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The impact of urban expansion in Beijing and Metropolitan Area urban heat Island from 1999 to 2019

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Abstract

This article is a quantitative study of the urban expansion of Beijing in the past two decades and its impact on the city's heat island effect. The overall idea of this paper is a 'basic fact description to phenomenon and law reveal-basic cause analysis-mechanism analysis-model simulation'. In this paper, the effects of urbanisation on warming in Beijing are deduced by nonlinear fitting method. Based on Google Earth Engine remote sensing image data within Beijing Inner Sixth Ring Road and using ArcGIS to retrieve Beijing's surface temperature, the heat island effect intensity index is calculated. This paper quantitatively analyses the temporal and spatial distribution characteristics and development trends of Beijing's urban heat island effect, combined with land use cover change (LUCC), Land Surface Temperature (LST), Normalised difference Vegetation Index (NDVI), Normalised difference Building Index (NDBI), which can explore the impact of surface vegetation distribution and building density on the urban heat island effect.

Keywords: simulation model, remote sensing image, NDVI, NDBI.**AMS 2010 codes:** 03E72

1 Introduction

Land use cover change (LUCC) has an important impact on the surface-atmosphere system. Urban expansion is one of the most prominent hotspots in China's current research on LUCC temporal and spatial pattern changes. And the heat island effect caused by urban expansion is also a typical representative of regional climate changes caused by land-use changes (Lu et al., 2020). The current global urbanisation process is becoming more and more intense. While the process of urbanisation brings economic and social benefits to mankind, it also produces a series of ecological and environmental problems. The urban heat island effect is one of the most

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important problems. With the rapid development of China's economy, Beijing, the capital of politics, culture, and economy, has seen significant urban expansion and steady population growth, so the thermal environment is bound to be affected (Cui et al., 2016). This paper is a quantitative study of the extent of urban expansion in Beijing in the past two decades and its impact on the city's heat island effect.

The overall methodology of this paper is following a description of basic facts, the revelation of phenomena and laws, basic cause analysis, mechanism analysis and model simulation. This paper utilises Bigmaper Beijing Sixth Ring Road remote sensing image data as the basic data, with ArcGIS to retrieve the surface temperature of Beijing. The heat island effect intensity index is also calculated. Then it can be used to quantitatively analyse the temporal and spatial distribution characteristics and development trend of the urban heat island effect in Beijing, combining with some factors, including land surface temperature (LST), normalised difference vegetation index (NDVI) and normalised difference building index (NDBI), to explore the impact of surface vegetation distribution and building density on the urban heat island effect. The results show that from 1999 to 2014, the area of urban construction land in Beijing continued to grow, and the growth rate was relatively fast from 2000 to 2003. The rate of urban expansion slowed down significantly from 2004 to 2012. Based on the core functional area, we can say the city gradually expands to the surroundings, showing that the external development is centred on the main urban area. The temperature of urban land gradually started to dominate the temperature level of the whole region, and the difference between the temperature of urban land and the average temperature of the region has decreased significantly. The urban heat island effect of Beijing has gradually increased from 2014 to 2019, and the spread of the heat island is mainly the extension of the urban new development zone and the transportation network. The urban surface temperature has an obvious negative correlation with the normalised vegetation index and an obvious positive correlation with the normalised building index. Further, the correlation between the surface temperature and the normalised vegetation index is particularly prominent. It is recommended that in the process of urban development and construction, increasing urban greening investment, rationally increasing urban vegetation coverage and moderately reducing urban building density can alleviate the urban heat island effect.

In this study, the model that analyse the impact of urban expansion on the urban environment can be determined using literature. From a quantitative point of view, the urban expansion process and basic characteristics of climate change in Beijing for the past 20 years can be analysed through the establishment of multi-period LUCC and meteorological data. Then, the remote sensing data is used to analyse the spatial distribution pattern of urban heat islands and the underlying surface, by mainly focusing on the correlation analysis of LST, NDVI and NDBI. In this paper, we have proposed to focus on analysing the relationship between urban building density distribution and the urban heat island effect. This paper takes Beijing as the research object. Based on high-resolution remote sensing images and through artificial visual interpretation, combined with the surface temperature data obtained from remote sensing inversion, we correlate the internal relationship between the urban building density distribution and the urban heat island effect. This paper discusses the impact of urban building density distribution on the urban heat island effect. It can provide a scientific basis for the planning and layout of urban construction and urban thermal environmental management.

Encroachment of urban lands causes constrained evaporation which arises from decreased thermal inertia and the vegetation index, and thus ultimately leading to reduced heat loss by latent heat flux; it is the flux of heat from the surface to the atmosphere that is associated with evaporation of water and subsequent condensation of water vapour in the troposphere (Goswami & Singh, 2008). UHI is further aggravated by reduction in speed of the environmental winds, congested transportation networks, increased energy demands, higher anthropogenic heat release and other sky-view factors (Chang Cao et al., 2016). Since urban development, occasioned by increased migration into the metropolitan areas, is relatively difficult to control, the only good urban form is the only way which can help sustain the metropolitan area's environmental condition.

Beijing is one of the leading growth drivers in the country getting some of the country's huge investments. Besides the manufacturing, processing and manufacturing industries, Beijing's growth also draws from the real estate segment that forms an integral economic zone, whose growth started from the mid-1990s. The city forms

part of the coastal economic zone even though it is geographically located on the North China Plain (Chang Cao et al., 2016). The Ring and Radial Highway System stands as the city's ideal transportation mechanism model. The system has received a great structural boost since its creation in the 1950s through new legislations like the 1982 and 1993 comprehensive plans for Beijing's spatial structure. The intercity highway connecting the city's 14 satellite towns is known as the 6th ring, while the 4th ring road acts as the edge of the city centre and 5th ring road as the linkage between 10 other scattered districts within the metropolitan area and the lower the number of rings, the closer it is to the centre, which also represents major buildings in these areas. Following the adoption of economic reform policies, China's land use/cover has undergone radical changes that also accelerated economic growth.

As reported by Qiao et al. (2014), from 1989 to 2010, Beijing's urban land grew by 775.82 km² at a rate of 184.31%. The mounting intensity and increasing UHI index grew at a high pace from 1989 to 2000 but at a declining pace from 2000 to 2010. The study also reports that 'the LSTs and urban heat island ratio index (URIs) of urban land in Beijing increased between 1989 and 2010, heat island areas expanded, and the UHI resulting from urban expansion increased' (Qiao et al., 2014).

