

Correlation Between Surface Temperature and Population Density In Xiong'an New Area Based on Nightlight Remote Sensing And Landsat8 Data

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Abstract. Xiong'an New Area was established in 2017. With the development of the city, the urban surface temperature has also changed. Taking Xiong'an New Area as the study area, the distribution of population density in the study area was simulated based on the night light value of noctilucent remote sensing data, and the land surface temperature in the study area was retrieved by Landsat8 image. Additionally, the study area's land surface temperature and population density's temporal and spatial variation characteristics were examined. The influence before and after development was also extracted, and the correlation between them was also analyzed. According to the results, the surface temperature in the study area is rising, and it is characterized with a heat island effect. At the same time, there is a positive correlation between population density and temperature, and population density is one of the important factors that affect the urban temperature change. The development of this study is conducive to improving people's quality of life and the distribution of urbanization resources.

Keywords: Xiong'an New Area; Nighttime light remote sensing; Surface temperature inversion; Grid.

1. Introduction

The official start of Xiong'an construction was in 2017. Xiong'an New Area is located 100 kilometers southwest of Beijing, in the core hinterland of Beijing, Tianjin and Hebei. With the development of Xiong'an New Area, the population is increasing gradually. Some natural vegetation and artificial landscapes are gradually replaced by artificial areas, which are used in daily work with the heat emission from human activities and equipment work. Human activities have a great influence on the surface temperature and have a negative effect on human life, production and health.

In recent years, some studies have shown that there is a certain correlation between surface temperature and human activities. Guo Hengliang's research shows that there is a significant correlation between population density and surface temperature using linear regression analysis [1]. Zhang Lilong's research shows that urban economic growth is closely related to urban population density [2]. Studies by Liu Xinxin and Chen Zhuo show that the influence of urban expansion on urban heat island effect is due to the increase of artificial heat dissipation and the decrease of natural underlying surface area caused by urban expansion, which leads to the increase of temperature [3]. Studies by Zhuo Li, Chen Jin and others show that there is a close relationship between population density and night light intensity [4].

As a special economic zone, Xiong'an New Area has a rapid population growth and rapid urbanization expansion. Therefore, the population and spatial distribution have also changed to some extent. The rapid growth of population will affect the regional ecological carrying capacity. When a large number of people gather, the impact on the surrounding surface temperature and economic development will also increase. Because there is a great correlation between population density and lighting value, this study first carries out domain processing such as projection conversion and resampling on night lighting data, and then carries out preprocessing such as radiation calibration and atmospheric correction on Landsat 8 for subsequent operation. The population density is simulated by night lighting data, and the surface temperature is retrieved by Landsat8 data, so as to explore the correlation between surface temperature and night lighting value. In the research process, the inverse

distance weight method is also used. Therefore, it is of great significance to study the influence of population density on land surface temperature in Xiong'an New Area, which can improve people's quality of life, ensure the orderly development of urbanization and rational allocation of land use.

2. Research Area and Data Overview

2.1. Study Area

The Xiong'an New Area is made up of the counties of Xiongxian, Rongcheng, and Anxin, and it has unrivaled geographical advantages, convenient transportation, an excellent ecological environment, abundant resources, and a large development space. The establishment of Xiong'an New Area is conducive to the relaxation of Beijing's functions as an unnecessary capital city, the exploration of a new model for optimizing the development of densely populated areas, and the reconstruction of the urban layouts of Beijing, Tianjin, and Hebei. The establishment of Xiong'an New Area is an important historical and strategic choice.

2.2. Data Source

(1) NPP/VIIRS night lighting data: NPP/VIIRS night lighting image started in 2012, with a spatial resolution of 500m, which can detect weak visible light radiation such as moonlight, starlight, city lights and atmospheric glow at night. The image quality is significantly improved after on-board calibration, which can be divided into two types: annual mean image and monthly mean image. This study adopts the annual mean image in 2017 and 2021. (2) Landsat8 data: Remote sensing image data of Landsat8 data in 2017 and 2021 are used in this study, with a spatial resolution of 30m, including a 15 m panchromatic band. In the selection of seasonal images of remote sensing images, Not only should the image quality of the study area in the image coverage area be considered, but also the seasonal differences in timeliness in different regions. So similar months in the data selection are chosen. In this study, the remote sensing image data of September 2017 and September 2021 were selected, and the temperature was mainly retrieved. (Landsat8 data comes from geospatial data cloud: www.gscloud.cn). (3) Xiong'an New Area vector boundary map are also used as other data.

