. 2019), China (Kong et al. 2014; Li et al. 2012; Zhang, Odeh, and Han 2009) and some Southeast Asia cities (Estoque, Murayama, and Myint 2017) than in African cities. Due to the differences and limitations of the geographical locations, regional climate conditions and patterns of urban form (compact versus dispersed) and economic growth levels, conclusions and implications drawn from these studies may not be comprehensive. Given this background, this study aimed to examine how landscape patterns or the spatial configuration of land cover types of built-up areas and vegetation, significantly influence LST in Harare metropolitan city, Zimbabwe.

2. Materials and methods

2.1. Study area

Harare metropolitan city is geographically located at 17.83°S latitude and 31.05°E longitude in the north-eastern part of Zimbabwe (Figure 1). The metropolitan city includes Harare urban, the dormitory towns of Epworth and Ruwa to the east as well as Chitungwiza to the south.

The population size of Harare metropolitan city was 2.42 million people as per the 2022 population census (ZIMSTAT 2022). The city has an area of approximately 980.6 km^2. The western, southern and eastern parts of the metropolitan city are largely composed of built up areas with the dominance of high-density residential areas. The northern portion is largely vegetated with predominance of low density residential areas.

2.2. Satellite data

The Landsat satellite image data series of the study area were acquired on 8 October 1994 (Thematic Mapper), 19 October 2001 (Enhanced Thematic Mapper Plus) and 23 October 2017 (Landsat 8 Operational Land Imager and Thermal Infrared Sensor). These Landsat imagery data were freely downloaded from Earth Explorer United States Geological Survey website (http://earthexplorer.usgs.gov/).

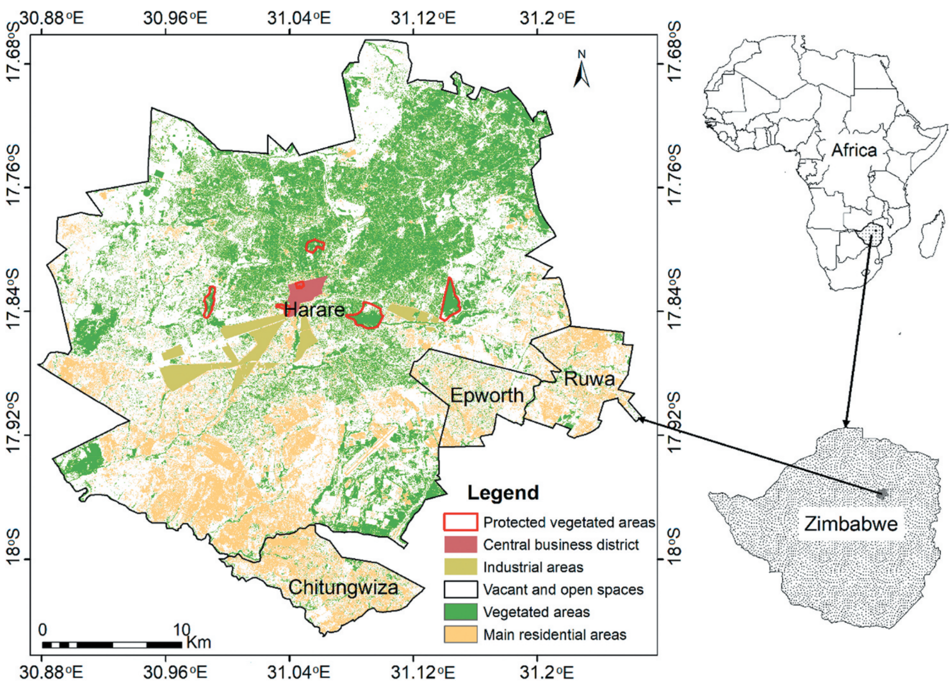

Figure 1. The geographical location map of Harare metropolitan city, Zimbabwe.