China's land legalities and policies have changed rapidly consistent with the changes in the social and economic conditions. As discussed by Liu, Dunford, Song and Chen (2016), most of these policies are 'reflected in Hukou reform, urban and rural rights, the Annual Land Use Quota system, public assets, and the local government finance vehicles.'

Committed to Habitat II in 1996 principle, the government of China implemented radical measures associated urban and rural housing. The goal of the policy was to ensure all households have self-contained rooms and to achieve a 9-metre per-capita construction space (Assembly, 2015). The policies have led to an increase in the overall level of urban housing in China. The yearly and persistent large-scale housing construction has reached an unparalleled level in China such that houses constructed increased from 1.22 billion in 1996 to 1.93 billion in 2013. During the same time housing space grew from 395 million to 1.07 billion m² in urban centres (Assembly, 2015).

Internationally recognised I-use regulations such as 'minimum lot sizes, minimum parking requirements, maximum floor-to-area ratios or floor space index (FSI)' have had a significant impact on UHI in Chinese cities such as Beijing (Menon et al., 2019). For instance, while FSI limits reduce the 'density of buildings', they cannot limit the 'density of people' since most individuals opt for smaller and especially informal spaces. Prohibitions on lower height structures inflated prices causing urban sprawl such as the case of Beijing, which caused a 12% expansion of its city boundaries (Deng & Huang, 2004).

China's land use/cover changes have led to the subdivision of surface structures into three layers based on the specific area's land use and climate (Siddique et al., 2020). Vegetation cover often acts as a sieve that purifies the air from dust particles and heating thereby improving evapotranspiration which in turn promotes precipitation. In Beijing, after the air passes through the green belt, it is intercepted by the city's built-up areas and experience solar radiation and absorption, and as a result greenhouse gas emission occurs at the cost of anthropogenic disturbances which makes it warmer, hence urban heat island (Yuan, 2020).

With the intensification of urbanisation, the building area continues to expand, and human activity has increased significantly. These factors may lead to an increase in the intensity of the heat island.

Jing (2019) studied the current situation of the heat island effect in the main urban area of Beijing's Fifth Ring Road in the summer of 2017, and selected 65 urban green spaces of different sizes and types within Beijing's Fifth Ring Road through a large amount of data linear fitting and controlled variable method on the influencing factors of the internal temperature of urban green space and the quantitative and influencing factors of the green space cooling range. The study suggests that there is a relatively obvious heat island effect in the main urban area of Beijing. The proportion of high-temperature areas from the Second Ring to the Fifth Ring gradually decreases, and the proportion of low-temperature areas gradually increases. The southwest and southeast quadrants of the study area have the highest proportion of high temperature, and the northeast and the northwest quadrant have the highest proportion of low-temperature areas. Large areas of high-temperature

heat island areas are mostly old bungalow residential areas, factories, wholesale markets, train stations, etc. The analysis of the factors affecting the cooling range of green space concludes that the smaller the green area, the smaller the cooling range. When the green area is between 0 ha and 7 ha or the perimeter of the green area is between 0 km and 1.5 km, the cooling range of the green area will follow the increase of green area increases. The percentage of impervious surface in the surrounding land of urban green space also has a significant impact on the cooling range of urban green space. In the case of the same green area, whenever the percentage of the impervious surface area surrounding the green area increases by 1%, the green area cooling range will be decreased by 4.01 m.

Li et al. (2008) used the temperature data from the meteorological observatory in Beijing from 1990 to October 2004 to analyse the characteristics of the urban heat island in autumn in Beijing for the past 15 years. The results showed that the urban heat island in the autumn night in Beijing is stronger than that in the daytime. Besides, a comparative analysis of the characteristics of a strong heat island, a weak heat island and their meteorological influence factors show that there is a strong heat island under certain conditions at night in Beijing in autumn. The formation and maintenance of a strong heat island is the result of the combined effects of multiple factors. During the day and sunny nights, the surface wind field in the suburbs of Beijing is very weak and the atmospheric wind field < 47 m in the vertical direction of the urban area continues to be very strong. The rate and amplitude of the atmospheric temperature drop in the suburbs after sunset are much greater than that in the urban area, which promotes the formation and maintenance of a strong heat island at night. The weakening of the urban atmospheric stability and the disappearance of the urban atmospheric inversion are the main reasons for the weakening of strong heat island and its final disappearance at night.

Based on discussing the concept and characteristics of urbanisation, Zhao et al. (2014) analysed the interaction between urbanisation and climate change. Urbanisation has caused significant effects on different climatic elements, but related research is mainly concentrated in terms of local microclimate changes. Climate change is a very complex process.

2 Methodology

Assuming the experimental data $(x_i, y_i), (i = 1, 2, \dots, n)$, find the function $f(x, \hat{y})$, and by guaranteeing the position of the function at the point XI, where $I = 1, 2, \dots, N$, the sum of squares of the deviation between the value of the function and the value of the observation in this region should be minimised, then the function conforming to the following conditions should be calculated:

$$\sum_{i=1}^n (f(X_i, \hat{y}) - y_i)^2$$

Therefore, the nonlinear fitting method should be used to solve the impact of the urbanisation process in Beijing on the urban warming. The following steps should be followed: First, the scatter diagram should be defined and the function category should be analysed; Second, the initial value of the undetermined parameters is obtained and the best parameters are calculated by using MATLAB software. Third, the determination coefficient is used to compare the effect. The formula of determination coefficient is as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

where $\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$, and the closer R^2 is to 1, the higher the actual fitting effect is. In MATLAB software to achieve the command of the coefficient of determination:

$$R2 = 1 - \text{sum}((y - y1).^2) / \text{sum}((y - \text{mean}(y)).^2)$$

If the coefficients are polynomial, it is called polynomial regression and the parameters are polynomial coefficients. But if it is of the following forms namely exponential function, logarithmic function, power function, trigonometric function, etc., then it is called nonlinear fitting. Equations with an S-shaped curve include the Rogersti model: $y = \frac{a}{1+\beta e^{-\gamma x}}$, Gompertz model: $y = a \exp(-\beta e^{-kx})$, Richards model:

$y = a/[1 + \exp(\beta - \gamma x)]^{1/\delta}$, and Weibull model: $y = a - \beta \exp(-\gamma t^\delta)$.