2.3. Pretreatment

(1) Annual night lighting data: First, Images' projection format is unified as Albers normal axis equal area tangent cone projection. A grid with resolution of 500*500 is added to the data and resample it using the nearest neighbor method.

(2)Landsat8 data: ,Radiometric calibration for panchromatic band and thermal infrared band is conducted. Atmospheric correction is performed.

3. Research Methods

3.1. Basic Idea

The preprocessed Landsat8 data is first used to calculate the NDVI, then the vegetation coverage, the land surface emissivity through the vegetation coverage, and finally the black body brightness value. Then, on this basis, the surface temperature is inversed. VIIRS data are preprocessed by projection conversion and nearest neighbor resampling, and then the inverse distance weight method is selected for interpolation analysis to form the night light brightness map. Finally, the correlation between brightness value and temperature value is analyzed.

3.2. Main Steps

3.2.1 VIIRS data

(1) Projection transformation

The original data is geographic projection WGS_1984, and the projection is converted into Albers normal axis equal area secant cone projection, which is convenient for subsequent data raster operation and other processing.

Nearest neighbor interpolation resampling

Nearest neighbor interpolation algorithm is also called zero order. As a result, the gray value of the input pixel closest to the position mapped by the pixel center is chosen. For two-dimensional images, the gray value of the nearest point among the four adjacent pixel points around the point to be sampled is taken as the pixel value of the point to be sampled.

Inverse distance weighted (IDW) interpolation.

Inverse distance weighted interpolation is a global weighted average interpolation method, which was originally proposed by Shepard [5]. This method uses inverse distance algorithm to insert the point data in the geographic information space into the specified position, and recognize and grasp the relationship in the geographic information space, so as to realize the reconstruction of spatial information.

IDW interpolation has the following characteristics. Firstly, IDW interpolation is a local interpolation method, which is only related to the nearby points of a certain point, but not to the distant points, so the calculation requirements are relatively low. Secondly, IDW interpolation can correctly reflect the position relationship of each point, and consider that the value of observation points will have less and less influence on the value of interpolation points because of the increase of distance, thus making the interpolation result more accurate and reliable [6]. Finally, the results of IDW interpolation will not be affected by the distribution of point data, which makes up for the shortcomings of traditional interpolation methods.

This is IDW interpolation expression:

$$Z^*(S_0) = \sum_{i=1}^N \lambda_i * Z(S_i) \quad (1)$$

In formula (1), $Z(S_i)$ is the measured value at the sample point, $Z^*(S_0)$ is the predicted value at the point, n is the number of neighboring sample points used for interpolation, and it is the weight of the sample point to the predicted point. It can be found using formula (2).

$$\lambda_i = \frac{d_{i0}^{-p}}{\sum_{i=1}^N d_{i0}^{-p}}, \sum_{i=1}^N \lambda_i = 1 \quad (2)$$

In formula (2), d_{i0} is the distance between the prediction point and the sampling point, and p is the power of the distance, meaning that as the distance grows between the sampling point and the prediction point, the sampling point's influence on the prediction point's weight decreases exponentially, and the total weight values equal one [7].

In this study, the inverse distance weight interpolation method is used to supplement the missing point data that have not been collected [7].

3.2.2 Landsat 8 data

(1) Normalized vegetation index (NDVI)

$$NDVI = \frac{NIR-R}{NIR+R} \quad (3)$$

NIR stands for the reflection value of the near infrared band, and R for the reflection value of the red band. Some radiation errors can be removed through the calculation of the normalized vegetation index (NDVI).