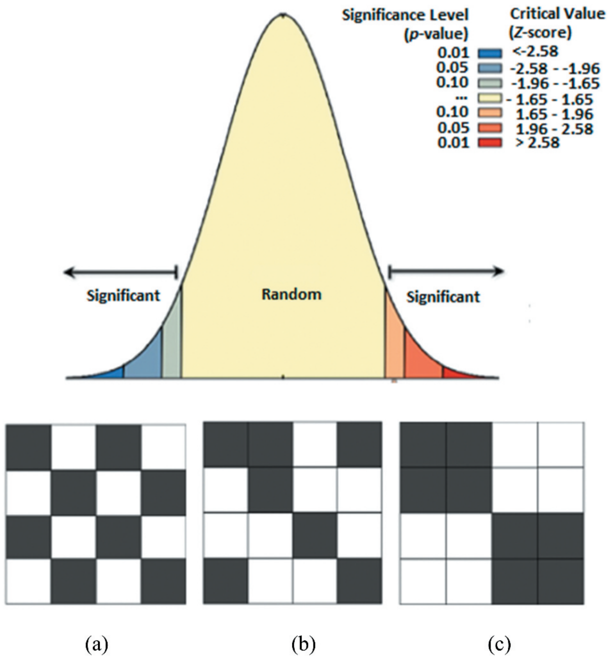

Figure 2. An illustration of spatial autocorrelation over a 4×4 regular grid. (a) Negative spatial autocorrelation (b) Random spatial autocorrelation and (c) Positive spatial autocorrelation.

In this study, the Getis-Ord *Gi** statistic (Getis and Ord 1992) was used to quantify the spatial configuration of built-up areas based on the NDBI data. On theother hand, the local Moran's *I* (Anselin 1995) was used to compute the spatial configuration of vegetation based on the NDVI data. The Getis-Ord *Gi** statistic and Local Moran's I index were chosen over other geostatistical methods because we were interested in defining spatial variation of built-up areas and urban green spaces at the local neighbourhood scale. The distinctive aspect of the Local Moran's *I* is to show the evidence of different spatial clustering pattern types of extreme (high or low) values and outliers. On the other hand, the Getis Ord *Gi** statistic is used to examine the strength of high and low clustering of observed values by providing positive and negative *Z*-score (standard deviation) and a corresponding *p*–value (significance level). The local Moran's *I* and Getis-Ord Gi^* statistic were later standardized and normalized to the range of −1 to 1. In this regard, low and negative values of local Moran's *I* and Getis-Ord Gi^* index and corresponding *Z*-score less than −1.96 indicate a significant spatial dispersion or "cold spot" (0 to ≥ −1) as indicated in Figure 2(a). A *Z*-score near zero indicates a tendency towards a random pattern in the absence of apparent spatial autocorrelation as illustrated in Figure 2(b). Whereas, high and positive values of local Moran's *I* index and Getis-Ord Gi^* statistic and corresponding *Z*-scores greater than 1.96 indicate statistically significant high spatial clustering or "hot spot" (0 to ≥ 1) as illustrated in Figure 2(c).

Table 1. Computation of built-up and vegetation indices derived from Landsat data.

Spectral index	Computation	Reference
Normalized Difference Built-up Index (NDBI)	$NDBI = \frac{SWIR1 - NIR1}{SWIR1 + NIR1}$	(Zha, Gao, and Ni 2003) Equation (1)
Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{NIR - RED}{NIR + RED}$	(Tucker 1979) Equation (2)

2.3. Spatial configuration of vegetation and built-up areas

The satellite-derived Normalized Difference Vegetation Index (NDVI) (Tucker 1979) which utilizes Near-infrared (NIR) and Red (R) wavelengths was used to quantify the amount and presence of green vegetation as indicated in Equation (1) (Table 1). The Normalized Difference Built-Up Index (NDBI) (Zha, Gao, and Ni 2003) based on NIR and Shortwave Infrared (SWIR) wavelengths as indicated in Equation (2), was used to quantify the amount and presence of built-up areas. (Table 1). High NDBI index indicates the presence of built-up areas where there is typically a higher reflectance in the SWIR wavelength region, when compared to the NIR wavelength region (Zha, Gao, and Ni 2003)

In urban areas, LISA indices of Getis-Ord *Gi** statistic and Local Moran's *I*, have been previously used to quantify the impact of fragmentation and spatial clustering (aggregation) of vegetation and built-up areas on land surface temperature largely determined by the patterns of residential and urban growth (Fan, Myint, and Zheng 2015; Kong et al. 2014; Zhang, Odeh, and Han 2009).

