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To cite this article: Qijiao Xie et al 2018 IOP Conf. Ser.: Earth Environ. Sci. 121 022009

View the article online for updates and enhancements.
Remote sensing study of the impact of vegetation on thermal environment in different contexts

Qijiao Xie1,3,4, Yingjiao Wu1, Zhixiang Zhou3 and Zhengxiang Wang1

1 School of Resources and Environmental Science, Hubei University, Wuhan, 430062, China;
2 College of Horticultural & Forestry Science/Key Laboratory of Horticultural Plant Biology (Ministry of Education), Huazhong Agricultural University, Wuhan 430070, China;
3 Hubei Key Laboratory of Regional Development and Environmental Response (Hubei University), Wuhan 430062, China.
4 xieqijiao@126.com

Abstract. Satellite remote sensing technology provides informative data for detecting the land surface temperature (LST) distribution and urban heat island (UHI) effect remotely and regionally. In this study, two Landsat Thematic Mapper (TM) images acquired on September 26, 1987 and September 17, 2013 were used to derive LST and the normalized difference vegetation index (NDVI) values in Wuhan, China. The relationships between NDVI and LST were examined in different contexts, namely built-up area, farmland, grassland and forest. Results showed that negative correlations between the mean NDVI and LST were detected in all observed land covers, which meant that vegetation was efficient in decreasing surface temperatures and mitigating UHI effect. The cooling efficiency of vegetation on thermal environment varied with different contexts. As mean NDVI increased at each 0.1, the decreased LST values in built-up area, farmland, grassland and forest were 1.4 ºC, 1.4 ºC, 1.1 ºC, 1.9 ºC in 1987 and 1.4 ºC, 1.7 ºC, 1.3 ºC, 1.8 ºC in 2013, respectively. This finding encourages urban planners and greening designers to devote more efforts in protecting urban forests.

1. Introduction

The urban heat island (UHI) effect, a phenomenon that urban areas experience higher surface and air temperatures than the surrounding rural areas do, has been worldwide detected not only in large metropolitan areas but also in cities with population less than 10,000 people [1]. It has an adverse effect on local climate and ecological environment [2]. Urban vegetation is regarded as an ecological measure to mitigate the UHI effect.

As a result, many investigators have devoted their attention to study the impact of urban green areas or parks on UHI effect. Their researches revealed that the efficiency of urban green areas in cooling the surroundings varied with their physical characteristics [3, 4]. Those larger green areas with more biomass, more complex geometry, construction and configuration were recorded to have more efficient cooling effect on thermal environment. While observations [5] indicated that effect of vegetation on reducing surface temperature in the urban area was more inefficient than that in the suburbs. These conclusions implied the environmental situation around green areas can also influence their cooling effect [6]. However, these experiments were based on fieldwork measurements, seldom...
conducted at larger scale. Other studies focused on the relationship between urban vegetation and urban temperatures or UHI effect at a city scale [7-9]. The normalized difference vegetation index (NDVI) and NDVI-related parameters were usually selected to express urban vegetation. In these studies, the estimated cities were assumed to be homogenous in environmental situation, without taking the complex contexts into account.

This study aims to examine the relationships between the NDVI and LST in different contexts based on Landsat Thematic Mapper (TM) imagines at a city scale. Remote sensing techniques were used to derive NDVI and LST values on urban or regional scale, which provides a significant method to informatively study the urban climate and environment in metropolitan areas.

2. Materials and methods

2.1. Study area

This study area is Wuhan city, the capital of Hubei province in China. It is located at 113°41'~115°05'E, 29°58'~31°22’N. With a total area of 8,467 km² and population of more than 8 million, Wuhan has been one of the most populous cities in China. It is situated in the north-subtropical climatic zone with well-defined seasons. The mean annual rainfall is 1269mm, mainly occurring during June to August. The annual temperature ranges from 15.8℃~17.5℃ with the extreme temperature peaks at 42.0℃ and bottoms at -18.1℃. Together with Nanjing and Chongqing, Wuhan is well known as one of the Three Furnaces of China due to the especially and oppressively hot, humid and uncomfortable summer.

2.2. Geometric and atmospheric correction

Wuhan has been suffering persistent heat pollution in summer in recent years due to rapid urbanization. In this study, two Landsat Thematic Mapper (TM) images acquired on September 26, 1987 (Landsat 5) and September 17, 2013 (Landsat 8) were selected. They were geometrically rectified to a common Universal Transverse Mercator (UTM-WGS84) coordinate system based on the rectified high resolution IKONOS image and a 1:100000 scale road map of 2013. When deriving quantitative NDVI and LST values from satellite images, it requires the radiometric and atmospheric correction to eliminate atmospheric effect. The original digital number (DN) was converted into spectral radiance by using gain and offset values obtained from the header file of the images [10]. The radiance value was then converted to top of the atmosphere (TOA) reflectance [10, 11].