(2) Vegetation fraction (FV)

$$FV = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad (4)$$

The calculated pixel's NDVI value is denoted by the letters NDVI, NDVI_v, and NDVI_s, respectively. NDVI_s is the pixel's NDVI value when there is no vegetation present. Because the acquisition and transmission of remote sensing data is inevitably disrupted by noise, and there is some error in image quality, the maximum and minimum values within a given confidence range are typically taken into account by NDVI_v and NDVI_s, and the confidence value is primarily determined by the actual situation of the image.

(3) Land surface emissivity

According to previous research, there are three categories for remote sensing images: natural surface, urban area and water body [8]. In this study, the land surface emissivity of the study area is calculated by the following methods: Water pixels have a specific emissivity of 0.995, and the specific emissivity of natural surface and urban pixels is estimated using the following (5) and (6) formulas:

$$\varepsilon(\text{surface}) = 0.01905F_v + 0.96767 \quad (5)$$

$$\varepsilon(\text{building}) = 0.021835F_v + 0.964885 \quad (6)$$

F_v is the vegetation coverage.

(2) Brightness value of blackbody radiation

$$B(T_s) = [L_\lambda - L_{up} - \tau * (1 - \varepsilon) * L_{down}] / (\varepsilon * \tau) \quad (7)$$

The brightness of blackbody radiation is $B(T_s)$, and L_{up} , L_{down} , τ are the upward and downward radiation of the atmosphere respectively, and the atmospheric transmittance can be obtained by NASA atmospheric calculator NASA. Emissivity ε needs to be calculated using vegetation fraction.

(3) Land surface temperature

$$T_s = K_2 / \ln(K_1 / B(T_s) + 1) \quad (8)$$

The blackbody radiation brightness is $B(T_s)$, which is 774.89 and 1321.08 respectively for Landsat 8.

4. Results and Discussion

4.1. Temporal and Spatial Characteristics of Night Light Data in Xiong'an New Area

Firstly, a grid with the resolution of 500*500 is established in this administrative area. After preprocessing the night lighting data, the total value of night lighting and the night lighting value in each grid are counted by the grid. In the noctilucent remote sensing data, the night light value generally reflects the gathering situation of population. The smaller the light value is, the sparser the population will be, while the larger the light value is, the denser the population will be.

Among them, the lighting value of rarefaction district is 0~1.2, the lighting value of less rarefaction district is 1.2~4.5, the lighting value of medium district is 4.5~20, the lighting value of densely inhabited district is 20~40, and the lighting value of congested district 40~80.

As can be seen from the Figure 1, from 2017 to 2021, the population density map with light value simulation feedback showed that sparse areas narrowed, dense areas and dense areas expanded in a small range, and the northern region developed rapidly.