2.4. Retrieving Land Surface Temperature (LST)

The thermal bands of Landsat satellite images of the study area were used to retrieve the LST data. First, the Digital Numbers (DNs) were converted to at-sensor radiance or top-of-atmosphere (TOA) according to radiometric rescaling coefficients recommended by the United States Geological Survey (USGS) (Karnieli et al. 2010). Next, the spectral radiances of Landsat data were converted to Brightness Temperature (TB) in Kelvin at the sensor by applying the inverse of the Planck radiance function for temperature. Lastly, the emissivity corrected and retrieved LST were later converted from Kelvin degrees to Celsius (^{o}C) degrees by subtracting 273.15 (Sobrino, Jimenez-Munoz, and Paolini 2004; Weng, Lu, and Schubring 2004).

2.5. The spatial pattern of UHI and non-UHI zones

To map the UHI and non-UHI zones, Equation 3 and Equation 4 were employed, respectively, following (Guha, Govil, and Mukherjee 2017; Guha et al. 2018).

$$LST > \mu + 0.5x\delta \tag{3}$$

$$0 < LST \leq \mu + 0.5x\delta \tag{4}$$

where μ and δ are the mean and standard deviation of LST in the study area, respectively. UHI zones refers to areas having extremely high LST (Guha, Govil, and Mukherjee 2017; Guha et al. 2018). Generally, UHI zones are extremely warmer parts of the city, irrespective of the season (Guha, Govil, and Mukherjee 2017; Guha et al. 2018). In the UHI zones, the built-up areas predominate the land coverage. On the other hand, non-UHI zones are the most cool and stable thermal areas with higher proportion of vegetation cover (Guha, Govil, and Mukherjee 2017; Guha et al. 2018).

2.6. Statistical analysis

A parametric test, Pearson's correlation coefficient (*r*) was used to compute the linear and bivariate correlations between the LST as the dependent variable and the local Moran's *I* of NDVI and Getis-Ord *Gi** of NDBI as independent variables in each year because our data exhibited a normal Gaussian-distribution. A negative correlation between LST and the LISA indices of Getis-Ord *Gi** statistic and Local Moran's *I* means a reducing effect on LST and a positive correlation means increasing effect on LST.

3. Results

3.1. Spatial and temporal variability pattern of LST

An increasing urban surface temperatures trend was observed in the study area between 1994 and 2017 (Table 2). The mean LST values were 29.85°C in 1994, 31.80°C in 2001 and increased to 38.26°C in 2017. The maximum LST increased by 4.14°C between 1994 and 2001, 2.91°C between 2001 and 2017 (Table 2). Higher values of LST were predominant in the western, southern and eastern side of the city (Figure 3). Conversely, the lower values of LST were more concentrated in the northern side of the city (Figure 3).

3.2. Spatial distribution of UHI and non-UHI zones

The UHI zones expanded whereas non-UHI zones declined indicating the increasing concentration of high LST in the study area (Table 3). The UHI zones were more dominant in the western parts in 1994 but spread to the southern and eastern of Harare between 2001 and 2017 (Figure 4). The non-UHI zones were more concentrated in the northern side of the city coinciding with the abundance of dense vegetation (Figure 4).

Table 2. Descriptive statistics of Landsat derived LST in 1994, 2001 and 2017.

Acquisition date	Mean LST (°C)	Minimum LST (°C)	Maximum LST (°C)	Standard Deviation LST(°C)
8 October 1994	29.85	14.71	41.45	3.27
19 October 2001	31.80	17.95	45.59	2.96
23 November 2017	38.26	23.81	48.5	2.89

Table 3. Change in the area covered by the UHI and non-UHI zones during the study period.

Year	UHI (ha)	Non-UHI (ha)
1994	30359.16	67704.48
2001	30876.57	67187.07
2017	31762.98	66300.66