In order to better realise nonlinear fitting, the function should be defined first: the definition function of inline can be used for numerical calculation of curve fitting. On the one hand, the M file should be built first, and on the other hand, $fun = inline('f(x)', 'DependingOnAParameter', 'x')$ should be obtained. In practical problems, in many cases, the scatter diagram is not necessarily the graph of the polynomial, but also may be other curves, which requires the combination of $[beta, r, J] = nl\ infit(x, y, fun, beta0)$ command to make guess the type. In the above equation, x and y represent the original data, fun represents the defined function in the M file, beta0 refers to the initial value of the parameter in the function, beta represents the optimal value of the parameter, r refers to the fitting residuals of each point and J represents the value of the Jacobian matrix.

After combining the factors that influence the urbanisation process of Beijing on the urban temperature increase, the scatter plot is constructed by combining the above nonlinear fitting method, and an appropriate nonlinear regression equation can be selected, as shown below:

$$y = \mu(\bar{x}, a, b \dots)$$

where a and b represent unknown parameters, and to calculate the estimated values of both, on the one hand, a linear model can be used for analysis, such as $y = b_0 + b_1 t + b_2 t^2$ and $x_1 = t, x_2 = t^2$, to obtain $y = b_0 + b_1 x_1 + b_2 x_2$. In this case, x_1 and x_2 can be regarded as independent variables, and y can be regarded as a linear function of the two variables. On the other hand, it cannot be directly converted into a linear model to calculate parameters, such that $Y = B_1 \ln(1 + B_2 V)$, and B1 and B2 are undetermined parameters, V represents urban warming and Y represents the urbanisation process and so the formula can be obtained as follows:

$$\begin{cases} b = \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^N (x_i - \bar{x})^2} = \frac{\sum_{i=1}^N x_i y_i - \frac{1}{N} \sum_{i=1}^N x_i \sum_{i=1}^N y_i}{\sum_{i=1}^N x_i^2 - \frac{1}{N} (\sum_{i=1}^N x_i)^2} \\ a = \bar{y} - b\bar{x} \end{cases}$$

In this case, $\bar{x} = \frac{1}{N} \sum_{i=1}^N x_i, \bar{y} = \frac{1}{N} \sum_{i=1}^N y_i$. After the values of A and B are determined, the regression equation $y = a + bx$ can be obtained, and B refers to the regression coefficient.

When calculating the least square method of data fitting, the concept of this theory should be clarified first. Assume that is a set of data given (x_i, y_i) ($i = 0, 1, \dots, m$), and ω_i ($i = 0, 1, \dots, m$) represents the weight coefficient of all points, which in general needs to be >0 , then in the function class:

$$\varphi = span\{\phi_0(x), \phi_1(x), \dots, \phi_n(x)\}$$

And the calculation function can be obtained:

$$S^*(x) = \sum_{j=0}^n a_j^* \phi_j(x), (n \leq m)$$

More in line with the following requirements:

$$\|\delta\|_2^2 = \sum_{i=0}^m \omega_i (S^*(x_i) - y_i)^2 = \min_{S \in \varphi} \sum_{i=0}^m (S(x_i) - y_i)^2$$

The Φ in the $S(x) = \sum_{j=0}^n a_j \phi_j(x)$ formula represents all functions. Based on the above analysis, represents the least square solution of $S^*(x)$, and S(x) refers to the fitting function.

Assuming $\Psi(a_0, a_1, \dots, a_n) = \sum_{i=0}^m \omega_i (S(x_i) - y_i)^2 = \sum_{i=0}^m \omega_i \left(\sum_{j=0}^n a_j \phi_j(x_i) - y_i \right)^2$, then the point of calculating the least squares solution is to specify the undetermined parameter a_j^* ($j = 0, 1, \dots, n$). The important conditions to be observed by the extreme value of the function are:

$$\frac{\partial \Psi}{\partial a_k} = 0, (k = 0, 1, \dots, n)$$

Make

$$\begin{aligned} \phi_r &= (\phi_r(x_0), \phi_r(x_1), \dots, \phi_r(x_m)), r = 0, 1, \dots, n \\ f &= (y_0, y_1, \dots, y_m) \\ \sum_{j=0}^n (\phi_j, \phi_k) a_j &= (f, \phi_k), (k = 0, 1, \dots, n) \end{aligned}$$

And define the inner product:

$$\begin{aligned} (\phi_j, \phi_k) &= \sum_{i=0}^m \omega_i \phi_j(x_i) \phi_k(x_i) \\ (f, \phi_k) &= \sum_{i=0}^m \omega_i y_i \phi_k(x_i) \end{aligned}$$

The system can be called:

$$\sum_{j=0}^n (\phi_j, \phi_k) a_j = (f, \phi_k), (k = 0, 1, \dots, n)$$

Then the normal equations of the function system at discrete points are as follows:

$$\begin{bmatrix} (\phi_0, \phi_0) & (\phi_0, \phi_1) & \dots & (\phi_0, \phi_n) \\ (\phi_1, \phi_0) & (\phi_1, \phi_1) & \dots & (\phi_1, \phi_n) \\ \vdots & \vdots & \ddots & \vdots \\ (\phi_n, \phi_0) & (\phi_n, \phi_1) & \dots & (\phi_n, \phi_n) \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} (f, \phi_0) \\ (f, \phi_1) \\ \vdots \\ (f, \phi_n) \end{bmatrix}$$

The determinant formed according to the basis function $\phi_r = (\phi_r(x_0), \phi_r(x_1), \dots, \phi_r(x_m)), r = 0, 1, \dots, n$ is:

$$\sum_{j=0}^n (\phi_j, \phi_k) a_j = (f, \phi_k), (k = 0, 1, \dots, n)$$

Therefore, the solution of the system is

$$a_j = a_j^*, (j = 0, 1, \dots, n)$$

And $S^*(x) = \sum_{j=0}^n a_j^* \phi_j(x)$ refers to the least square solution, $\|\delta\|_2^2 = \sum_{i=0}^m \omega_i (S^*(x_i) - y_i)^2$ refers to the square error of the multiplication solution and $\|\delta\|_2 = \sqrt{\sum_{i=0}^m \omega_i (S^*(x_i) - y_i)^2}$ represents the mean square error. The specific formula is as follows:

$$\|\delta\|_2^2 = |(f, f) - (S^*, f)| = \left| \sum_{i=0}^m \omega_i y_i^2 - \sum_{k=0}^n a_k^* (\phi_k, f) \right|$$

