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ANALYZING LAND USE TYPES' EFFECTS ON LST USING THE GWR MODEL AND CASE STUDIES IN BEIJING

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Highlights

- Discusses the correlation between land use types and increasing temperature.
- Uses Landsat 8-9 remote sensor tools and recent decades registered statistics.
- Images show more LST in urban centers compared to green lands.
- Presents ways for landscape and land use management.

Abstract. The development of urbanization and the transformation of green lands into impermeable land increase temperature and create urban heat islands (UHIs). Our observations with remote sensing instruments of Landsat platforms show considerable changes in land use types in Beijing city with the shrinking of green lands, expansion of built environments, and a slight increase in the temperature during the recent four decades. Using remote sensing instruments of Landsat platforms and registered data from two meteorological stations in Beijing, this study finds the relationship between land surface temperature (LST) and the increasing conversion of cultivated lands into built-up areas. This article presents innovative research that shows the mutual correlation well and recommends revisions in the land use policies for better weather. The geographically weighted regression model (GWR) with a Gaussian weighting kernel function analyzes the impact of various urban land use types on the LST and the increase UHIs. In Beijing city, green lands show fewer standard deviations (SD) in the average temperatures equal to 0.109, while the industrial spaces exhibit a high SD equal to 0.212. The outcomes of this paper contribute to finding optimal land use policies everywhere in the world with the increasing urbanization through simulating its model for a more comfortable life.

Keywords: landscape management, land use type, urban heat island, land surface temperature, remote sensing, captured images, geographically weighted regression.

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Introduction

Major unprecedented fires, lasting droughts, devastating urban floods, terrible forest fires, the alarming increase in greenhouse heat, and extreme weather have been experienced in the world related to the increasing land surface temperature. The land surface temperature has raised since 1975 at a rate of roughly 0.15 to 0.20 °C per decade (*United States Geological Survey*, 2023; Dobruskin, 2022). Climate change has been introduced as a cause for the increasing land surface temperature but confirmed pieces of evidence indicate that anthropogenic actions, particularly urbanization and the conversion of fields, pastures, and forests into streets and buildings are responsible for warming urban areas. The impacts of anthropogenic activities on climate change have also been recognized. The unprecedented growth of the urban population caused the rapid expansion of cities, particularly developing cities

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with changes in the natural physical characteristics of the earth's surface. Urban heat island is another negative impact of climate change and global warming, which scientists are studying.

This research aims to find the relationship between the increase in the temperature of urban lands with the increasing changes of natural and barren lands to impervious surfaces and built environments. For this purpose, it benefits recent advanced Landsat 9 remote sensing technological tools and the recorded statistics by two meteorological stations in Beijing city comprehensively.

The method of this research includes remote sensing of Landsat 8, 9, 4, and 5 and reviewing recorded data from two separate meteorological stations about the temperature of Beijing City in recent decades. This research builds a geographically weighted regression, GWR, model for assessing the surface temperature on various land uses and landscapes in Beijing. Concerning research findings in the past, this research applies an innovative and accurate method. It uses collected and archived spatial resolution multispectral image data by Landsat 9 about Beijing. Images provided by the Landsat 9 are sufficiently consistent with data from the earlier Landsat missions. This study also benefits from reviewing data about the temperatures in the city provided by two meteorological stations in recent decades to find land surface temperature variations. The Landsat-acquired images and the meteorological sources assist in testing the analyses and proving the accuracy of our findings. The research method is more novel compared to past research when it uses remote sensing and on-ground recorded data to suggest feasible land-use policies for Beijing City. This study about Beijing confirmed the relationship between the urban land surface temperature and various land use categories. We have had the chance to benefit latest remote sensing technologies of Landsat 9 in studying the impacts of land use policies in the LST in Beijing City. This research applies a geographically weighted regression to model mutual relations between LST and urban land use types in Beijing City.

We hypothesize that environmentally friendly land use policies will decrease the LST and the number of UHIs. To prove this hypothesis, we use registered data in two meteorological stations to reconcile them with multispectral images of Beijing's earth obtained by remote sensing. Fortunately, recent advances in Landsat, databases, national land cover dataset (NLCD), and ArcGIS with the application of geographically weighted regression (GWR) are helpful tools for conducting our study. Additionally, the recorded data of meteorological and environmental departments of counties, including Beijing, provide valuable information for analyzing the warming process of the earth's surface and its relationship with the types of urban land use. The outcomes of this study determine the trends of temperature changes in Beijing and show the temperature differences in various urban land uses to assist urban physical development planners in optimal land uses. Finally, this paper recommends the appropriate adaptation of strategic land use types to impact positively the quantity, allocation, and LST of urban lands.