Changes in population density from 2017 to 2021

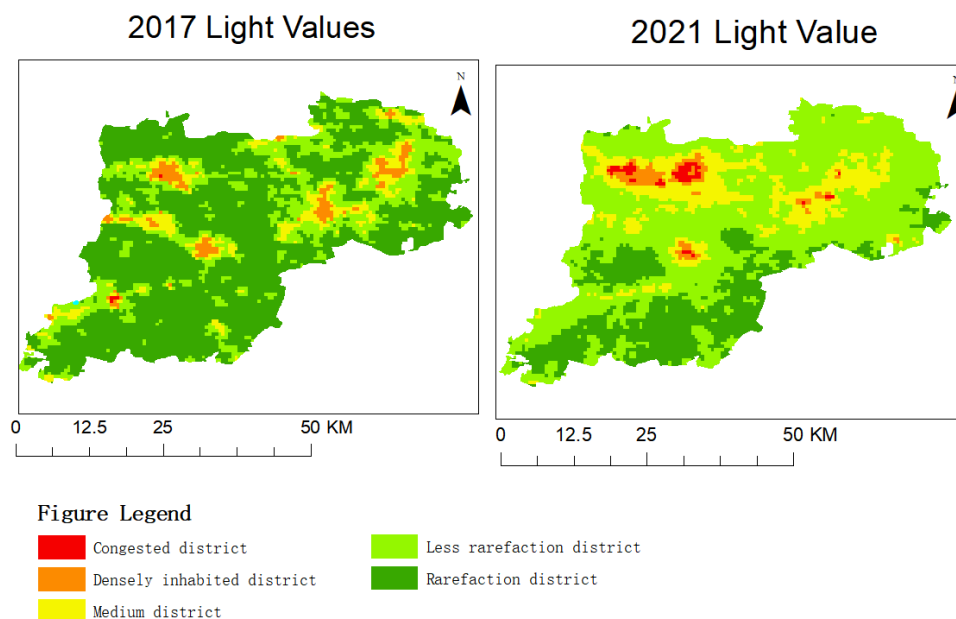


Fig. 1 Changes in population density from 2017 to 2021

4.2. Temporal and Spatial Characteristics of Night Surface Temperature in Xiong'an New Area

After preprocessing Landsat8 data, the surface temperature is retrieved by ENVI, and the grid is established, which is combined with the night light information counted by the above grid and corresponds one by one, and its correlation is analyzed. Low temperature district, lower temperature district, the medium temperature district, higher temperature district, and ultra-high temperature district are the five temperature districts that are formed by the inverted surface temperature.

Among them, areas with temperatures of below 24 degrees Celsius is defined as the low temperature district; 24 degrees Celsius to 27 degrees Celsius as the lower temperature district; 27 degrees Celsius to 31 degrees Celsius as the medium temperature district; 31 degrees Celsius to 35 degrees Celsius as the higher temperature district; and 35 degrees Celsius to 42 degrees Celsius as the ultra-high temperature district.

As can be seen from the Figure 2, from 2017 to 2021, the surface temperature increased, and the area of geothermal area decreased obviously, and at the same time, a few hotspots dominated by urban centers emerged, indicating that Xiong'an New Area construction was progressing. The figure shows that the surface temperature is relatively high in the study area city's center and relatively low in the suburbs and surrounding areas, with a centralized connection between the high temperature district and the ultra-high temperature district. With the development of the city, the high temperature area has obviously expanded and tends to be integrated.