2.3. LST derivation

LST is useful to predict the energy and water exchanges between land surface and atmosphere, which plays an important role in human–environment interactions [12]. The derivation of LST from TM images requires several processes: sensor radiometric calibrations, brightness temperature calculation, atmospheric and surface emissivity corrections, characterization of spatial variability in land cover, etc. In this study, Single-Channel Algorithm [13, 14] and Split-Window Algorithm [15, 16] were conducted to derive LST data from Landsat-5 Thematic Mapper (TM) image acquired on September 26, 1987 and Landsat-8 image acquired on September 17, 2013, respectively.

2.4. Land cover classification

Land cover properties (such as albedo, soil water content, thermal capacity, and heat conductivity) can significantly impact the heat, water and energy flux in a given area. They are important in expressing the conditions and functions of urban ecosystem [17]. In this study, a hybrid classification procedure was performed in Erdas Imagine 9.2 for the two imagines. Initially, unsupervised classification was conducted based on an overall spectral separability. Then, the combined method of maximum likelihood classification and decision tree algorithms was undertaken [12]. The overall accuracies of classification and kappa coefficients were 87.54% and 0.83 for 1987, 83.25% and 0.81 for 2013. All of the pixels were grouped into five classes: built-up area, farmland, grassland, forest and water.
2.5. Statistical analysis
To better investigate the quantitative correlation of vegetation and LST, a zonal analysis was carried out in ArcGis 9.2 to account for the mean LST at each 0.01 increment of NDVI from 0 to 1. To emphasize the impact of vegetation on LST, it is necessary to exclude water bodies from the images before applying the procedure [18, 19]. Because water accounts for a large percentage in the study area, which can significantly influence the relationship between NDVI and LST. The modified normalized difference water index (MNDWI) was used to extract the water bodies [19, 20]. Then the quantitative output from ArcGis 9.2 was plotted in SPSS 17.0 to illustrate the correlation of the mean LST and mean NDVI.

3. Results and discussion

3.1. LST variation over land covers
Figure 1 shows the LST distribution maps in different land covers, with water cover unaccounted. They shared similar spatial patterns in 1987 and 2013, though the extent significantly differed from each other. The highest surface temperatures occurred in built-up area for both 1987 and 2013, as shown in Figure 1(a) and (e). The built-up area covered the central business district (CBD), high dense residential area, industrial area and main urban roads and highways. It exhibited relatively higher surface temperatures and was identified as the main heat islands. As shown in figure 1(b) and (f), farmland captured most of the observed area, indicating medium or medium high surface temperatures. As expected, the green spaces concentrated in the north and northeast of the study area, expressing relatively lower surface temperatures (shown in figure 1(c), (d), (g) and (h)). When masking the LST maps of certain land covers in 1987 over the corresponding ones in 2013, a noticeable result was found. From 1987 to 2013, built-up extent had dramatically expanded with rapid urbanization. As a result, more and more urban areas were identified as heat islands. During this period, many farmers flooded into city for urban jobs, leaving most farmlands uncultivated. Fast-growing tree species such as Populus Deltoides then were planted in these fallow fields, which could partly explain the forest area increase. Correspondingly, land surface temperatures in suburban district were decreased. Thus, the widening temperature gap aggravated urban heat island effect.

Figure 1. LST distribution maps in different contexts in September 26, 1987 and September 17, 2013.
To better understand the thermal response of individual land covers, the mean LST of each type was counted in ArcGis 9.2 (Table 1). The highest mean surface temperature was observed in the built-up area (47.9℃), followed by grassland (44.2℃), forest (40.4℃) and farmland (40.0℃) in 1987. While in 2013, the thermal gradient of land covers decreased from built-up area (33.4℃) to grassland (31.2℃) to farmland (31.0℃) then to forest (29.7℃). Generally, the built-up area exhibited much higher surface temperatures than the vegetated areas in both observed years (as confirmed in Figure 1). This is because urban areas usually have higher solar radiation absorption and a greater thermal capacity and conductivity due to the impervious surfaces such as asphalt and concrete. They are fully exposed to solar radiation without canopy shading and evaporative cooling effect provided by vegetation.

### Table 1. Mean LST values in different contexts in September 26, 1987 and September 17, 2013.

| types         | built-up area | farmland | grassland | forest         |
|---------------|---------------|----------|-----------|----------------|
|               | Mean          | SD       | Mean      | SD             | Mean            | SD             | Mean      | SD             |
| 1987          | 47.9          | 4.3      | 40.0      | 4.1            | 44.2            | 4.6            | 40.4      | 5.0            |
| 2013          | 33.4          | 2.9      | 31.0      | 2.6            | 31.2            | 2.6            | 29.7      | 2.7            |