1. Literature review

Scientists have declared increasing LST and UHIs as alarming phenomena around the globe (Mostafa et al., 2023; Wasif Ali et al., 2022). The impacts of vegetation cover loss on surface temperature and carbon emission in the fast-growing city of Comilla in Bangladesh have been studied (Kafy et al., 2022). Scientists have also found the anthropogenic activities behind climate change. Human-induced climate change, including more frequent and intense extreme events, has caused widespread adverse impacts and related losses and damages to nature beyond natural climate variability (Fonseka et al., 2019). Amid growing concerns about global warming, the population has reached unprecedented figures, which means that it has a destructive effect on natural resources and the climate. On November 15, 2022, the population is projected to reach 8 billion people, a milestone in human development (United Nations Department of Economic and Social Affairs, Population Division, 2022). The mentioned cities are replacing green lands and natural resources with lands covered by building materials. As a result, a significant change emerges, which we call urban heat islands, UHIs. Scientists have suggested that built-up surfaces contribute to weather warming, which affects urban heat islands (Gyimah, 2023). Research on UHI has a long history back to the 1970s. Scientists have found the causes and impacts of the UHI (Schott & Schimminger, 1981; Henry & Dicks, 1987). Investigating the weather and forecasting and simulating the urban warming in Metro Manila illustrated hotspots there, especially during the nighttime. The same research indicated that the number of urban heat islands reached a maximum during the daytime. The results have been used as a baseline for projects and policy recommendations to reduce urban heat (Bilang et al., 2022). Scholars believe the expansion of urban areas is a source of increasing global warming (Shen et al., 2023). Studies confirmed the relationship between the increase in the urban land surface temperature and various land use types. Scientists have noticed the Landsat platforms' technological advances and evolution since Landsat 1 was launched on July 23, 1972, with two Earth-viewing imagers (Masek et al., 2020; Wulder et al., 2022). With the development and evolution of remote sensing technologies, features of earth's land surfaces, the impact of humans on the environment, weather, and natural resources have increasingly been observed and considered as indicators for urban and regional planning and development (Feng & Fan, 2022; Al Kafy et al., 2021; Olorunfemi et al., 2020; Islam et al., 2022). The mentioned technologies and databases in remote sensing satellite platforms provide thermal data with land use and land cover information (Sayler, 2022; Galland & Stead, 2022). Dhaka is one of the most densely populated cities in the world with increased built-up areas and reduced wetlands. It has uncomfortable weather compared to its surrounding rural areas and experiences warmer weather. Research about finding optimal urban land use for potential improvement and cooling in the city is under discussion (Shahjahan, 2018). Scientists have used a geographically weighted regression to model the relationship between urban land surface temperature and land use types. Scholars have already used the GWR to measure the rate of interconnections of land surface temperatures with land use policies and landscape types (Siqi et al., 2022; Ullah et al., 2023; Zhi et al., 2020). Given the correlation between land surface temperature (LST) and urban land uses, we hypothesize that cities that have preserved the natural characteristics of the land and the earth's morphology during urban development planning and design and have emphasized green construction have less increase in LST. The cities that have conducted many construction projects to the detriment of green spaces and natural resources due to the uncontrolled increase in population and their needs for newly built environments have faced further warming (Bouton et al., 2015; Shahraki, 2020). UN SDGs are practical guides for implementing land use policies in cities to avoid further LST and warming. The UN SDGs have been defined as follows:

The 17 Sustainable Development Goals (SDGs) are the best plan to build a better world for people and our planet by 2030. Adopted by all United Nations Member States in 2015, the SDGs are a call for action by all countries – poor, rich, and middle-income – to promote prosperity while protecting the environment (United Nations & Regional Information Centre for Western Europe, n.d.). The UN Sustainable Development Goals (SDGs) indicator 11.3.1 is designed to test urban land use efficiency by using the model provided by UN metadata to calculate the land use efficiency rates from 1990 to 2015 in Wukang (Cai et al., 2020). The United Nations' Sustainable Development Goals (SDG) have been used to determine potential policies to address land use and land cover changes due to increasing population, suburbia, and rubber plantations in Semarang, Indonesia between 2006 and 2015 (Kelly-Fair et al., 2022). Further, Scholars and engineers respect the UN-Habitat standards in planning and designing cities, which prevent increasing LST and global warming (Sykes et al., 2023; De Miguel González & Vallvé, 2023).

2. Introducing case study region

2.1. The expansion process of the Beijing

We have studied some features of Beijing City with 16 urban, suburban, and rural districts. The geographical position of the city, its increasing physical expansion in recent decades, and land surface temperatures are necessary parameters for our analysis of the mutual connection of LST and land use categories. Beijing with 39° 54′ 24″ N and 116° 23′ 51″ E is located in northern China. By the end of 2017, Beijing had a population of 21.7 million and an urbanization rate of 86.5%. In the past 30 years, the city's population has nearly tripled, and its build-up area has nearly eight-folded, making it one of the largest cities in the world (Shi & Cao, 2020). The physical development of Beijing City shows that by 2010, it had 13 outer counties. Six of them were already part of the area in 1995. Other seven counties have been included in Beijing since 1995. In the first five years of this period, the expansion of Beijing was moderate, and only Miyun and Sanhe had been incorporated. Then, in the next five years (2000–2005), the city had been experiencing an accelerated spatial expansion: three counties within Beijing (Pinggu, Daxing, and Yanqing) and one county outside Beijing (Dachang) were incorporated. The development started to slow down between 2005 and 2010. During this period, only Xianghe

