Assessing the effects of water structure on urban heat islands using HJ-1B remote sensing imagery in Wuhan, China

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Abstract

Urban heat islands (UHIs) have attracted attention around the world especially in metropolis because they profoundly affect human life. Understanding and assessing the effects of the spatial structure of water body on UHIs is essential to better understand environmental problem. Based on existing research, this paper presents water body structure could cause many small but stable effects to the urban heat islands. The relationship between the mean land surface temperature (LST) and the attributes of water body was revealed via Pearson's correlation analysis and multiple stepwise regression analysis. The results have showed that mean LST is related to five landscape metrics. These findings can help us understand the impacts of the spatial structure of water body on UHIs, which is helpful for improving the planning and management of urban environment.

Introduction

Wuhan, the capital of Hubei province, in central China, is famous for the title of "one of four furnaces in China."And it has another name: "the city of hundreds lakes," whose water area covers around 25% of the territory and the coverage of water area ranks first in the whole country. In recent years, Wuhan city has experienced rapid urbanization and economic development. As a result, many urban water bodies in Wuhan city have been disappeared because of the pressure to gain extra land profit in the process of urban development. Therefore, Wuhan city is chosen as the case area to estimate the relationship between LST and the water pattern from the view of landscape ecology （**Fig.1**）. Based on existing research, this paper used the HJ-1B remote sensing imagery data to retrieve LST and land use/cover for water. Then, taking Wuhu as the center, the proportion of water body and vegetation surface occupied by 500-5000m buffer distance is calculated, and the change trend is analyzed in combination with mean LST value and Selecting the Hanyang District (a large distribution of lake water) for fishing net cutting (30 4500m*5000m samples) and calculating landscape index and mean LST of each sample, and performing correlation analysis. Finally, based on the existing research, 17 (study metrics)/12 (traditional metrics) landscape indexes of the samples of Hanyang District were selected for stepwise regression analysis and the equations were fitted.

Objective

Wuhan, which is the capital of Hubei Province, is the largest city along the middle part of the Yangtze River and lies between 113°41′and 115°05′E longitude and between 29°58′and 31°22′N latitude. The total territorial area of Wuhan is about 8494.41 km2, and the water area is about one-fourth of the city's total area. The famous rivers and lakes in Wuhan city are Yangtze River, Han River, East Lake, South Lake, and so on. These rivers/lakes mentioned above, together with other water bodies of Wuhan, are scattered and distributed in the study area. And they have a big influence on humidity, purifying atmosphere of Wuhan climate. The urbanization results in not only the rapid expansion of built areas but also large modifications to the water bodies landscape structure, which causes many serious impacts to the urban ecological environment. Of these effects, the UHI is the most important and dramatic reflection of rapid urbanization.

Methods

Computation of NDVI and Fv:

As for HJ-1B image, NDVI was expressed as:

$$NDVI = \frac{\rho_4 - \rho_3}{\rho_4 + \rho_3}$$

Where ρ_4 is the reflectance of the near-infrared band and ρ_3 is the reflectance of the red band.

The fractional vegetation (Fv) of each pixel was determined from the NDVI using the following equation:

$$\mathrm{Fv} = \left(\frac{NDVI - NDVI_s}{NDVI_v - NDVI_s}\right)^2$$

where NDVI_s is the NDVI value of pure soil (0.05) and NDVI_v is the NDVI value of pure vegetation (0.7).

Land surface temperature retrieval

The HJ-1B thermal infrared band data were radiometrically and geometrically corrected and were then used to derive the land surface temperature of Wuhan. The steps of the land surface temperature retrieval process are as follows.

$$\mathrm{Tb} = \frac{K_2}{\ln(K_1 / L_\lambda)} + 1$$

where T_b is the at-sensor brightness temperature in Kelvin. For the HJ-1B remote sensor, K_1 is $579.20\mathrm{Wm}^{-2} ster^{-1} \mu m^{-1}$ and K_2 is 1245.58 K, which are the calibration constants.