In the case that the basis is $\phi_j(x) = x^j$ ($j = 0, 1, \dots, n$), the relevant normal equations are as follows:

$$\begin{bmatrix} \sum_{i=0}^m \omega_i & \sum_{i=0}^m \omega_i x_i & \dots & \sum_{i=0}^m \omega_i x_i^n \\ \sum_{i=0}^m \omega_i x_i & \sum_{i=0}^m \omega_i x_i^2 & \dots & \sum_{i=0}^m \omega_i x_i^{n+1} \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{i=0}^m \omega_i x_i^n & \sum_{i=0}^m \omega_i x_i^{n+1} & \dots & \sum_{i=0}^m \omega_i x_i^{2n} \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} \sum_{i=0}^m \omega_i y_i \\ \sum_{i=0}^m \omega_i x_i y_i \\ \vdots \\ \sum_{i=0}^m \omega_i x_i^n y_i \end{bmatrix}$$

When calculating the data fitting method of least square integration, it is necessary to make clear its concrete concept. First, it is clear that n groups of observed data are (x_i, y_i) $i = 1, 2, \dots, n$, and they are all obtained by the same model:

$$y(x) = g(x) + \varepsilon(x), x_1 = a < x < b = x_n$$

Wherein, $G(x)$ refers to the error function of function $\varepsilon(X)$, $Y(x)$ refers to the function obtained by interference of $G(x)$ when function $\varepsilon(X)$ and $y(x_i) = y_i, \varepsilon_i = \varepsilon(X_i), X_i \in [a, b]$ ($i = 1, 2, \dots, n$). Here, y_i represents the observed value, and ε_j represents the random error of observation.

Assuming that $\hat{g}(X)$ is a data fitting function with p parameters, it can be calculated as:

$$\begin{aligned} e(X) &= y(X) - \hat{g}(X) \\ e_k &= y_k - \hat{g}(X_k) \end{aligned}$$

Then in the fitting problem of the traditional least square method, the following formula can reach the minimum value if all the parameters contained therein are calculated according to the above formula. This method is called the least square sum method.

$$S = \sum_{k=1}^n e_k^2 = \sum_{k=1}^n (y_k - \hat{g}(X_k))^2$$

By taking the observed data (x_i, y_i) $i = 1, 2, \dots, n$ as a point on the $y(x)$ function, and assuming that $\varepsilon(X)$, $y(x)$ and $g(x)$ are all continuous functions in combination with model analysis, the fitting function can be transformed into:

$$Q = \int_a^b e_k^2(x) dx = \int_a^b (y(x) - \hat{g}(x))^2 dx$$

In general, the fitting function $G(x)$ represents:

$$g(x) = F(c, d, x) = c_1 \phi_1(d, x) + c_2 \phi_2(d, x) + \dots + c_l \phi_l(d, x)$$

Where $\phi_i(d, x)$, $i = 1, 2, \dots, l$, belongs to a group of linearly independent functions, also known as the basis function, which refers to the nonlinear function of X , while $c = (c_1, c_2, \dots, c_l)$ represents the linear fitting parameter and $d = (d_1, d_2, \dots, d_q)$ refers to the nonlinear fitting parameter. In this case, if you satisfy the condition $\phi_i(d, x) = e^{d_i x}$, $i = 1, 2, \dots, l$, then you get $g(x) = \sum_{i=1}^l c_i e^{-d_i x}$.

Here, we first analyse the specific situation when $g(x)$ is used as a linear fitting function, and then we can get:

$$g(x) = c_1 \phi_1(x) + c_2 \phi_2(x) + \dots + c_l \phi_l(x)$$

Where, $c_i, i = 1, 2, \dots, l$ refers to the regression coefficient, also known as the linear regression model. According to the following formula:

$$Q = \int_a^b e^2(x) dx = \int_a^b (y(x) - g(x))^2 dx = \int_a^b (y(x) - c_1 \phi_1(x) - c_2 \phi_2(x) - \dots - c_l \phi_l(x))^2 dx$$

Calculate the minimum value, which is $\frac{\partial Q}{\partial c_i} = 0, i = 1, 2, \dots, l$, and you can get:

$$\sum_{i=1}^l \left[\int_a^b \varphi_i(x) \varphi_k(x) dx \right] c_i = \int_a^b y(x) \varphi_k(x) dx, k = 1, 2, \dots, l$$

Assuming that $(f, g) = \int_a^b f(x) g(x) dx$ is regarded as the inner product of an integral, then the above formula can be solved:

$$\begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_l \end{bmatrix} = (X'X)^{-1} X'Y$$

$$\text{The } X = \begin{pmatrix} (\varphi_1, \varphi_1) & \dots & (\varphi_1, \varphi_l) \\ \vdots & \ddots & \vdots \\ (\varphi_l, \varphi_1) & \dots & (\varphi_l, \varphi_l) \end{pmatrix}, Y = \begin{pmatrix} (y, \varphi_1) \\ (y, \varphi_2) \\ \vdots \\ (y, \varphi_l) \end{pmatrix}$$

In data fitting analysis, two of the most common fitting function is: $\varphi_i(d, x) = h_i(x) (i = 1, 2, \dots, l)$ on the one hand, the basis function is orthogonal polynomial fitting function, according to the basis function analysis, the $h_i(x)$ refers to the weight function of 1 integral inner product of orthogonal polynomials, and as a result of the (x) function h_i conform to the requirements of the $\int_a^b h_i(x) h_j(x) dx (i \neq j)$, so can be combined with least square integral:

$$\begin{bmatrix} \int_a^b h_1^2(x) dx \\ \int_a^b h_2^2(x) dx \\ \vdots \\ \int_a^b h_l^2(x) dx \end{bmatrix} \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_l \end{bmatrix} = \begin{bmatrix} \int_a^b h_1(x) y(x) dx \\ \int_a^b h_2(x) y(x) dx \\ \vdots \\ \int_a^b h_l(x) y(x) dx \end{bmatrix}$$

The corresponding regression coefficient is:

$$c_i = \frac{\int_a^b h_i(x) y(x) dx}{\int_a^b h_i^2(x) dx}, i = 1, 2, \dots, l$$

On the other hand, the basis function is an exponential fitting function. First observe the data $(t, y_i) (t = 1, 2, \dots, n)$, and then confirm the m-th algebraic equation with the coefficient of the first term 1 as follows:

$$P(\lambda) = \lambda^m + a_1 \lambda^{m-1} + \dots + a_{m-1} \lambda + a_m = 0$$