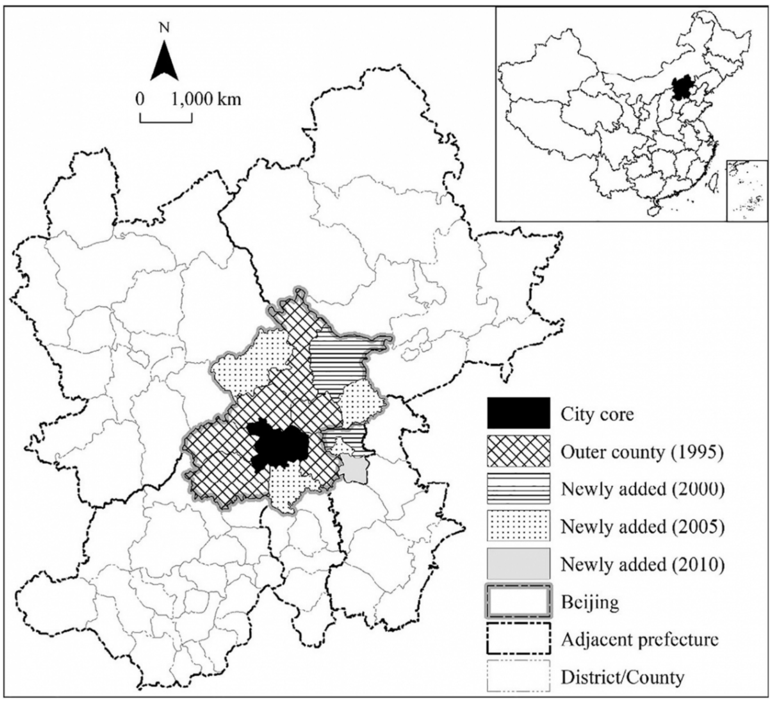

Figure 1. Shows the expansion of Beijing in recent decades (source: Shi & Cao, 2020)

integrated into the already fully developed Beijing City. The spatial coverage in 1995 and the continuous expansion in the following 15 years indicate that Beijing not only had an early formation but also became very dynamic soon after. Figure 1 exhibits the expansion of Beijing City.

The dramatic expansion of Beijing City since 1995 has been a result of a mutual-reinforcing process between industrialization and suburbanization. Some counties, such as Daxing, became part of Beijing because of their economic connections with the downtown. Daxing developed an economic-technological area in 1996, which is now the most successful in Beijing. Other counties, such as Sanhe, were counted as part of the metropolitan mainly because they accommodate thousands of commuters who work in the inner city. Despite the spatial expansion of Beijing City, its economy increasingly has been powered by the downtown, which is insignificant from the used urban land area view. The dominant economic sector in this area is dramatically different from that in 1995 (Shi & Cao 2020). Beijing's inner city has experienced more land surface temperature increases, which resulted in effects like the emergence of urban heat islands on the concentrated economic and administrative areas (Meng et al., 2022).

Table 1. The temperature of Beijing City on February 15 in 2012–2022 (source: Time and Date, n.d.)

Year	Temperature		
	Max	Min	Average
2010	–5	–	–5.5
2011	–6	–7	–6.5
2012	–2	–2	–2
2013	–1	–3	–2
2014	–4	–4	–4
2015	–1	–3	1
2016	–4	–6	–5
2017	–2	–2	–2
2018	–3	–6	–4.5
2019	–4	–5	–4.5
2020	–3	–3	–3
2021	–2	–1	–1.5
2022	–1	–1	–1

2.2. Beijing's weather temperature

Beijing's monthly average temperature in January is –2.9 °C, while in July is 26.9 °C (Wang et al., 2021). Exploring the urban land surface temperature in Beijing shows that it has gradually increased. For a sample, note the registered temperature on February 15, 2012–2022 in Table 1.

Beijing's average temperature on February 15th every year from 2010 to 2022 is shown by the curve in Figure 2, which shows the direction of temperature changes in this city.

The curve of Figure 2 and its trend line shows an increase in the temperature in Beijing City in 2010–2022, although small with an *R*-square value of $R^2 = 0.1379$.

Because of the degradation of natural resources, the land surface temperature in Beijing City has increased slightly. The increase in the LST might relate to land use policies, degradation of natural resources, and expansion of built environments in the city of Beijing with impervious land.

2.3. Land use categories in Beijing

Scientists suggest that urban surfaces like green lands, natural landscapes, environmentally friendly constructions, and anthropogenic activities influence urban areas' LST (Sun et al., 2019; Feng et al., 2019). This study uses the classification of land use types in Beijing with the areas according to Li and colleagues in Table 2.