The next step is to convert the brightness temperature to land surface temperature.

$$\mathrm{T_s} = \frac{T_b}{(1 + (\lambda_{eff} \times T_b / C)\ln\varepsilon)}$$

where T_s is the land surface temperature, T_b is the at-sensor brightness temperature from above and λ_{eff} is the wavelength of the emitted radiance. The constant C was calculated with the expression $h \times c / \sigma$, where h is Planck's constant ($1.626 \times 10^{-34}\mathrm{Js}$), c is the velocity of light ($2.998 \times 10^8 \mathrm{m}/s$) and σ is Boltzmann's constant ($1.380 \times 10^{-23} \mathrm{J}/K$). The surface emissivity ε, which is more complicated than the variables described above, was determined by the NDVI Thresholds Method （**Fig.3**）.

Photos & Tables

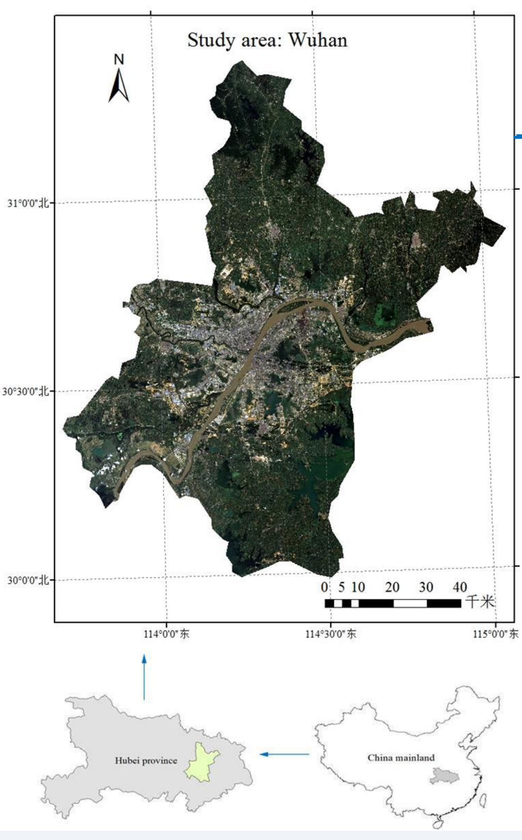

Fig.1 Location of the study area

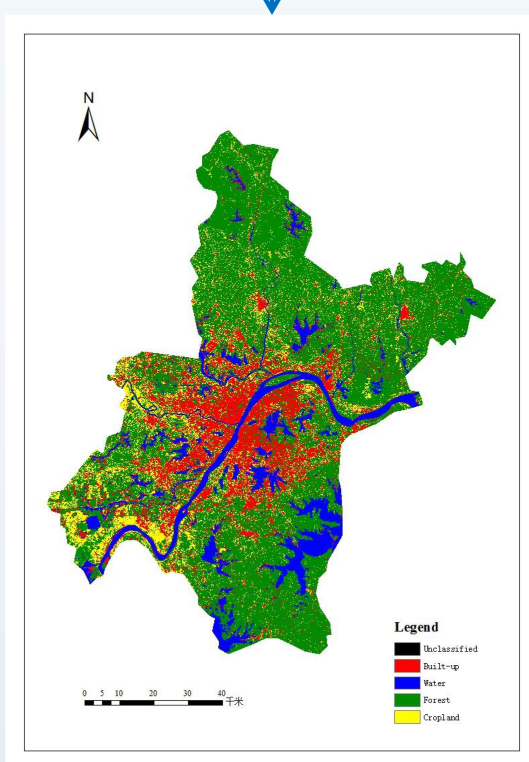

Fig.2 Land use map

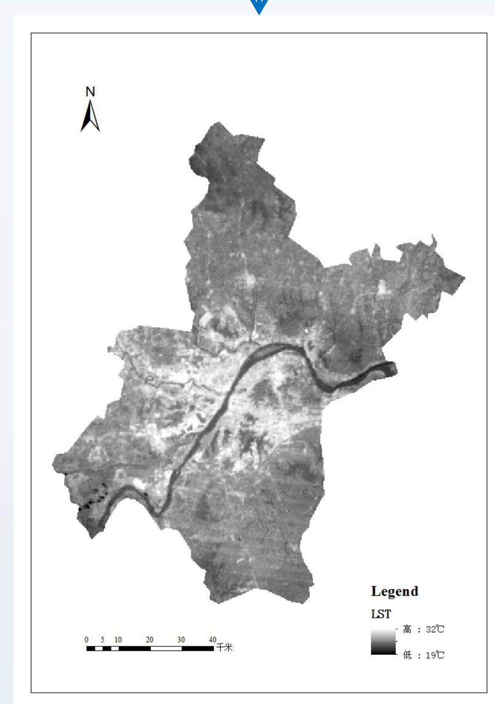

Fig.3 LST map

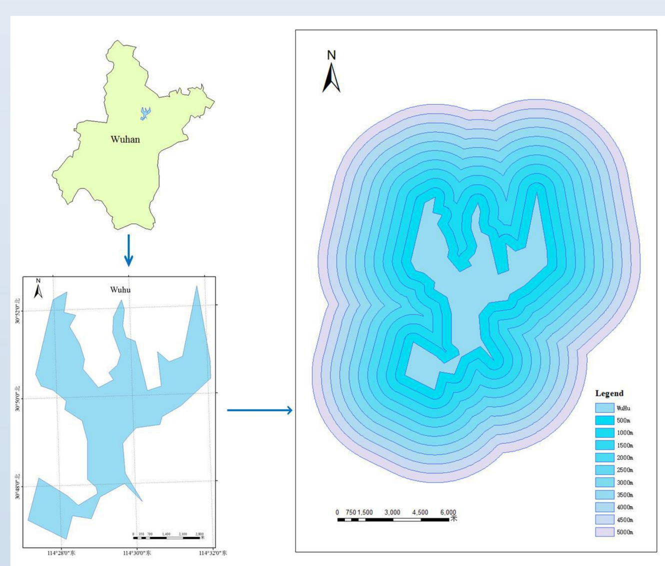

Fig.4 Buffer distance from 500m to 5000m

Table.1
Area percentage of each land use and mean LST of patch

Radius	Built-up	Water	Forest	Cropland	Mean LST
500	0.161	0.113	0.687	0.040	24.384
1000	0.123	0.074	0.751	0.052	24.507
1500	0.105	0.057	0.775	0.063	24.590
2000	0.095	0.050	0.778	0.077	24.667
2500	0.090	0.043	0.779	0.088	24.753
3000	0.088	0.038	0.779	0.096	24.809
3500	0.086	0.033	0.782	0.099	24.866
4000	0.086	0.030	0.780	0.103	24.919
4500	0.090	0.029	0.776	0.105	24.964
5000	0.098	0.027	0.763	0.112	25.007