In addition, the above coefficient A_i is defined. At the same time, the root $\lambda_1, \lambda_2, \dots, \lambda_m$ of the above formula is regarded as the basis function of X return trip. Then, the fitting function can be obtained as:

$$g(x) = c\lambda_1^x + c\lambda_2^x + \dots + c\lambda_m^x$$

According to different characteristic root analysis, clear λ_i^x . In the above formula, it is clear that $x=r+k$, and both r and k are positive integers, and multiply both sides by λ_i^{-r} , and then sum r from 1 to m . In this process, $g(r+k) = y_{r+k}, a_1 = 1$ so we can get:

$$\sum_{r=0}^m y_{r+k} a_{m-k} = 0, k = 0, 1, \dots, m$$

[illegible]
$$\lambda_j = e^{ai}(\cos \beta_j + i \sin \beta_j), \lambda_{j+1} = e^{ai}(\cos \beta_j - i \sin \beta_j)$$
$$\varphi_i(x) = e^{a_i x} \cos \beta_i x, \varphi_{i+1}(x) = e^{a_i x} \sin \beta_i x$$
$$\lambda_i = e^{a_i} (\cos \beta_i \pm i \sin \beta_i) \ (i = 1, 2, \dots, t)$$

$$\begin{aligned} g(x) &= c_1 \varphi_1(x) + c_2 \varphi_2(x) + \dots + c_m \varphi_m(x) \\ &= c_1 \lambda_1^x + c_2 \lambda_2^x + \dots + c_k \lambda_k^x + c_{k+1} e^{a_1 x} \cos \beta_1 x + c_{k+2} e^{a_1 x} \sin \beta_1 x \\ &\quad + \dots + c_{m-1} e^{a_l x} \cos \beta_l x + c_m e^{a_l x} \sin \beta_l x \end{aligned}$$

According to the above steps, we can not only master more influencing factors, but also put forward better solutions based on the numerical changes obtained from calculation and analysis.

The idea of this paper follows the path of problem discovery, subject research and practical reflection, in which both qualitative and quantitative analyses are applied. Figure 1 shows the workflow of this main methodology. One of the main concerns of qualitative researchers is their emphasis on the description of the urbanisation process, and the research analysis model. In this study, literature research can give the key influencing factors of the urban warming effect. Quantitative research is guided by a positivist methodology to explore the different indexes of urbanisation and the heat island effect. At the same time, the model that analyses the impact of urban expansion on the urban environment can be determined from the literature. From a quantitative point of view, the urban expansion process and basic characteristics of climate change in Beijing can be analysed for the past 20 years through the establishment of multi-period LUCC and meteorological data. Then the remote sensing data is used to analyse the spatial distribution pattern of urban heat islands and the underlying surface, mainly focusing on the correlation analysis of LST, NDVI and NDBI. Through this paper, we are hopeful to focus on analysing the relationship between urban building density distribution and the urban heat island effect. This paper takes Beijing as the research object; using high-resolution remote sensing images and through artificial visual interpretation in combination with the surface temperature data obtained from remote sensing inversion, correlation of the internal relationship between the urban building density distribution and the urban heat island effect is obtained. This paper discusses the impact of urban building density distribution on the urban heat island effect. It can provide a scientific basis for the planning and layout of urban construction and urban thermal environmental management.

The measurement system in this paper uses WGS 1984 and the projection uses equal area projection. The landsat5 and landsat8 data are established through the geospatial data cloud platform, including five dates and specific satellites. The cloud coverage is $<10\%$.

Table 1 Database

Time	Tool
1999.08.10	Landsat 5
2005.07.25	Landsat 5
2010.08.08	Landsat 5
2014.08.19	Landsat 8
2019.08.17	Landsat 8

Through ENVI, LST and LUCC are established by data processing, sample establishment, classifier selection and post-processing.

Fig. 1 Workflow of some index of heat island.

Urban heat island remains one of the biggest attention-drawing environmental problems in China (Zheng & Li, 2016). The data of Beijing districts and counties can be downloaded from the National Basic Information Centre. The datasets used for the study of urban heat island, as an impact of urban expansion, can be obtained through periodic data collection at three different times to get a comparative basis for the changes that occur over a given period. Landsat TM images are then chosen and corrected radiantly to retrieve the land cover types followed by visual interpretation to differentiate false-colour composites of TM/ETM.

Beijing city covers approximately 16410 km², longitudinally and latitudinally lying at about 2°05' and 1°37', respectively (Zhi et al., 2014). The city is graced by a sub-humid warm temperate continental monsoon climate that gives rise to four distinct seasons, humid, hot summer, cold and windy winter. Beijing has continued to experience rapid urbanisation, which has consequently led to increased environmental problems like UHI, pollution haze and dust and sandstorms in the urban areas (UA) (Siddiue et al., 2020). The study area is mapped into specific distinctive portions as UA and non-urban areas (NUA). The calculation of urban area land can be performed using various ways depending on the precision and accuracy of the method, using satellite images and change detection. In this study special nets with specific dimensional measurements that match the Moderate-

Fig. 1 Layout of Beijing Metropolitan Area.

resolution Imaging Spectroradiometer are created for the calculation of the land area percentage.

4 The Use of Landsat to determine trends in LST, NDBI, NDVI and UHI

NDVI is a common parameter in exploring the influencing factors of ground temperature. It can be used to detect vegetation coverage, growth status and seasonal changes. The formula is as follows,

$$NDVI = (RNIR - R) / (NIR + RNIR)$$

In the formula, NIR is the near-infrared band reflectivity, R is the red-light band reflectivity, which is represented by the 5th and 4th bands respectively in Landsat 8 TIRS. The value of NDVI ranges from -1 to 1. $NDVI > 0$ means all vegetation. The higher the NDVI, the higher the vegetation coverage, which means good growth and the rich types of vegetation in the area.

LST is a good indicator of the energy balance of the earth's surface and the greenhouse effect. It is a key factor in the physical process of ground strikes on a regional and global scale. It can reflect the energy flow and material exchange of the soil-vegetation-atmosphere system. It is very necessary for many fields such as climate, hydrology, ecology and biogeochemistry. The ground temperature retrieved from satellite data can reflect in more detail the average temperature of the underlying surface of each pixel and can reflect the spatial distribution characteristics of the underlying surface temperature field. Although the error of using remote sensing data to retrieve the surface temperature is inevitable, it is still the most effective and easiest way to obtain the surface temperature of a large area at present. This is also an advantage of LANDSAT images to reflect the difference of the surface temperature distribution in a large area.