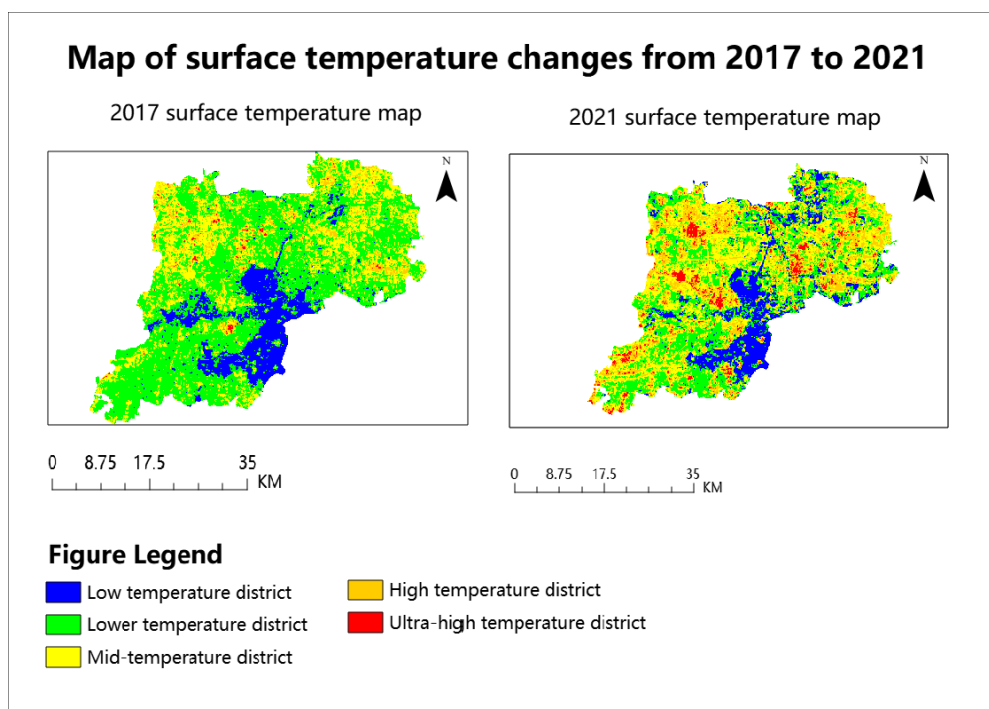


Fig. 2 Temperature change map

4.3. Correlation Analysis

In this study, firstly, the abnormal maximum and minimum values are removed. In order to reduce the differences among individuals in the region, the statistical method of zoning is adopted for the study area, and the night light values within the study area are in increments of 1. Through re-classification of the noctilucent remote sensing image values through natural breaks, the average value of surface temperature corresponding to each category is obtained by partition statistics, and the correlation and linear regression between the nighttime lighting value and the average surface temperature are performed [9]. Therefore, as can be seen from the Figure 3 and Figure 4, $R^2=0.5699$ and $R^2=0.6394$ are obtained in 2017 and 2021, respectively. Pearson correlation analysis between surface temperature and night lighting data shows that Pearson index is 0.75 in 2017 and 0.80 in 2021.

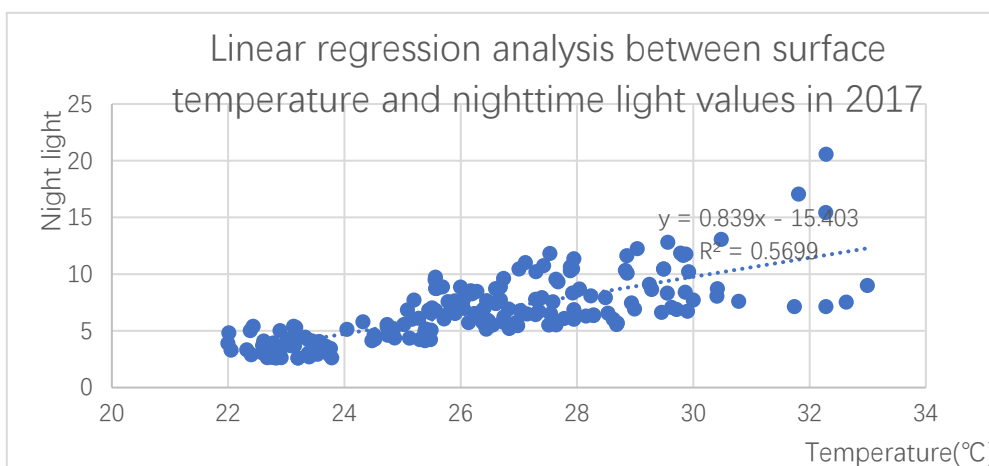


Fig. 3 Linear regression analysis between surface temperature and night light value in 2017

