Impact of Land Use Change and Urbanization on Urban Heat Island of Fuzhou City

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Abstract:

In the past decades, the economy and modern industry of Fuzhou area have made great progress. However, the serious environmental problems can be seen behind the growing economic and industrial growths. The purpose of this research is that the land surface temperature (LST) change in Fuzhou area during the period from 1999 to 2019 was studied and the impact of land use and land cover (LULC) and vegetation cover were analyzed. Moreover, the spatial distribution of the LULC and its effects on thermal environment of Fuzhou city have been studied by land surface temperature information processed from Landsat TM, ETM+ and 8 satellite data. The result is that the land use change resulted from urbanization is the main cause affecting spatial distribution of LST and the temperature in the central portion of Fuzhou city kept an increased trend from 1999 to 2019.

Keyword: land use and land cover; land surface temperature; thermal environment;

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) predicted that the average global surface temperature may rise about 1.4-5.8\textdegree C and the concentration of carbon dioxide in the atmosphere will be much higher than in the pre-industrial period by 2100\textsuperscript{[1]}. With the rapid development of urbanization since the twentieth century, anthropogenic activities have largely changed the land use and land cover (LULC) in order to adapt the rapidly growing population and promote economic development\textsuperscript{[2]}. The changes in land...
use and land cover play an essential role in the city heat island, ecosystem imbalance and
global warming [3]. However, a series of environmental problems caused by land-use
change have different degrees of severity between regions with different speeds of
urbanization [4].

Among all these environmental problems, the rise of land surface temperature (LST)
has become the most serious issue in urban areas, especially caused by ‘man-made’
interventions and modifications to the land patterns [3]. Moreover, the urban heat island
(UHI) phenomenon is one of the representative negative outcomes produced by the
increase in LST [5]. According to [6], UHI can be defined as some of urban areas which
have higher air and land temperatures compared with their rural surrounding areas due to
the changes of heat storage of the land surface and buildings. The reason for this
phenomenon is that the dramatic urbanization has changed natural environment into
densely populated urban areas with less vegetation cover rage, more modern building
structures and more impervious surfaces. Another definition of UHI is warmer surface
caused by anthropogenic activities leads to rising temperature of urban areas [7].

Recently, a number of researches have been produced from China cities on impact of
changes of LULC and urbanization through remote sensing, which have been as a bases
of further studies on the Urban Heat Island and its potential effect [8-11]. According to
Yang’s study (2010) on the assessment of urban heat island intensity for Shanghai city,
the result is that the urbanization and the reduction of natural vegetation are main causes
leading to rising land surface temperature in urban areas.

In the past decades, the economy and modern industry of Fuzhou area have made great
progress. However, the serious environmental problems can be seen behind the growing
economic and industrial growths [12]. The purpose of this research is that the land surface
temperature (LST) change in Fuzhou area during the period from 1999 to 2019 was
studied and the impact of land use and land cover (LULC) and vegetation cover were
analyzed.

2. Geographic information and data

The natural wetlands distribution area (NWDA) of Fuzhou city is studied in this
research. It is located between latitudes 25°55’N and 26°10’N and longitudes 119°10’E
and 119°35’E and it covers an area of around 1491 square kilometers with a population
of around 2.71 million [13].
In addition, the details of remote sensing data used in this paper are given in Table 1 and the processed remote sensing product such as Google-Earth images are also used for accuracy assessment.

<table>
<thead>
<tr>
<th>Satellite Sensor</th>
<th>Data collection date</th>
<th>source</th>
</tr>
</thead>
<tbody>
<tr>
<td>LANDSAT7 ETM+</td>
<td>23rd September 1999</td>
<td></td>
</tr>
<tr>
<td>LANDSAT 8 oli</td>
<td>22nd September 2019</td>
<td></td>
</tr>
</tbody>
</table>

3. Methodology

In this paper, ENVI Classic has been used for data-processing. Generally, the satellite Landsat dataset downloaded from USGS comprises of various band images and then these single band images were able to combined to form a multi-band image through ENVI software. After the initial data-processing and calibrations, this satellite images ware then used for direct study on LST, LULC and UHI through some of algorithm in ENVI Classic and Arc GIS 10.4 software.