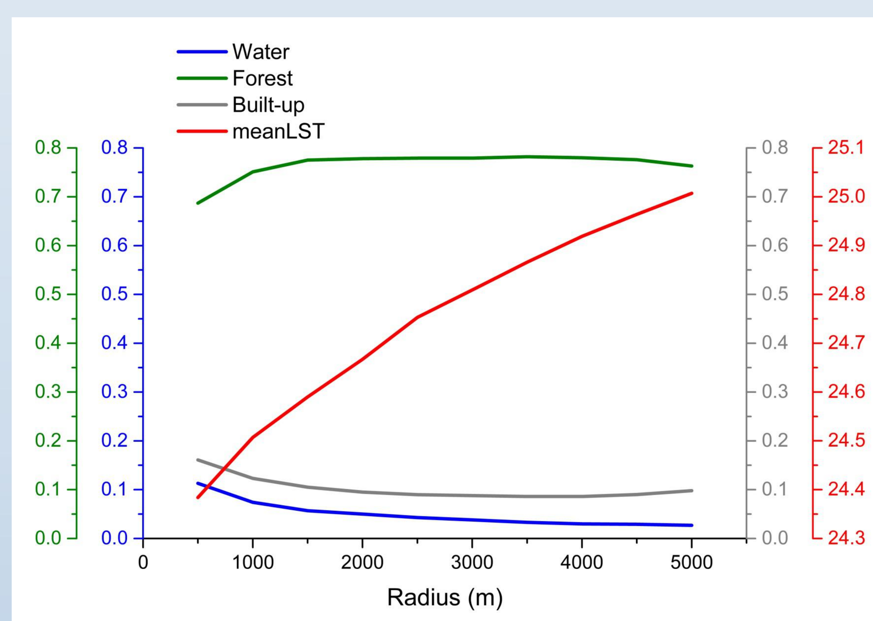

Fig.5 Relation between mean LST and area percentage of each land use

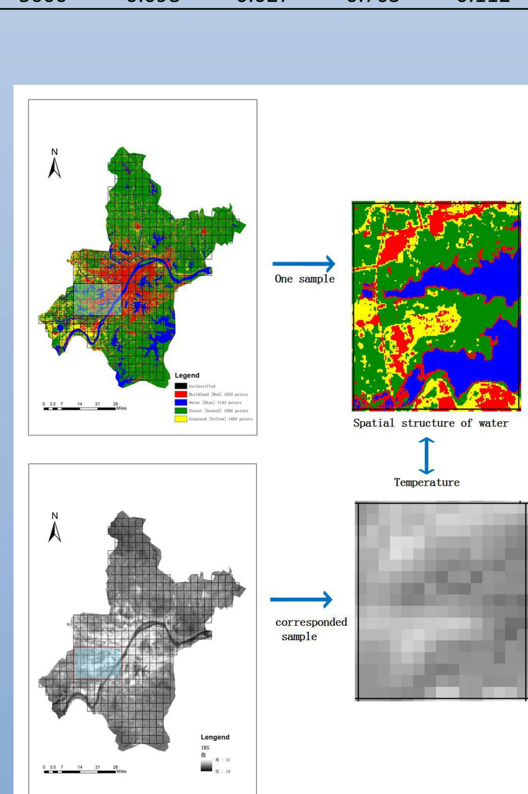

Fig.6 Water spatial structure and its corresponding mean temperature in sample areas

Table.2
Comparison of water landscape metrics and forest landscape metrics

Landscape metrics	Pearson	p value	Landscape metrics	Pearson	p value
NP	-0.537	0.002	ENN_MN	0.853	0.000
PD	-0.536	0.002	CA	-0.780	0.000
ENN_MN	0.476	0.008	PLAND	-0.780	0.000
LSI	-0.474	0.008	ED	-0.711	0.000
ED	-0.415	0.023	LPI	-0.646	0.000
SHAPE_MN	0.228	0.225	PD	0.463	0.010
CA	-0.156	0.409	NP	0.462	0.010
PLAND	-0.156	0.411	SHAPE_MN	-0.368	0.045
LPI	-0.081	0.672	IJI	-0.097	0.611
IJI	-0.051	0.788	LSI	-0.001	0.995

Table.3
Comparison of regression equation considering water landscape metrics and traditional landscape metrics

	Study Metrics	Traditional Metrics
Before	LPI_B、CA_B、PD_B、LSI_B、SHAPE_MN_B、NP_W、PD_W、ED_W、LSI_W、ENN_MN_W、ENN_MN_F、CA_F、ED_F、LPI_F、PD_F、ENN_MN_C、IJI_C	LPI_B、CA_B、PD_B、LSI_B、SHAPE_MN_B、ENN_MN_F、CA_F、ED_F、LPI_F、PD_ F、ENN_MN_C、IJI_C
After	CA_B、PD_B、LSI_B、ENN_MN_W 、ED_F、ENN_MN_C	CA_B、PD_B、LSI_B、CA_F、ED_F、ENN_MN_C
Equation	Y1= 27.58+0.001372CA_B+0.1957PD_B-0.09073LSI_B+0.0001743ENN_MN_W-0.009972ED_F-0.01107ENN_MN_C	Y2=27. 7464679+ 0.0017593 CA_B+ 0.1438871 PD_B-0.0651763 LSI_B+ 0.0004103 CA_F- 0.0109093 ED_F-0.0193909 ENN_MN_C
R^2	0.9506	0.9343
p	＜0.01	＜0.01

Discussion

1.The results show that, with the increase of buffer radius, the area of water body, vegetation and building remains unchanged, but the mean LST is higher, which means that the closer the center of Wuhu, the vegetation remaining the same, the mean LST is reduced （ **Fig.4** ）. It shows that there are other surface types (water bodies) besides vegetation that affect mean LST and produce cooling effect （ **Fig.5** ）.