Landsat bands can be used in land detection with the wavelength of 433 nm to 2300 nm and the spatial resolution is 30 m. LST product images, with particular desired properties and resolution levels, are used for analytical purposes. For instance, the Landsat product, which is capable of averaging the LST after every 16 days can be used to obtain the daily LST produced by the split-window algorithm, which is the method for LST retrieval from satellite data. On the other hand, the Landsat Vegetation Index product can be used to obtain data for the EVI data by determining the vegetation index for a given period at a specific spatial resolution. The mean EVI, which is commonly used to determine the vegetation abundance, is calculated for the whole period of the

study i.e. 1999 to 2019. The NDBI data is generated using a specific Landsat Surface Reflectance product at a particular spatial resolution. This determination provides the estimated surface spectral reflectance of the study bands, which is then corrected for atmospheric conditions. The NDBI is defined by the equation:

$$NDBI = (RSWIR - RNIR) / (RSWIR + RNIR),$$

NDBI can be used to characterise the density of urban land where RSWIR is the surface spectral reflectance of the second last band and RNIR is the surface spectral reflectance of the second band used in the study process.

Using the difference in averaged LST value between the urban and rural areas of study, followed by a determination of the urban area's pixel levels as the difference in the averaged nonurban LST and each pixel's LST in the urban area, the SUHII levels of the study areas can be determined by calculation. Investigation of the data obtained from temporal trends of variables like SUHII, EVI, LST and NDBI from 1999 to 2019 is performed at every pixel by the use of linear regression models and ordinary least squares (Minghong et al., 2011). Using the LST as the dependent variable and the study year as the independent variable, multiple ordinary least squares models are run at each pixel to examine the regression coefficient that is used in measuring the annual change in the LSTs magnitude and trend. The significance is then tested at a specific level e.g. at 0.05. Thus, any positive trend with $p < 0.05$ indicates a significantly increased LST at that specific pixel from 1999 to 2019.

Spatiotemporal variation of UHI using LST data using remote sensing images formed at different periods of the study is the major focus of this method. Quantification of the UHI is then performed by introducing URI based on bright temperature normalisation (Siddique et al., 2020). However, the surrounding conditions of the rural areas affect the magnitude of a UHI and the fact that UHI focuses on the LST's relative spatial intensity. Normalisation of LSTs is done to allow comparison of their spatial distribution to provide a spatiotemporal pattern variation of the HUI because the remote sensing images only change LST values at different study periods as opposed to changing the spatial LST distribution. The normalised LSTs are then classified into five different thermodynamic levels by density segmentation method to characterise their distribution levels and the area of each level calculated. URI is then introduced for the quantification of the rate of distribution of the urban land to UHI using the following equation:

$$Ts = K1 / \ln(K2 / B(Ts) + 1)$$

Where: T_s is the surface temperature; $B(T_s)$ is the blackbody at the same temperature. $K1$ and $K2$ can be obtained from the image header file.

Based on Landsat TM data The URI often reflects the degree of UHI development in built-up land; thus, the more extensive the URI, the more severe the UHI effects and vice versa (Jia Wang et al., 2019). Computational analysis of the UHI area to urban land ratio while considering each temperature level's weighted values provides the URI value.

Table 2 Classification of heat island intensity

Thermal grade	Range
High temperature	$T > u + \text{std}$
Sub high-temperature	$u + 0.5\text{std} < T < u + \text{std}$
Mid temperature range	$u - 0.5\text{std} < T < u + 0.5\text{std}$
Sub low temperature	$u - \text{std} < T < u - 0.5\text{std}$
Low temperature	$< T < u - \text{std}$

u is the average temperature of surface; std is the standard difference of temperature.

5 Result and analysis

5.1 Metro population and LUCC in Beijing from 1999 to 2019

According to the Figure 2, the population of Beijing has been rising linearly for the past two decades, from 9,866,000 to 20,035,000, but in terms of growth rate, it can be seen that 2010 is a cut-off point, 4.82%, after 2010. The average increase rate is around 2.1%. The birth rate is 8.12‰, the death rate is 5.49‰ and the natural growth rate is 2.63‰. The permanent population density is 1,312 people per square kilometre.

Fig. 2 Population division in Beijing from 1999 to 2019.

This study mainly uses six Districts in Beijing as the research area, and the three phases of LandsatTM remote sensing data are utilised in 1999, 2010 and 2019, combined with GIS technology. This aims to use a comprehensive analysis index system of land use dynamic changes, and reveal the land use of the study area in the past 20 years. The magnitude, speed and direction of change are analysed based on the driving force of land-use change. The results show that the urbanisation of Beijing is very rapid. In the past 20 years, due to the expansion of urban population, economic development and the impact of increasing land use demand has led to a sharp decrease in arable land, while construction land, including residential areas, has increased significantly. The built-up land has increased from 38% in 1999 to 72% in 2019. Due to the dry climate, low annual rainfall, and the interference of human activities on the environment, the water area has become slightly smaller. And it is located in UA. The small part of woodland and grassland on the edge has not changed much due to the influence of topography. The woodland is decreasing after 2010. Comparing with the population trend, there is no correlation between population and LUCC.

5.2 LST, NDBI and NDVI in Beijing

LST has a significant correlation with NDBI and NDVI. It can be seen from Figures 3–5 that there are two stages of urbanisation in Beijing, while 2010 is the crest.

LST acts as the interface temperature between the atmosphere and the underlying surface of the city as solar radiation. The analysis of spatial pattern characteristics is of great significance for studying the urban thermal environment, microclimate and optimising the spatial configuration of urban ecological land. The LST data is

Table 3 Land Use Classification

Land use	Year 1999	Year 2010	Year 2019	Year 1999	Year 2010	Year 2019
	Percentage			km ²		
Cropland	47.44%	31.13%	12.97%	1075.81	705.97	294.04
Woodland	7.40%	8.84%	7.55%	167.71	200.50	171.27
Grassland	6.07%	2.81%	5.67%	137.56	63.61	128.64
Water body	1.07%	1.12%	1.67%	24.20	25.40	37.87
Built-up land	38.03%	56.10%	72.14%	862.31	1272.11	1635.79

Fig. 3 LUCC in Beijing from 1999 to 2019. LUCC, land use cover change. **Fig. 4** LST in Beijing from 1999 to 2019. LST, land surface temperature.

obtained by ETM image inversion of the study area. The spatial analysis results show that the high-temperature patches in the study area are generally distributed in a pattern of more south and less north, and about 80% of the area is located south of the east-west central line, and the high-temperature patches have low landscape connectivity and tend to be regular in shape. Low-temperature patches are concentrated on the boundary of the study area, with relatively high connectivity and their shape is related to the shape of green spaces and water bodies. In terms of the number and area of patches, low-temperature patches are dominant in the second ring and outside the fourth ring, and the second ring to the fourth ring road is dominated by hot patches. The water

Fig. 5 NDBI in Beijing from 1999 to 2019. NDBI, normalised difference building index.

inside the fourth ring road plays a leading role in the generation of low-temperature patches, and outside the fourth ring road is dominated by low-temperature patches with the forest as the underlying surface.