Table 2. Overview of land use types with their area/km^2 (source: Ullah et al., 2023)

Land-use category	Sign	Area/km^2	Percentage	Count of areas of interest
Residential	X_1	398	41.2	9525
Business	X_2	95	9.83	4198
Commercial	X_3	48	4.97	3376
Industrial	X_4	39	4.04	1242
Administrative	X_5	15	1.55	1432
Medical	X_6	11	1.14	798
Cultural	X_7	11	1.14	535
Green space	X_8	264	27.33	929
Educational	X_9	85	8.80	3782
Total	$\sum_{i=1}^{9} X_i$	966	100	25817

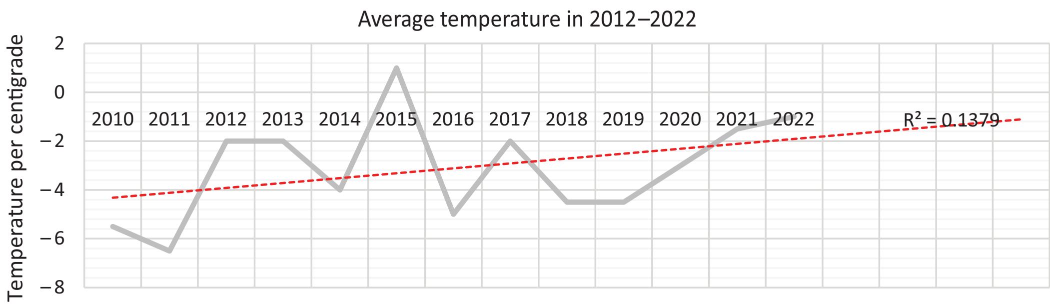

Figure 2. The trend line of the average temperature of Beijing in 2010–2022

Land uses and landscapes in the metropolitan area of Beijing include nine types with various LSTs.

3. Methods and data

The research method is based on the review of the research done so far, using recent Landsat technology, and case studies. We model the relationship between urban land use and LST with a GWR and suggest revision in urban land use policies to avoid the further disappearance of natural resources. Our research methods apply remote sensing technology to observe the case study area and provide images showing rates of LST in different land uses. The methods use recorded temperatures in two meteorological stations in Beijing to predict the trend of LST. This research builds a mathematical model based on a geographically weighted regression procedure to show land use types' correlation with thermo-spatial characteristics like land surface temperature.

3.1. Remote sensing

We used the Landsat 8 and 9 platforms to provide thermal maps concerning Beijing City. Landsat 8 and 9 ensure the continued acquisition and availability of Landsat data using a two-sensor payload, an operational land imager (OLI), and a thermal infrared sensor (TIRS). Two thermal bands of TIRS capture data with a minimum of 100-m resolution but are registered and delivered by the 30-m OLI data product. The aim is to evaluate surface-emitted radiance in thermal infrared wavelengths with collection 2 (C2) and level 1 (L1) tools. Please read the supplemental file that reports remote sensor platform conditions and the place position in which the land surface temperature image in Figure 3 has been captured. By adding the coordinates of Beijing City to the algorithms, our observation area has been limited to Scene Center Lat DMS = 40° 19′57.40″ N and Scene Center Long DMS = 116°42′11.77″ E including 39° 54′ 24″ N and 116° 23′ 51″ E, which is visible in the image 3. The remote sensor platforms with features listed in the supplemental file retrieved a land surface temperature (LST) image of Beijing by thermal bands shown in Figure 3.

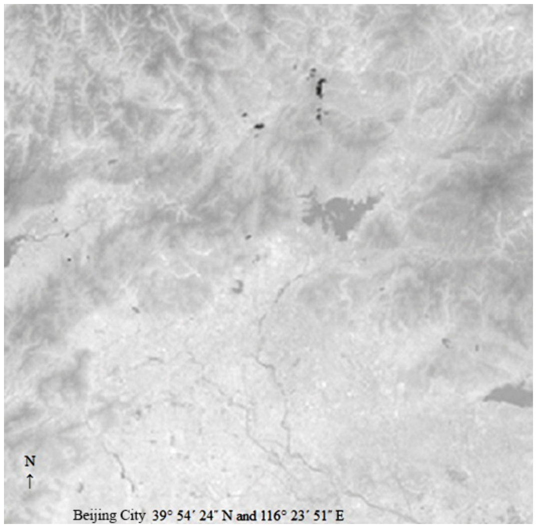

Figure 3. Thermo-spatial image of Beijing City using Landsat 9 and its TIRS sensor, acquired in 2022