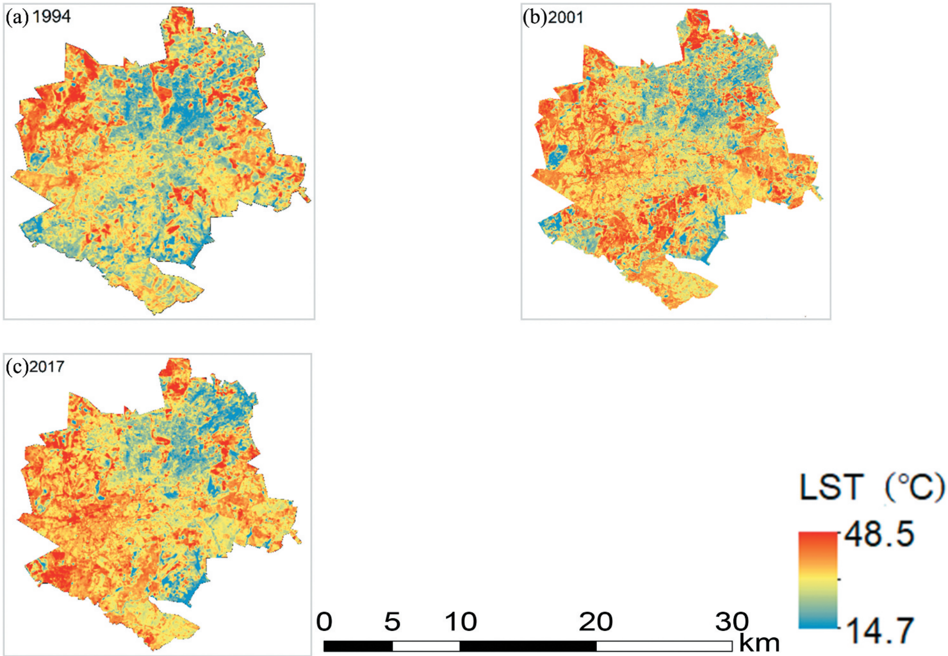

Figure 3. The spatial distribution of land surface temperature (LST) in Harare metropolitan city in different years (a) 8 October 1994 (b) 19 October 2001 and (c) 23 October 2017.

The mean LST values were higher in UHI zones than in non-UHI zones as indicated in Table 4. Furthermore, the differences in mean LST between UHI zones and non-UHI zones were 4.43°C in 1994, 3.72°C in 2001 and 4.47°C in 2017. However, the standard deviation values of LST showed more variability for non-UHI zones than UHI zones (Table 4).

Min-Minimum, Max (Maximum), SD (Standard Deviation)

3.3. Relationship between spatial configuration of built-up areas and LST

The Pearson correlation coefficients between the spatial configuration of built-up areas and urban vegetation and LST are shown in Table 5. The Getis-Ord *Gi** of built-up areas had a moderate and positive relationship with LST between 1994 and 2017. It ranged from ($r = 0.66$, $p < 0.05$) in 1994, ($r = 0.30$, $p < 0.05$) in 2001 to ($r = 0.32$, $p < 0.05$) in 2017, suggesting that the magnitude and the impact of spatial configuration of built-up areas on LST varied between the years. The visual inspections of LST and Getis-Ord *Gi** of NDBI maps indicate that urban surface temperatures are higher when built-up areas are highly and spatially clustered (Figures 3 and 5). This can be visually seen with high positive values of Getis-Ord *Gi** of NDBI in the western, southern and eastern side of the city. On the other hand, LST was low in areas with highly dispersed patterns of built-up areas as indicated with low and negative values of Getis-Ord *Gi** of NDBI (Figure 5). This can be apparently observable in the northern part of the city (Figure 5).