Beijing's intense heat island centres are mainly distributed in the core areas and expansion areas of the city. The closer to the city centre, the stronger the heat islands. The thermal field variation index of Dongcheng and Xicheng in the centre is more than ten times that of Tongzhou. The heat island effect in the southern part of the entire study area is stronger than that in the northern part. The average surface temperature in the centre of the heat island in different regions is very different from the average surrounding ground temperature. On the whole, the surface temperature values in all directions decrease as the distance from the centre increases, and the surface temperature decreases significantly along the south profile line. In the range of 1/3 of the distance from the centre, the LST value changes relatively smoothly, and the latter fluctuates greatly with the increase of the distance, and the closer to the centre, the more frequent LST high values appear.

NDBI and NDVI can give a clear explanation and relationship between building intensity and vegetation intensity. NDBI shows that from 1999 to 2014, the building index increased from the range -0.35 to 0, which means the Building intensity was higher. Initially, only the downtown building index was high, while the edge area was low, but in 2014, both the downtown and surrounding building index were high.

The NDVI can accurately reflect the vegetation coverage on the ground. At present, the NDVI time-series data obtained from satellite remote sensing images such as SPOT/VEGETATION and Landsat have been obtained from the research of vegetation dynamic change monitoring, land use/cover change detection, macro-vegetation coverage classification and net primary productivity estimation in various scale areas. Wide range of applications. It can be seen from 1999 to 2010 that the increase in the red area (NDVI from 0.01 to 0.20) means that the vegetation coverage is reduced. After 2010, it can be seen that the area with NDVI > 0.50 is getting larger and larger, indicating that the vegetation coverage rate is good.

The results of the study reveal the spatial distribution of the correlation between buildings and temperature in a better manner, thus provide a certain scientific basis for Beijing's future city and green space planning.

5.3 UHII in Beijing

The Beijing urban development developed slowly prior to the reforms and opening up. After the reform and opening up, the growth rate of the Beijing urban development increased by dozens or even a hundred times

Fig. 6 NDVI in Beijing from 1999 to 2019. NDVI, normalised difference vegetation index.

Fig. 7 UHII in Beijing.

than prior to the reforms and opening up. From 1999 to 2010, the high-temperature area expands outward from the urban centre, and by 2010, >80% of the area reaches moderate temperature. From 1999 to 2019, the high-temperature area shifted from the middle to the southwest.

Comparing the UHII with the LUCC and LST results, it is observed that the increase in temperature caused by human activities in Beijing has exceeded the increase in temperature caused by natural factors, and thus it can cause the temperature changes in the city.

6 Discussion and Conclusion

6.1 Conclusion

Since 1999 in Beijing, the increase in urban temperature has been consistent with the development of urbanisation. They have a long-term coordinated and balanced relationship. This helps the planner to formulate urban planning to reduce the urban heat island effect and a reasonable population-scale city development strategy. Based on high-resolution remote sensing images, this paper extracts the distribution of different building density areas in Beijing's Sixth Ring Road. Through the analysis of the relationship between the distribution of different building density areas and the surface temperature, it is found that Beijing's urban building density is getting higher year by year, vegetation density distribution, and there is a certain correlation between the urban thermal environment.

Both the building index and the plant index of the study area present a distribution pattern with a high centre and a low edge. However, from 1999 to 2019, the overall trend of centralisation has weakened. The building density of the entire area is getting higher and higher, and the plant index is showing a downward trend of decentralisation. LST has a significant correlation with NDBI and NDVI. In the south and southwest of the city, there are more areas >310 K. This is related to the acceleration of these trends in urbanisation. The higher the building index, the higher the temperature and the building has a positive effect on temperature. Vegetation was affected by the increase in building density, and its density was getting lower and lower, and the value was around 0.20 to 0.40 by 2019.

Affected by the key development of the southern area of Beijing, the southern area has an advantageous geographical location. It is connected to the central city of Beijing in the north, the Xiong'an New District in the south and the sub-centre of Beijing city and the Yizhuang Economic Development Zone in the east. Therefore, it can be seen from UHII that the high-temperature area shifted from the central part of 1999 to the south in 2019.

In the past 20 years, Beijing's urban construction land has gradually expanded to the surrounding area based on the original core functional areas. It is an extensional development centered on the main urban area. The construction land in the surrounding districts and counties is also based on the original urban construction land. The above shows an extensional expansion to the surroundings. With the progress of urbanisation, the heat island effect has always been also obvious. The temperature of urban land gradually dominates the temperature level of the whole area, and the difference between the temperature of urban land and the regional average temperature has been significantly reduced.

6.2 Prospects of future work

The development of urbanisation is also reflected in many aspects such as changes in the internal industrial structure of cities, changes in population composition and so on (Cui et al., 2016). There are still seasonal changes and day-night differences in the urban thermal environment under the influence. The impact of urbanisation on the regional surface thermal environment needs to be more comprehensive and in-depth research.

The spatial resolution is relatively insufficient. The morphological and structural characteristics of urban heat islands are the basis for the study of urban heat island effects. The spatial resolution of TM/E TM thermal infrared bands of 60 m or 30 m makes it difficult to observe the detailed features of the ground surface on a smaller spatial scale (Zhou et al., 2019). Moreover, the lack of spatial resolution will inevitably cause the problem of mixed pixels, that is, there will be multiple urban feature components in one pixel, in this way, whether it is in the inversion of the true surface temperature or in the morphological structure and formation of the urban heat island. Moreover, there will be certain errors in mechanism of research.

Because the acquisition of remote sensing images is greatly affected by weather conditions, the weather conditions at the time of image acquisition may have a certain impact on the accuracy of the model (Khanal et al., 2020). At the same time, this article only studies the Beijing area. Therefore, whether the relationship

between urban heat island and vegetation greenness studied in this paper applies to other areas requires more data to verify.

The goal is not to study the urban heat island effect, but fundamentally to eliminate and weaken the heat island effect. Therefore, in future research, there should be a focus on the use of Landsat data to study the simulation and prediction of the urban heat island process, the ecological effects and regulation of the urban heat island effect. The study aims to seek mitigation and governance measures for the urban heat island on this basis.