2. The results show that（**Table.2**）:

NP reflects the spatial pattern of the landscape. LST is negatively correlated with the NP of water, the larger the NP value, the higher the fragmentation, the lower the LST, indicating that the higher the water fragmentation, the more obvious the cooling effect.LST is positively correlated with the NP of vegetation, the larger the NP value, the higher the fragmentation, the higher the LST, which indicates that the higher the fragmentation degree of vegetation, the less obvious the cooling effect. PD has a strong linear relationship with NP （ **Fig.6** ）.

Mean LST and water body ENN_MN are positively correlated, the larger the ENN_MN, the more discrete the distribution, the greater the mean LST, the less obvious the cooling effect.

LST is negatively correlated with the LSI of water, the larger the LSI, the more irregular the shape of the plaque (the more deviating from the square), the lower the LST, the more obvious the cooling effect. The correlation between LST and the LSI of vegetation is very small, and there is no obvious relationship between LST and the LSI of vegetation.

CA and PLAND have a strong correlation. PLAND its value tends to 0, indicating that the type of tile in the landscape becomes very rare; when its value is equal to 100, it indicates that the entire landscape consists of only one type of tile. The LPI is equal to the proportion of the largest block in a patchwork type that occupies the entire landscape area.LST and vegetation CA, PLAND, LPI are negatively correlated, the larger the three indicators, the larger the total area of plaque at the same time also concentrated, the lower the LST, the more obvious the cooling effect, indicating that vegetation and water are the opposite.

3. As we all know, the building has a warming effect on the UHI, vegetation has a cooling effect on the UHI, this paper proposes that the water body also has a cooling effect on the UHI, and on the basis of the previous, the landscape index of the water body is added to establish the fitting equation with the LST.

The results show that r^2 (study metrics) >r^2 (traditional metrics), the regression fitting equation considering the landscape index of water body structure, compared with the equation constructed by the landscape index which does not take into account the structure of water body, the fitting effect is better （**Table.3**）.

The influence of built-up on landscape vegetation is CA, PD and LSI, the influence landscape index of water body is ENN_MN, and the influence index of vegetation is ED.

ENN_MN (mean Euclidean nearest neighbor Distance) value is large, reflecting the distance between the same type of plaque, the distribution is more discrete; Conversely, it shows that the same type of patch is close to each other, is a agglomeration distribution. Mean LST and water body ENN_MN are positively correlated, the larger the ENN_MN, the more discrete the distribution, the greater the mean LST, the less obvious the cooling effect.

Compared with the regression equation which does not consider the water body, the equations obtained by considering water body in this paper is better when the significance test is passed by.

Conclusions

1.Water body was also a factor affecting mean LST.

2.Mean LST is negatively correlated with NP and PD of water body, and positively correlated with ENN_MN. The conclusion is: Within a certain threshold, there is a negative correlation between mean LST and the dispersion degree of water body, and after exceeding the threshold, mean LST is positively correlated with the dispersion degree of water body.

3.Conclusion: Within a certain threshold, there is a negative correlation between mean LST and the degree of dispersion of water body, and after exceeding the threshold, mean LST is positively correlated with the degree of dispersion of water body. Analysis: The distance between the plaque of water is very important to the cooling effect, because of the large heat capacity of water, the heat required to increase 1 ℃ during the day, has a cooling effect, and by the night, the reduction of 1 ℃ the release of more calories, all usually in the morning water temperature is higher than other features, the afternoon is lower than other features. If the concentration of water bodies is high, the distance between water bodies will have an impact on the heat absorption, heat dissipation effect, and if the distance is too large, then the heat absorption and heat dissipation effect of water bodies will be weakened. It is similar to the conclusion reached in the third part.

Reference

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