3.1 Mono-window algorithm for the land surface temperature (LST)

In this paper, the Mono-window algorithm produced by Liu and Weng \[21\] have been used for driving maps of Land surface temperature of Fuzhou city from the single thermal infrared bands of Landsat satellite data during the period from 1999 to 2019. There are three main parameters in this algorithm (emissivity, transmittance and atmospheric temperature respectively) and the radiation spectral range from 10.40 to 12.50 for Landsat TM, and from 10.60 to 11.19 for Landsat 8 have been recorded in these TIR bands. Therefore, the data from TIR wavelengths (Landsat ETM band 6, Landsat TM band 6 and Landsat 8 band 10 respectively) were processed by Eqn. (1) to retrieval LST:

\[
Tc = \langle a(1 - C - D) + [b(1 - C - D) + C + D]Ti - D \ast Ta \rangle / C \quad (1)
\]

Where:

\[
a = -67.355351
\]

\[
b = 0.4558606
\]

\[
C = \varepsilon_i \ast \tau_i,
\]

\[
D = (1 - \tau_i) \langle I + (I - \varepsilon_i) \ast \tau_i \rangle
\]

\[
\varepsilon_i = \text{emissivity}
\]

\[
\tau_i = \text{transmissivity}.
\]
3.2 Transformation of digital number to radiance value

The Eqn. (2) and (3) have been used in band math of ENVI classic due to transforming the digital number of TIR band 6 of Landsat TM/ETM and TIR band 10 of Landsat 8 into spectral radiance values.

3.2.1 As for Landsat TM and ETM sensor

\[ L_\lambda = \frac{(L_{MAX\lambda} - L_{MIN\lambda})}{[(Q_{CALMAX} - Q_{CALMIN})+(Q_{CAL} - Q_{CALMIN})+L_{MIN\lambda}]}} \]

(2)

Where:

- \( L_\lambda \) is the cell value as radiance
- \( Q_{CAL} \) = digital number
- \( L_{MIN\lambda} \) = spectral radiance scales to \( Q_{CALMIN} \)
- \( L_{MAX\lambda} \) = spectral radiance scales to \( Q_{CALMAX} \)
- \( Q_{CALMIN} \) = the minimum quantized calibrated pixel value (typically = 1)
- \( Q_{CALMAX} \) = the maximum quantized calibrated pixel value (typically = 255)

3.2.2 As for Landsat 8 sensor

\[ L_\lambda = M_L Q_{Cal} + A_L \]

(3)

Where:

- \( L_\lambda \) = TOA spectral radiance (Watts/(m\(^2\) * srad * µm))
- \( M_L \) = Band-specific multiplicative rescaling factor from the metadata (RADIANCE_MULT_BAND_x, where x is the band number)
- \( A_L \) = Band-specific additive rescaling factor from the metadata (RADIANCE_ADD_BAND_x, where x is the band number)
- \( Q_{cal} \) = Quantized and calibrated standard product pixel values (DN)

3.3 Brightness temperature

In the paper, brightness temperature has been calculation by the inverse of Plank function which uses radiance values from digital number of the TIR wavelengths.

\[ T = \frac{K^2}{ln(K/L_\lambda)+1} \]

(4)

Where:
\[ T = \text{Top of atmosphere brightness temperature (K)} \]

\[ L_\lambda = \text{TOA spectral radiance (Watts/(m}^2\times \text{srad} \times \mu\text{m}) produced by Eqn. (3)} \]

\[ K_1 = \text{Band-specific thermal conversion constant from the metadata} \]

(K1_CONSTANT_BAND_x, where x is the thermal band number)

\[ K_2 = \text{Band-specific thermal conversion constant from the metadata} \]

(K2_CONSTANT_BAND_x, where x is the thermal band number)

3.3.1 Atmospheric transmittance

In this paper, the atmospheric transmittance index from Landsat TM/ETM and Landsat 8 data have been inquired through: http://atmcorr.gsfc.nasa.gov/.

3.3.2 Land surface emissivity

Land surface emissivity has been calculated by the Eqn. (5) which is related to the values of Normalized Difference Vegetation Index (NDVI) and the details of this method are given in Table 2.