#### 3.2. NDVI variation over land covers

NDVI value was usually identified to express the vegetation amount and fractional vegetation cover in urban climate study. Higher NDVI value typically indicates a larger vegetation amount and greater forest coverage. Figure 2 shows the spatial distribution maps of NDVI for the two observed dates. NDVI values ranged from -0.44 to 0.78 (mean value of 0.18 and standard deviation of 0.27) September 26, 1987 (Figure 2a) and from -0.64 to 0.71 (mean value of 0.14 and standard deviation of 0.24) for September 17, 2013 (Figure 2b). As shown in Figure 2, the dark blue areas with negative NDVI values were mainly restricted to water bodies. A large light blue area with medium NDVI values was found to correspond to the urban built-up area, rural developed area and exposed farmland. Green areas with high NDVI values were observed in the surrounding areas, where forest was dominant. The detailed information on NDVI values of different land covers (with water excluded) were summarized in Table 2. The highest mean NDVI value was found in forest (0.56 in 1987 and 0.57 in 2013) and the lowest one in built-up area (0.30 in 1987 and 0.27 in 2013) for both studied dates, as expected. Farmland expressed nearly equal mean NDVI values to grassland in 1987 and to forest in 2013.

#### Table 2. Mean NDVI values in different contexts in 1987 and 2013.

| types         | built-up area | farmland | grassland | forest         |
|---------------|---------------|----------|-----------|----------------|
|               | Mean          | SD       | Mean      | SD             | Mean            | SD             | Mean      | SD             | Mean          | SD             |
| 1987          | 0.30          | 0.11     | 0.53      | 0.14          | 0.50            | 0.12           | 0.56      | 0.10           |               |                |
| 2013          | 0.27          | 0.08     | 0.54      | 0.09          | 0.47            | 0.06           | 0.57      | 0.08           |               |                |
3.3. Relationship between mean NDVI and mean LST

Figure 3 shows the linear regression models of mean NDVI and LST for the whole study area of the two dates. Strong negative correlations between the two indexes were observed with the coefficient of 0.954 for September 26, 1987 and 0.962 for September 17, 2013. The high coefficient values meant that mean LST variation can be well explained by mean NDVI in both 1987 and 2013. LST values tend to negatively correlate with the mean NDVI. In other words, LST values increased when the mean NDVI decreased. Surface temperature can be decreased by nearly 1.7°C for September 26, 1987 and about 1.8°C for September 17, 2013 with mean NDVI increasing at each 0.1.

![Figure 3](image_url)

**Figure 3.** Relationship between the mean NDVI and LST for 1987 (a) and 2013 (b).

Figure 4 displays the correlations of mean NDVI and LST in different contexts. Regression coefficient between surface temperatures and mean LST was highest over built-up area (0.925), followed by farmland (0.870), forest (0.834) and grassland (0.655) for September 26, 1987 and highest over farmland (0.983), followed by forest (0.968), built-up area (0.963) and grassland (0.829) for September 17, 2013. Generally, there existed strong linear relationship between LST and mean NDVI, suggesting that the LST variation could be accounted for very well by mean NDVI in different contexts. Negative correlations between mean NDVI and LST were detected in all observed land covers. This implied that vegetation was efficient in decreasing surface temperatures and in mitigating UHI effect. As mean NDVI increased at each 0.1, the decreased LST values varied from 1.1 to 1.9°C for September 26, 1987 and from 1.3 to 1.8°C for September 17, 2013 with different contexts. The decreased LST values of forest were 1.9°C in 1987 and 1.8°C in 2013, much more efficient than that of the other three land covers. It meant that in hot summer, forest provides dense canopy and large amount of green biomass, which cool the surrounding environment and enhance the cooling effect of vegetation.

4. Conclusions

In this study, emphasis was placed on the analysis of quantitative relationship between mean NDVI and LST. To give prominence to the cooling effect of vegetation on environment in different contexts, water was extracted. Results revealed that strong negative correlation existed between mean NDVI and LST in all land covers, especially in relatively more Homogeneous contexts such as built-up and forest areas. While grassland had the weakest correlation partly due to the largest internal heterogeneity. This finding helps understand the important role of urban plant in lowering surface temperatures and mitigating UHI effect and encourages urban planners and greening designers to devote more efforts in protecting urban forests. The specific cooling effect of vegetation varied with land covers. The most efficient cooling effect was detected to occur in forest and inefficient one in grassland in both 1987 and 2013. Noticeably, though forest, farmland and grassland were all covered by natural materials, they significantly differed from each other in cooling effect. Therefore, further examination should be performed in detecting how and why these differences exist.
Figure 4. Relationship between the mean NDVI and LST in different contexts for 1987 and 2013.

Acknowledgments
This research was sponsored by the National Natural Science Foundation of China (Grant No. 41401186), the Natural Science Foundation of Hubei Province of China (2014CFB346) and the opening fund of Key Laboratory of Regional Development and Environmental Response (Hubei Province) [2015 (C) 003]. The authors would like to thank Elizabeth Lord from the University of Toronto, Canada for reviewing and correcting the paper.
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