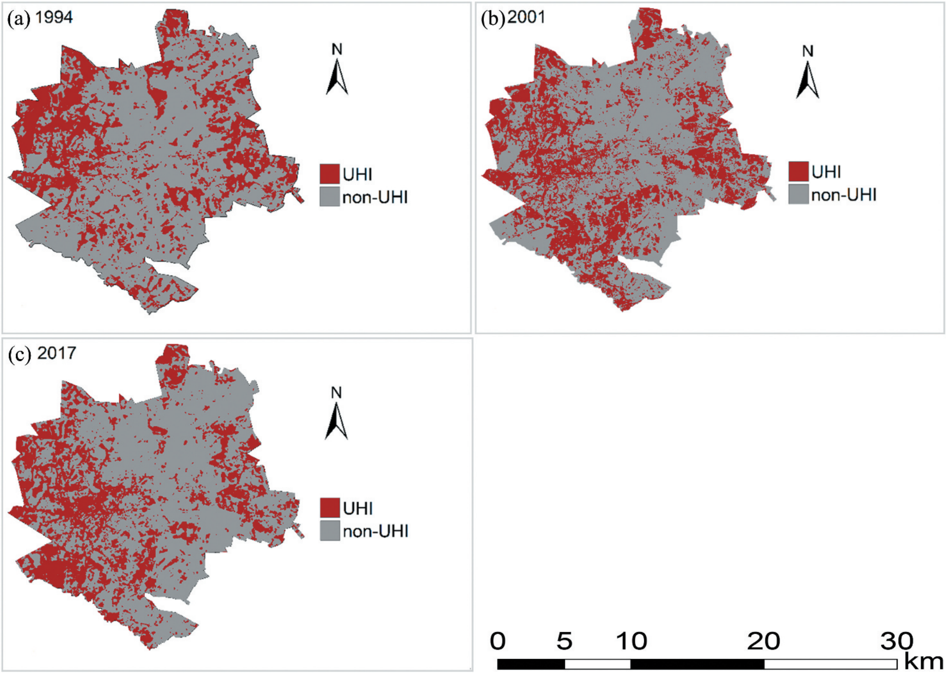

Figure 4. Spatial distribution of UHI and non-UHI zones in Harare metropolitan city in a) 8 October 1994 (b) 19 October 2001 and (c) 23 October 2017.

Table 4. Descriptive statistics of LST (°C) in UHI and non-UHI zones.

	1994		2001		2017	
Statistics	UHI	Non-UHI	UHI	Non-UHI	UHI	Non-UHI
Min*	31.65	25.01	31.31	28.78	39.41	35.85
Max*	35.71	31.44	37.53	33.95	43.70	39.70
Mean	33.64	29.21	34.89	31.17	41.32	36.85
SD*	0.78	0.95	0.57	0.90	0.51	0.65

Min-Minimum, Max (Maximum), SD (Standard Deviation)

Table 5. Pearson correlation coefficients (*r*) between LST and LISA indices of Getis-Ord *Gi** of NDBI and local Moran's *I* of NDVI in 1994, 2001 and 2017.

Year	Getis-Ord *Gi** of NDBI	Local Moran's *I* of NDVI
1994	0.66	−0.58
2001	0.30	−0.33
2017	0.32	−0.34

3.4. Relationship between spatial configuration of urban green vegetation and LST

A weak to moderate and negative relationship between LST and local Moran's *I* of green vegetation (NDVI) were observed in the study area (Table 5). The Pearson correlation coefficients between LST and local Moran's *I* of green vegetation were ($r = -0.58$, $p < 0.05$) in 1994, ($r = -0.33$, $p < 0.05$) in 2001 and ($r = -0.33$, $p < 0.05$) in 2017. The visual inspections of LST and