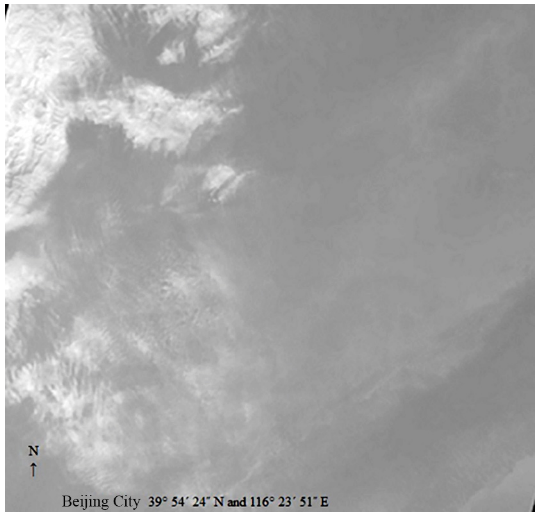

Figure 4. Thermo-spatial image of Beijing City using Landsat 4-5, TM C2 L1 acquired 1982

The thermal image in Figure 3 is a grayscale image that shows the intensity of radiance measured in the thermal infrared channels that bright areas are warmer and dark areas are cooler. Layers of land use/land cover, population density, and building density have been illustrated with bright colors, which means higher LST. We also used the Landsat 4-5 C2 L1 to observe the thermal image of the Beijing metropolitan area acquired on February 12, 1982, the results of which are in Figure 4.

A comparison of images 3 with 4 shows the changes in LST and the fact that the lands had lower LST in 1982, which are dark gray in image 4. This image exhibits that the lands have become warmer in 2022, which is in light gray in image 3. Images 2 and 3 provided by the remote sensing show the change in the use of agricultural lands and pastures in favor of the expansion of urban space and concentration of residences, businesses, workshops, and transportation in the last 40 years in the Beijing metropolitan area.

Again, we used Landsat 8 and 9 with (OLI), (TIRS), (C2), and (L1) to supply a hydrograph image of the Beijing metropolitan area in natural color. The natural color image uses visible channels of Landsat 8 and 9 to simulate what would be seen with eyes in Figure 5.

Landsat 4-5 with C2 L1 provides an observed hydrographic image of Beijing City acquired on February 12, 1982, which shows green lands, wetlands, and lakes in Figure 6.

The upper hydrographic images assist us to measure and describe the physical features of bodies of water and neighboring lands to use in future urban land-use categories. A comparison of images 5 and 6 shows that the green lands of picture 6 in 1982, which were used for agriculture and pasture, are no longer green in 2022 and have been replaced by population centers and urban development.

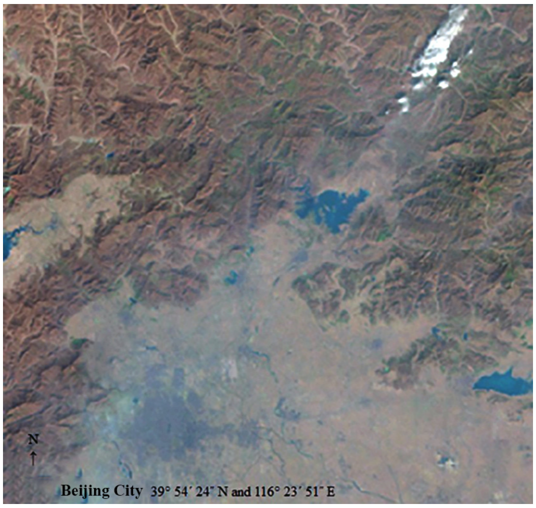

Figure 5. Hydrographic image of Beijing City using Landsat 9 and its TIRS sensor in natural color acquired on 2022

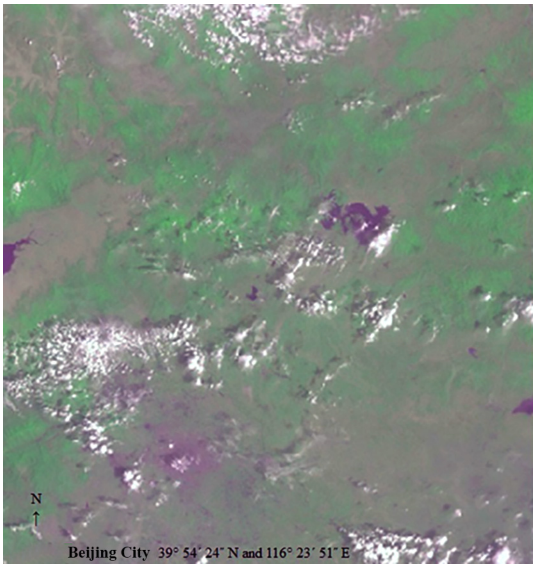

Figure 6. Hydrographic image of Beijing City using Landsat 4-5, TM C2 L1 in natural color acquired on 1982

3.2. Use of registered data

We reviewed the land surface temperature with registered data, which have been gathered from two meteorological stations of DX (Daxing) and BJ (Beijing). The DX meteorological station is in the Daxing district of Beijing City where the airport exists. The BJ station belongs to the Beijing municipality. We studied the highest, lowest, and average temperatures for February 1982–2022 from the meteorological stations. In Figure 7, we have used the average data of two DX and BJ stations.