<table>
<thead>
<tr>
<th>value of NDVI</th>
<th>value of Land surface emissivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>( NDVI &lt; -0.185 )</td>
<td>0.995</td>
</tr>
<tr>
<td>(-0.185 \leq NDVI &lt; 0.157 )</td>
<td>0.970</td>
</tr>
<tr>
<td>( 0.157 \leq NDVI \leq 0.727 )</td>
<td>( 1.0094 + 0.0047 \ln(NDVI) )</td>
</tr>
<tr>
<td>( NDVI &gt; 0.727 )</td>
<td>0.990</td>
</tr>
</tbody>
</table>

3.4 Normalized difference vegetation index (NDVI)

The density of vegetation of Fuzhou city from 1999 to 2019 in this research has been calculated by NDVI. The rationale of Eqn. (6) is by measuring reflectance from the data of the red and near infrared (NIR) wavelengths, which classified the brightness temperature of each pixel. The images processed by Eqn. (6) then were divided into five classes that based on the intensity of vegetation in order to more quantitative analysis.

\[ NDVI = \frac{(p_{NIR} - p_{RED})}{(p_{NIR} + p_{RED})} \]  (6)

Where:

\( NDVI = \) Normalized difference vegetation index (ranged from 0 to 1 and representing the fraction of incoming radiation reflected by the surface, uncorrected for atmospheric effects)
\[ \rho_{NIR} = \text{the value of reflectance in band 4 of Landsat TM/ETM and band 5 of Landsat 8} \]

\[ \rho_{RED} = \text{the value of reflectance in band 3 of Landsat TM/ETM and band 4 of Landsat 8} \]

### 3.5 Urban thermal field variance index (UTFVI)

The ecological changes of Fuzhou city during the period between 1999 and 2019 have been studies in order to more accurate analysis of impact of urban heat island and the urban thermal field variance index which is divided into six level \[^{[15]}\] with Table. 3 is powerful method to quantitatively describe it.

**Table.3.** the relationship between intensity of UTFVI and intensity of UHI

<table>
<thead>
<tr>
<th>Intensity of urban heat island</th>
<th>The condition of ecological system</th>
<th>UTFVI</th>
</tr>
</thead>
<tbody>
<tr>
<td>none</td>
<td>excellent</td>
<td>&lt; 0</td>
</tr>
<tr>
<td>weak</td>
<td>good</td>
<td>0.000 – 0.005</td>
</tr>
<tr>
<td>middle</td>
<td>normal</td>
<td>0.005 – 0.010</td>
</tr>
<tr>
<td>strong</td>
<td>bad</td>
<td>0.015 – 0.015</td>
</tr>
<tr>
<td>stronger</td>
<td>worse</td>
<td>0.015 – 0.020</td>
</tr>
<tr>
<td>strongest</td>
<td>worst</td>
<td>&gt; 0.020</td>
</tr>
</tbody>
</table>

And the Eqn. (7) is:

\[ UTFVI = \frac{(T_s - T_{mean})}{T_{mean}} \] (7)

Where:

\( T_s = \text{land surface temperature (a specific point)} \)

\( T_{mean} = \text{the mean of the land surface temperature (study area / Fuzhou)} \)

### 3.6 Land use and land cover (LULC)

The method of supervised classification has been used in the paper in order to effectively study changes in LULC of Fuzhou city from 1999 to 2019. The purpose of image classification is that spectral classes in the data can be matched to the certain information classes and multispectral image can be converted into thematic map. In the process of supervised classification, Maximum Likelihood classifier (MLC) has been used for spectral pixels to assigned to the class of maximum probability. Therefore, LULC of images processed by the method image classification has been
divided into six categories, namely, Bare land, Built-up land, Water, Grassland, Forest
land and Crop land in this paper.

4. Results

4.1 Relationship between LULC changes and LST

As can be seen from the Fig. 1, there are notable changes in LULC classes of Fuzhou
city during the period from 1999 to 2019. Among these changes, the change in Built-up
area (Urban and semi-urban) is the most obvious, increased from 176.02 km$^2$ of 1999 to
313.67 km$^2$ of 2009 to 532.23 km$^2$ of 2019 (Table 4). This is the major factor leading to
the rising of temperature in the city.

Figure 1 LULC maps of Fuzhou city for 23 September 1999 (a), 06 June 2009 (b) and 22 September 2019
(c). These maps are derived from 30m spatial resolution Landsat 7 ETM+, Landsat 5 TM and Landsat 8
oli data respectively (path = 119, row = 042), processed using Maximum Likelihood classifier (MLC) of
supervised classification. There is no cloud impact of three images in study area. The image spatial extent
of Landsat 8 is 185 km*185km and of Landsat TM/ETM+ is 170km*183km.