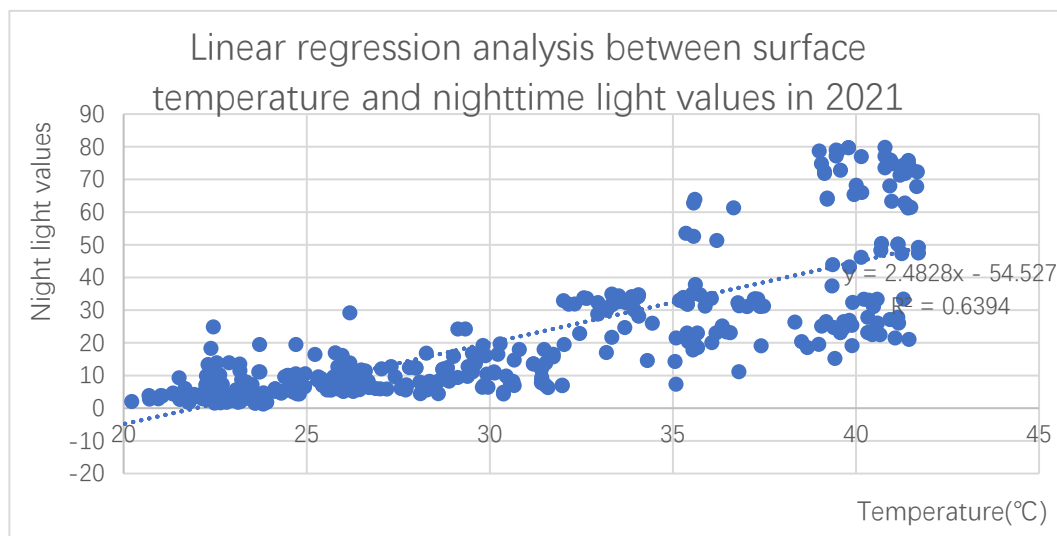


Fig. 4 Linear regression analysis between surface temperature and night light value in 2021.

4.4. Discussion

There are various factors which may affect the accuracy of the results. For example, the small scope of the study area, the small-time scale of the study and the population control in the study area are also important factors that cause the low correlation. At the same time, considering that the study area is still in the developing stage, the area near the machine in the industrial land, storage land and foreign transportation facilities will have higher lighting brightness values, which are similar to those in the densely populated areas in the urban core area, so there will be errors [10].

5. Conclusion

This paper examines the changes in population density and temperature in the study area from 2017 to 2021, as well as their correlation, using luminous remote sensing data and Landsat8 images. The findings show that the study area's densely populated areas are progressively growing, and that this is also having a gradual impact on the rise in surface temperature. It is implied that as Xiong'an New Area develops, this region will eventually create a heat island environment with high urban temperatures and relatively low surrounding temperatures. According to the correlation of the study, the population density in urban areas has certain influence on the surface temperature.

References

- [1] Guo Hengliang, Feng Zhenzhen, He Xiaohui, Tian Zhihui, Qiao Baojin. Analysis of the influence of land cover and population density changes on urban land surface temperature-taking Zhengzhou as an example [J]. Journal of Inner Mongolia Normal University (Chinese version of natural science), 2019,48(04):298-306.
- [2] Zhang Lilong. Study on the impact of urban population density on economic growth [D]. Jinan University, 2019.
- [3] Liu Xinxin, Chen Zhuo, Liang Jiyue, Yan Jiale, Gao Zilong, Cui Zhuangjie. Study on the relationship between urban expansion and heat island effect in Taiyuan [J]. Henan Science and Technology, 2021,40(33):126-129.
- [4] Zhuo Li, Chen Jin, Shi Peijun, Gu Zhihui, Fan Yida, Yi Zhi Jun Ming. Simulation of population density in China based on night lighting data [J]. Journal of Geography, 2005,(02):266-276.
- [5] Daly C. Guidelines for assessing the suitability of spatial climate data sets [J]. International Journal of Climatology, 2010, 26(6): 707-721.

- [6] Gao Zhen, Ye Xueyi, Zhou Tianqi, et al. Underwater acoustic data visualization algorithm based on inverse distance weighted interpolation [J]. Computer Engineering, 2015, 41(9): 266-270, 275.
- [7] Fan Shengnong, Li Huadong, Wang Shuoheng, Tan Mengyi, Meng Xin, Ge Meihong, Lin Dian. Prediction of spatial distribution of soil nutrients in Huolong orchard in Hainan Province based on IDW and factor analysis [J]. Journal of Southwest Agriculture, 1-12[2023-02-02].
- [8] He Hao, Zhang Yun, Tang Zhi, Huang Jing, Ding Yue. Improvement of land surface emissivity estimation method in Landsat8 thermal infrared band [J]. Journal of Anhui Normal University (Natural Science Edition), 2020,43(05):475-482.
- [9] Zhou Siyan, Tan Yongbin, Hou Mengfei, Ai Jinquan, Zhang Zezhi, Zhu Shangjun. Correlation analysis between population density and surface temperature in Changsha-Zhuzhou-Xiangtan area based on luminous remote sensing data [J]. Jiangxi Science, 2021,39(01):105-110.
- [10] A method of population density inversion based on night lighting data [P]. China patent: cn104809572a.2015.4.27.