Figure 7 shows three curves with trend lines for maximum, minimum, and average temperatures. The equations on the chart for max, min, and aver are as follows, respectively.

$$Y = 0.9422 \ln(X) + 10.882; \; R^2 = 0.0528; \quad (1)$$

$$Y = 0.6979 \ln(X) - 12.234; \; R^2 = 0.0715; \quad (2)$$

$$Y = 0.703 \ln(X) - 0.5762; \; R^2 = 0.0707. \quad (3)$$

The three trend lines in the curves clearly show a gradual increase in the temperature. Previously, the curve in Figure 2 showed the temperature-increasing trend with $R^2 = 0.1379$, which is almost twice the average temperature-increasing trend in the above figure. Although both values are small, they report a slowly increasing LST in Beijing City. Statistical data mining with upper remote sensing observations proves the hypothesis that the surface temperature in Beijing City has gradually increased from 1982 to 2022. This research suggests this increase is related to the increasing change of land uses to impervious surfaces and built environments.

3.3. Geographically weighted regression model

Geographically weighted regression modeling has been *applied in various applications, i.e.,* analysis of spatially varying relationships with LST and the UHIs (Wang et al., 2023). Newly, Liu et al. applied the GWR to show

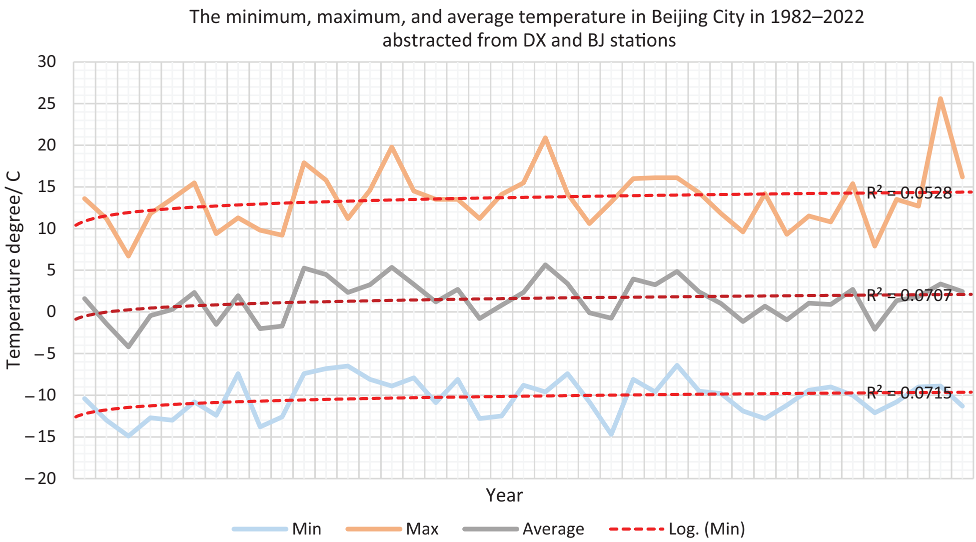

Figure 7. Temperature increases in Beijing in 1982–2022 (source: National Center for Environmental Information, 2022)

the correlation between urban green space and decreasing LST compared to constructed areas (Liu et al., 2022). We apply the GWR for Beijing's thermo-spatial data regression to show land use types' correlation with land surface temperature as the following overall relationship in Equation (4).

$$Y_i = \propto_0 \sum_{i=1}^{n} X_i + \sum_{j=1}^{n} \propto_j \left(\sum_{i=1}^{n} X_i \right) X_{ij} + r_i. \quad (4)$$

In Equation (4), Y is usually the dependent variable, here is the LST, $X_{ij} = j-th$ represents independent variables, where X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, and n is the number of independent variables, here = 9. Additionally, r_i denotes the residual of our model. $\propto_j =$ regression coefficient.

To adjust weighted values, the following equation determines the necessary regression coefficients.

$$\propto \left(\sum_{i=1}^{n} X_i \right) = X^T W \left(\sum_{i=1}^{n} X_i \right)^{-1} X^T W \left(\sum_{i=1}^{n} X_i \right) Y, \quad (5)$$

where W is a weight matrix.

Equation (6), below, is a Gaussian weighting kernel function to adjust the weights.

$$W_{ij} = \sigma \left(\frac{S_{ij}}{\delta b} \right), \quad (6)$$

where σ is a standard distribution function, S_{ij} is the space between the regression land-use type i and the adjacent land-use category j, and δb represents variations in bandwidths.

To develop the GWR model and evaluate the impact of different land use and landscape types on LST, we used a Gaussian kernel function with Math Type software and a cross-validation (CV) method. Our analysis optimizes the bandwidth parameters by running the algorithm that found the R^2 values equal to 0.0707 and 0.1379 as have been calculated for variations of average temperature in 1982–2022 as Table 3.