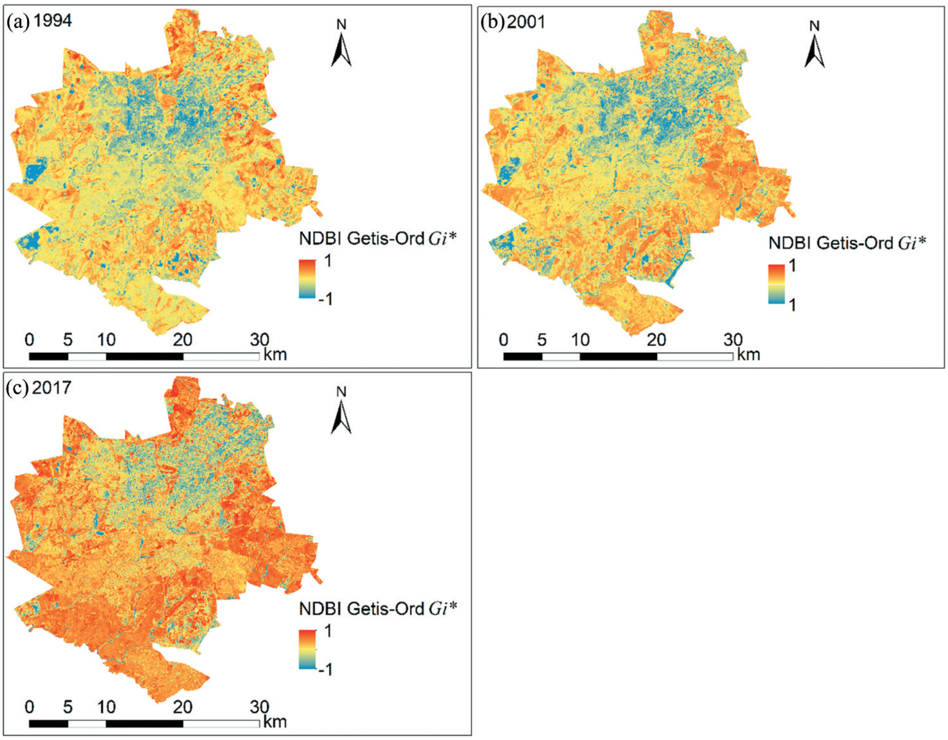

Figure 5. The map of standardized and normalized values of Getis-Ord *Gi** of NDBI in (a) 1994 (b) 2001 and (c) 2017. The high positive values represent highly clustered pattern and low negative values represent highly dispersed patterns of built-up areas.

local Moran's *I* of vegetation maps indicated that LST was low in areas with relatively high and positive clustering of vegetation patches in the northern part of Harare (Figures 3 and 6). This therefore indicates that vegetation cover that exhibit a higher level of spatial clumping and abundance in coverage is negatively related to the LST, thereby producing greater cooling effects. Conversely, LST was high in areas with low, negative clustering and dispersed vegetation patches in the western, southern, and eastern parts of the city (Figures 3 and 6).

4. Discussion

4.1. Impact of built-up areas and green vegetation on LST

The overall results of this research revealed an increasing LST trend between 1994 and 2017. This finding is consistent with previous studies by Mushore et al. (2017) that Harare metropolitan city has experienced higher urban surface temperatures in recent years. The western, southern and eastern side of the city has more built-up areas and tends to experience higher surface temperatures due also to significant urban developments and infrastructure expansion (Mushore et al. 2017). The northern part of the study area experiences lower surface temperatures due to the dominance and abundance of vegetation cover as compared to built-up areas. This indicates that LST decreases with increases

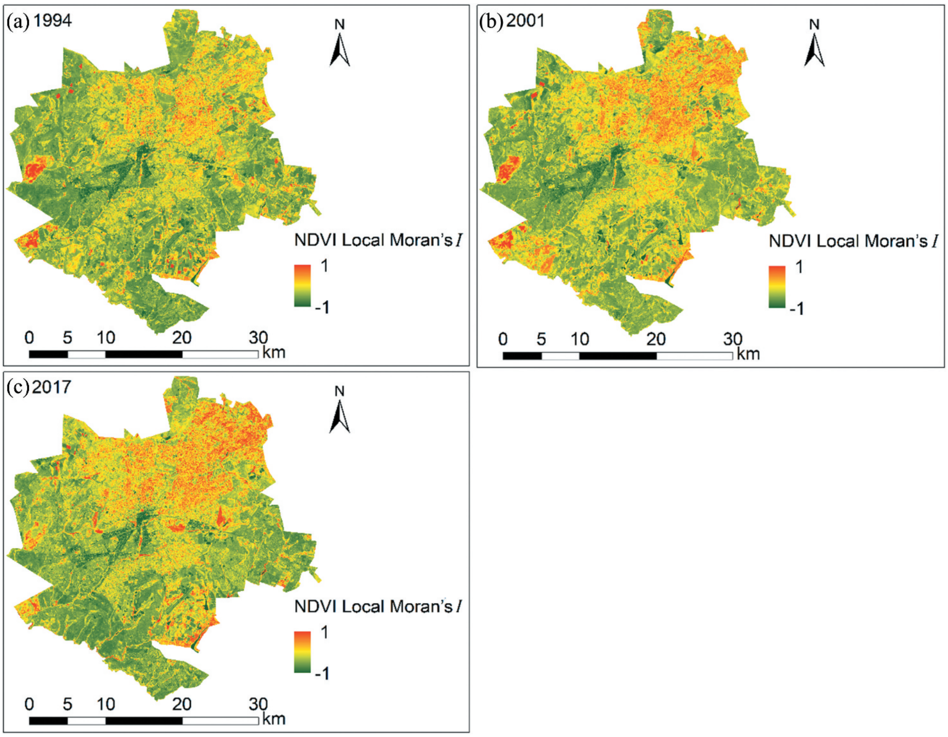

Figure 6. The map of standardized and normalized values of local Moran's *I* of NDVI in (a) 1994 (b) 2001 and (c) 2017. The high positive values of local Moran's *I* of NDVI represent highly clustered pattern and low negative values represent highly dispersed patterns of vegetation cover.

in vegetation cover and increases with an increase in the built-up areas (Weng, Lu, and Schubring 2004).