References

- [1] Amir Siddique et al., 2020, Assessment and simulation of land use and land cover change impacts on the land surface temperature of Chaoyang district in Beijing China, PeerJ.
- [2] Assembly, G., 2015. United Nations Conference on Housing and Sustainable Urban Development (Habitat III) regional report for Africa: transformational housing and sustainable urban development in Africa.
- [3] Bahi, H., Rhinane, H., Bensalmia, A., Fehrenbach, U. and Scherer, D., 2016. Effects of urbanization and seasonal cycle on the surface urban heat island patterns in the coastal growing cities: A case study of Casablanca, Morocco. *Remote Sensing*, 8(10), p. 829.
- [4] Chang Cao et al., 2011, Urban heat island in China enhanced by haze pollution, Yale University.
- [5] Chen, B., Dong, L., Liu, X., Shi, G.Y., Chen, L., Nakajima, T. and Habib, A., 2016. Exploring the possible effect of anthropogenic heat release due to global energy consumption upon global climate: a climate model study. *International Journal of Climatology*, 36(15), pp. 4790-4796.
- [6] Chen, W., Zhang, Y., Gao, W. and Zhou, D., 2016. The investigation of urbanization and urban heat island in Beijing based on remote sensing. *Procedia-Social and Behavioral Sciences*, 216, pp. 141-150.
- [7] 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.
- [8] Deng, F. F., & Huang, Y. (2004). Uneven land reform and urban sprawl in China: the case of Beijing. *Progress in planning*, 61(3), 211-236.
- [9] Goswami, R. K., & Singh, B.. (2008). An Analysis of Causes of Urban Landslides in Residual Lateritic Soil.
- [10] Imran, H.M., Kala, J., Ng, A.W. and Muthukumaran, S., 2019. Impacts of future urban expansion on urban heat island effects during heatwave events in the city of Melbourne in southeast Australia. *Quarterly Journal of the Royal Meteorological Society*, 145(723), pp. 2586-2602.
- [11] Jia Wang, Weiqi Zhou, and Jing Wang, 2019, Time-series analysis reveals intensified urban heat island effects but without significant urban warming, University of Chinese Academy of Science.
- [12] Jing Chao. (2019) Research on the current status of heat island effect in Beijing and the influence factors of green space on mitigating heat island effect. (Doctoral dissertation, Beijing University of Agriculture).
- [13] Khanal, S., KC, K., Fulton, J. P., Shearer, S., & Ozkan, E. (2020). Remote sensing in agriculture—accomplishments, limitations, and opportunities. *Remote Sensing*, 12(22), 3783.
- [14] Li Xingrong, Hu Fei, Shu Wenjun, & Liang Biling. (2008). Beijing's autumn urban heat island effect and its meteorological factors. *Climatic and Environmental Research* (03), 291-299.
- [15] Lu, L., Weng, Q., Xiao, D., Guo, H., Li, Q., & Hui, W. (2020). Spatiotemporal variation of surface urban heat islands in relation to land cover composition and configuration: A multi-scale case study of Xi'an, China. *Remote Sensing*, 12(17), 2713.
- [16] Meng Jijun, & Yan Fen. (2009). Research on the temporal and spatial differentiation of the driving force of Lucc in the fringe area of big cities: Taking Changping District of Beijing as an example. *Journal of Peking University (Natural Science Edition)* (02), 125-132.
- [17] Menon, A., Hodkinson, G., Galal, H., Reckford, J. and Charles, A., 2019. Making affordable housing a reality in cities. In *Insight Report*. Geneva: World Economic Forum http://www3.weforum.org/docs/WEF_Making_Affordable_Housing_A_Reality_In_Cities_report.pdf accessed on (Vol. 26, No. 01, p. 2020).
- [18] Qiao, Z., Tian, G., Zhang, L. and Xu, X., 2014. Influences of urban expansion on urban heat island in Beijing during 1989–2010. *Advances in Meteorology*, 2014.
- [19] Tan Minghong et al., 2011, Urban spatial development and land use in Beijing: implications from London's experience, Science Press.
- [20] Tang, X. M., Liu, H., Jing, L. I., Xie, Z. Y., & Zhao, W. H.. (2015). Response analysis of haze/particulate matter pollution to land use/cover in Beijing. *China Environmental Science*.
- [21] Wang, J., Zhou, W., & Wang, J. (2019). Time-series analysis reveals intensified urban heat island effects but without significant urban warming. *Remote Sensing*, 11(19), 2229.

- [22] Wu Di. (2017). Quantitative research on land use change trajectory and urban heat island effect. (Doctoral dissertation, China University of Mining and Technology).
- [23] Yang Chunhua, Lei Bo, Wang Yechun, & Zhang Sheng. (2014). Analysis of the heat island effect and its influencing factors in the main urban area of Chongqing based on tm. *Journal of Applied Basic Science and Engineering* (02), 227-238.
- [24] Yuan, J. (2020). Investigation of Spatial and Temporal Changes in the Land Surface Albedo for the Entire Chinese Territory. *Geosciences*, 10(9), 362.
- [25] Zhi Qiao, Guangjin Tian, Lixiao Zhang, Xinliang Xu, 'Influences of Urban Expansion on Urban Heat Island in Beijing during 1989–2010', *Advances in Meteorology*, vol. 2014, Article ID 187169, 11 pages, 2014. <https://doi.org/10.1155/2014/187169>.
- [26] Zhou, D., Xiao, J., Bonafoni, S., Berger, C., Deilami, K., Zhou, Y.,... & Sobrino, J. A. (2019). Satellite remote sensing of surface urban heat islands: Progress, challenges, and perspectives. *Remote Sensing*, 11(1), 48.
- [27] Zheng, S., Zhao, L., & Li, Q.. (2016). Numerical simulation of the impact of different vegetation species on the outdoor thermal environment. *Urban Forestry & Urban Greening*, 18, 138-150.
- [28] Z.Qiao, G. J. Tian, and L. Xiao, 2013, Diurnal and seasonal impacts of urbanization on the urban thermal environment: a case study of Beijing using MODIS data,' *Journal of Photogrammetry and Remote Sensing*.
- [29] Zhuoga, Pubu Tsering, & Liu Weidong. (2009). Analysis of the heat island effect and its influencing factors in Lhasa, Tibet. 2009 Plateau and Mountain Meteorological Research and Southwest Regional Meteorological Academic Exchange Conference.
- [30] Zhao Shoudong, Wang Jingfan, He Xin, Liu Yang, Wang Xiaomin, & Tian Yuhong. (2014). The impact of urbanization on climate change and its feedback mechanism. *Journal of Beijing Normal University: Natural Science Edition*, 000(001), 66-72.

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