Table 3. Values of statistical factors

Statistical factor	Value
Neighbors	713
Residual squares	2823.345671
Effective number	5.434921
σ	1.120176
AIC_c	4121.183309
R^2	0.1043
R^2 adjusted	0.0860

In Table 3, the neighboring line represents the number of controlled ground points by the sensors equal to 713, $R^2 = 0.1043$, which has been obtained by Equation (3) and calculated from two meteorological stations' recorded data. Additionally, the standard deviation of regression coefficients has been obtained in Table 4.

Table 4. Min, max, and average temperature with standard deviation calculated for February in Beijing

Land-use category	X_i	Min	Max	Ave.	SD
Residential	X_1	–6.2	15.01	1.6	0.201
Business	X_2	–6.1	15	1.55	0.207
Commercial	X_3	–6.1	15	1.55	0.207
Industrial	X_4	–6.3	15.4	1.7	0.212
Administrative	X_5	–6.15	14.9	1.55	0.200
Medical	X_6	–6	14.8	1.4	0.192
Cultural	X_7	–5.9	14.9	1.4	0.191
Green space	X_8	–5.6	14.	1.8	0.109
Educational	X_9	–6.1	15	1.55	0.203

We considered the number of neighbors, 713, as a fixed Kernel to calculate the standard value of deviation (SD) for different land use types in Table 4.

4. Findings and discussions

Scholars analyzed the process of urbanization growth in Beijing, Tianjin, Shanghai, Raipur, Tehran, and Hebei to see the signs indicating the likely increase of LST and the creation of UHIs. Their comparisons between cities' urban agglomeration using multi-source data in 2000, 2005, 2010, and 2015 confirmed similarities in the development processes in all cities. One similarity was the average land surface temperature increase and the creation of urban heat islands. The comparisons illustrated a direct relationship between urban expansion, the LST, and the phenomenon of UHIs (Chen et al., 2020). Scholars have found that two-dimensional (2D) and three-dimensional (3D) landscape patterns and land use policies are insufficient to explain the complex urban thermal phenomenon in cities of different sizes (Xu et al., 2023). Natural variability and climate change have been introduced as causes of increasing land surface temperature. Nevertheless, confirmed evidence indicates that human activities, particularly urbanization and the conversion of fields, pastures, and forests into streets, buildings, infrastructure, and workplaces are responsible for the increasing temperature. Scholars studied the characteristics of the urban heat islands in Iași city of Romania by the temperature variations. They found that the land-use policy influences the creation of UHIs (Sfîcă et al., 2018). Since Beijing has hot, humid summers and cold, dry winters, concentrated built environments create urban heat islands (UHIs). A comparison of images 3 and 4 with each other shows the increase of LST well. Remember that image 4 illustrated the lands with dark gray had lower LST in 1982 compared to image 3 with bright gray-colored lands in 2022. As it was visible clearly, the bright-gray-colored lands in 2022 had a higher rate of LST compared to the dark gray-colored