4.2. The impact of spatial configuration of land cover on LST

The negative correlation between local Moran's *I* of green vegetation and LST indicates that clustered patterns of vegetation tend to lower land surface temperature. This finding corroborates other studies that found clumped or clustered green vegetation producing stronger cooling effect than scattered, dispersed green spaces (Li et al. 2012; Maimaitiyiming et al. 2014; Zhang, Odeh, and Han 2009). Furthermore, a study by Dugord et al. (2014) showed that larger and clumped forest patches were associated with lower surface temperatures and significant cooling effects in the city of Berlin, Germany. In most climate regions with hot and dry summer, highly clustered or abundance of vegetation cover is associated with higher atmospheric moisture and evapotranspiration rate that offset the warming effects of built-up areas (Wang et al. 2019). Conversely, in our study, LST was high in areas with low, negative clustering and dispersed vegetation patches in the densely built-up areas of western, southern and eastern parts of the city. Previous studies have demonstrated that increasing fragmentation of vegetation patches can raise LST (Kong et al. 2014, 2014b, Zhang, Odeh, and Han 2009; Zhou, Huang, and Cadenasso 2011).

The positive correlation between Getis-Ord *Gi** of built-up areas (NDBI) and its influence on LST indicates that clumped or clustered patterns of built-up areas tend to increase land surface temperature, which is consistent with the results of some previous studies (Estoque, Murayama, and Myint 2017; Wu et al. 2019; Zheng, Myint, and Fan 2014). This is because aggregated, clumped or clustered built-up areas generally increase ground heat fluxes and sensible heat fluxes during the daytime by converting shortwave radiation from the solar energy into longwave radiation to heat up the lower atmosphere, thereby reducing latent heat fluxes and evapotranspiration (Oke 1982; Ma, Wu, and He 2016). Furthermore, clumped or clustered built-up areas can also concomitantly increase anthropogenic heat emissions from buildings, roads, paved and tarmac surfaces, all of which lead to increased LST (Zhang et al. 2010; Zhou et al. 2014). On the other hand, the spatial configuration of built-up exhibited a spatially heterogeneous and dispersed pattern in the northern part of Harare with relatively lower LST. Fan and Wang (2020) also found that dispersed patterns of built-up areas were responsible in reducing the LST in Boise-Meridian metropolitan area, the United States of America (USA).

5. Conclusion

In urban planning and landscape design, spatial configuration (clustered or dispersed) is an essential aspect because it measures the spatial arrangement, distribution and organization of urban land covers which are responsible for various heat exchange, energy flow and thermal processes in a city in either optimizing, elevating or mitigation the UHI effect. In particular, this study contributes to the local knowledge and insights of spatio-temporal impacts of the spatial configuration patterns of built-up areas and urban vegetation on land surface temperature (LST) based on the remotely sensed spectral and local spatial autocorrelation indices. The results of the study revealed that clustered vegetation cover effectively lowers LST while the abundance or spatial clustering of built-up areas contribute to elevated LST. Therefore, increasing clumped green spaces instead of small, isolated vegetation patches should be encouraged to promote greater cooling and to minimize urban heat island effects caused by increase in built-up areas and rapid urban expansion. Our results have important scientific and policy implications for landscape and urban planning, particularly in rapidly growing and urbanizing cities as in our case study, where the available land area for increased urban development or urban expansion and greenery space is limited. Urban planners and landscape designers should focus on optimizing the spatial configuration patterns of land cover of built-up area and urban vegetation patches, in order to maintain a rational balance between the sustainability of cities and mitigating the UHI effects and maintaining healthier and more comfortable urban living conditions. These recommendations and suggestions may not only be relevant to the cities in the Zimbabwe only, but may also have the potential to be applicable to other cities in Southern Africa that have similar or diverse climate zones and backgrounds.

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