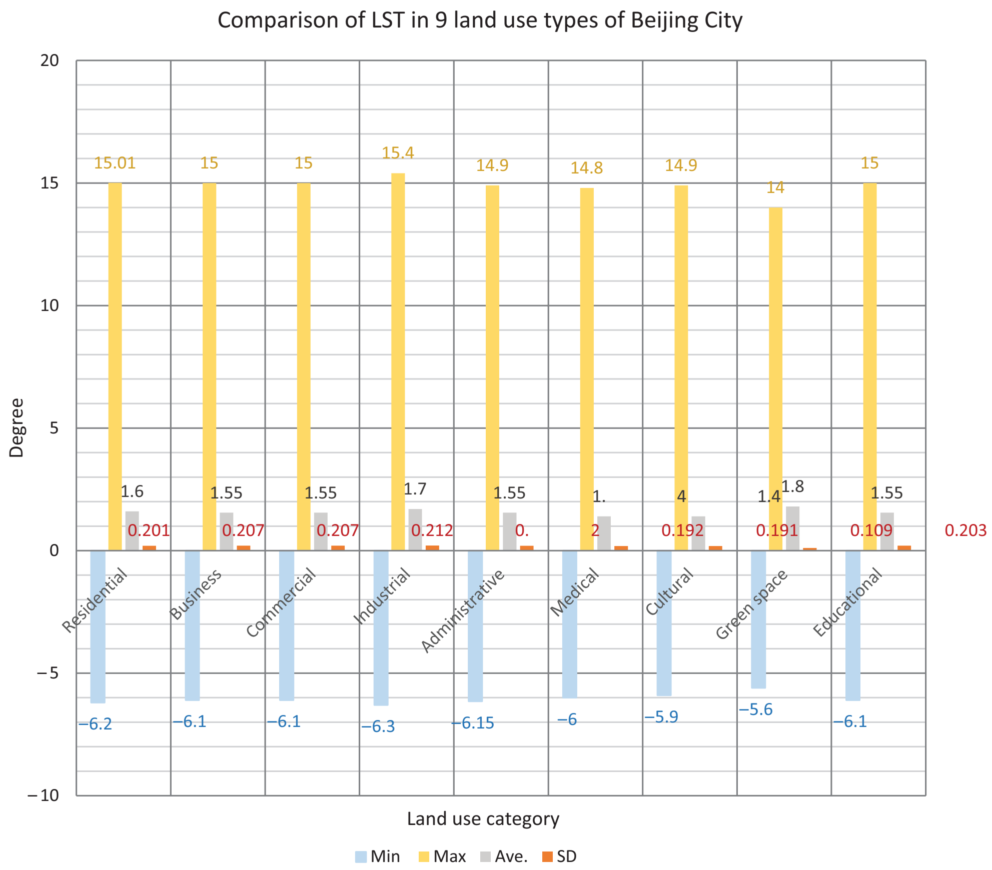

Figure 8. Results of min, max, average LST, and SD variations in 9 types of land use in Beijing City

image belonging to Beijing City in 1982. Exploring the causes of this phenomenon proves that Beijing City has experienced a dramatic shift from an overall agricultural economy to an industrial economy with rapid growth in urbanization. Urban land use change has increased the LST during 1982–2022 in the city. The physical expansion has happened through the disappearance of natural and barren lands and increasing urbanization by up to 86%. We also observed this change by spatial thermal and hydrographic images captured by Landsat remote sensing tools. An overview of land use types in Beijing, provided in Table 2, estimated that green land covers 27% of the total area of the metropolitan. This percentage is still acceptable compared to the UN-Habitat standard recommendations (UN-Habitat, 2020). However, the result from the land cover classification presented in Table 2 reveals an increase in LST and the number of UHIs in highly dense urban spaces. Scientists demonstrated the fact that green lands decrease LST as we have proved in Beijing too. A decline in Beijing's water resources and green lands has been observed in images 5 and 6 captured by remote sensing. Consequently, the LST has increased in Beijing that remote sensors pictured in images 3 and 4. The curves and trend lines in Figure 7 show the temperature increase in Beijing from 1982–2022. Illustrating the results in Table 4 by columns chart in Figure 8 shows well max, min, average temperature, and SD differences between green space lands and other land uses in Beijing City.

In Figure 8, green lands have experienced fewer SD, equal to 0.109, while industrial lands exhibited the highest SD, equal to 0.212. The SD in the commercial, business, educational, residential, medical, and cultural was 0.207, 0.207, 0.203, 0.201, 0.192, and 0.191, respectively, of the types, showing higher SD compared to the green land category.

The outcome of land surface temperature studies, which this applied research has conducted by the Landsat remote sensing and field studies, could provide information for the sake of sustainable urban land use policies.

The findings of this study suggest the appropriate adaptation of strategic land use types to impact positively the quantity, allocation, and LST of urban lands. Urban land cover simulation with spatially explicit models of the united nations' sustainable development goals (UN's SDG) and united nations habitat standards (UN-Habitat) will control consumption rates of urban lands and urban population growth rates.

Conclusions

This paper introduced landscape and land use types as significant factors influencing land surface temperature (LST) increase. It hypothesized that appropriate adaptation of strategic land use types reduces the number of urban heat islands (UHIs). This paper showed a relationship between the increase in the LST with the recent dramatic changes in landscapes and land use policies in Beijing City. This study aimed to use lands in favor of environmentally friendly urban development and to prevent increasing LST. Methodologically, this innovative research used remote sensor tools of Landsat 8-9 and 4-5 and simultaneously reviewed the recorded temperature data in two meteorological stations in Beijing to ensure the accuracy of its findings. This research built a geographically weighted regression model (GWR) with a Gaussian weighting kernel function for assessing the surface temperature on various land use types. Results of our observation and analysis concerning minimum, maximum, and average temperatures in 1982–2022 in 9 types of land use confirmed the hypothesis that LST has increased in populated Beijing's urban spaces. Additionally, we saw that green lands had less SD, equal to 0.109, compared to industrial lands, with a high SD, equal to 0.212. We noticed that the trend lines of the average temperature in Beijing City, which have been drawn in curves of Figure 7, went up slowly. Therefore, we recommended that current land use policies should be replaced with an appropriate adaptation of strategic land use types. Land use policies like simulation with spatially explicit models of UN's SDG and UN-Habitat reduce consumption rates of urban lands and LST. The outcome of this work assists future applied research on hindering the increasing LST in the world by new looks at urban land use policies.

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Author contributions

All authors participated in the design of this study, and Liyan Liu performed the statistical analysis. Wenmo Li carried out the study and collected background information. Zigang Yao, Abdol Aziz Shahraki wrote the paper and supervised the research project, and Yan Pang drafted the manuscript. All authors read and approved the final outcomes of the study and the final manuscript.

Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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