Table 4. the changes in LULC of Fuzhou city from 1999 to 2019 (in sq.kms)
<table>
<thead>
<tr>
<th>LULC</th>
<th>23rd Sep 1999</th>
<th>06th Jun 2009</th>
<th>22nd Sep 2019</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cropland</td>
<td>669.85</td>
<td>442.15</td>
<td>438.33</td>
</tr>
<tr>
<td>Forest land</td>
<td>956.89</td>
<td>1150.84</td>
<td>948.98</td>
</tr>
<tr>
<td>Grassland</td>
<td>135.61</td>
<td>10.76</td>
<td>11.33</td>
</tr>
<tr>
<td>Water</td>
<td>414.15</td>
<td>400.61</td>
<td>358.64</td>
</tr>
<tr>
<td>Built-up land</td>
<td>176.02</td>
<td>313.67</td>
<td>532.23</td>
</tr>
<tr>
<td>Bare land</td>
<td>29.03</td>
<td>63.05</td>
<td>92.05</td>
</tr>
</tbody>
</table>

Moreover, the result from Fig. 1 and Table. 4 shown that many natural areas such as Cropland and Grassland were replaced by majority of urban area for the growth of urbanization. The cropland decreased from 669.85 km$^2$ to 438.33 km$^2$ in the past two decades and the grassland also decreased from 135.61 km$^2$ to 11.33 km$^2$. In comparison with Fig. 2, it revealed that most area of built-up lands and the area of high LST value mainly occurred in the central part of Fuzhou city.

Therefore, urbanization and increased LST are closely related to more urban built-up, less cropland and less vegetation cover through further comparative analysis of changes in LULC, NDVI and LST. In addition, class confusion matrix has been produced by classified image and file in order to accuracy assessment, which result overall accuracy and Kappa coefficient of LULC was 98.88% and 0.9835 for 1999, 97.29% and 0.9614 for 2009 as well as 96.61% and 0.9453 for 2019.\[16\].
Figure 2 LST maps of Fuzhou city for 23 September 1999 (a), 06 June 2009 (b) and 22 September 2019 (c). These maps are derived from 30m spatial resolution Landsat 7 ETM+, Landsat 5 TM and Landsat 8 OLI data respectively (path = 119, row = 042), processed using Eqn. (1). There is no cloud impact of three images in study area. The image spatial extent of Landsat 8 is 185 km*185km and of Landsat TM/ETM+ is 170km*183km.

4.2 Relationship between LST and NDVI
The change in NDVI value of Fuzhou city from 1999 to 2019 are given in Fig. 3 and further detailed data of NDVI change are given in Table 5. It shows that overall NDVI values kept increased trend apart from the Low value class during this period and the change of the higher NDVI value class was most obvious. It increased from 8.89% to 21.24% by 2019. However, the low NDVI value was reduced from 28.51% to 24.76% for two decades. This result also revealed that while the vegetation coverage is decreasing,
the area of built-up land is increasing rapidly through comparative assessment of Fig.3 and Fig1.

In addition to this, there are certain relationship between rising temperature and decreasing vegetation through comparing the overlapping regions of Fig.3 and Fig.2.

4.3 Urban heat island

As can be seen from Fig.4, there was a noticeable increase in the heat island phenomena during the 1999 to 2019. During 1999, only a part of Fuzhou city showed UHI phenomena and had normal ecological evaluation index but with time the heat island phenomenon increased dramatically and covered almost the whole study area because of rapid change of LULC. According to Table 3, it can be seen that ecological evaluation index decreased to the worst level by 2019 because the UTFVI value of most Fuzhou areas more than 0.020 and this result also can be related to Fig.3. Therefore, there is a positive relationship between the intensity of heat island phenomena and the decreasing trend of vegetation.

Figure 4 UTFVI maps of Fuzhou city for 23 September 1999 (a), 06 June 2009 (b) and 22 September 2019 (c). These maps are derived from 30m spatial resolution Landsat 7 ETM+, Landsat 5 TM and
Landsat 8 oli data respectively (path = 119, row = 042), processed using Eqn. (7). There is no cloud impact of three images in study area. The image spatial extent of Landsat 8 is 185 km*185km and of Landsat TM/ETM+ is 170km*183km.

5. Discussion

With the rapid development of social economy urbanization, the environmental problems resulted from heat-island phenomena have attracted more and more attention around the world. Therefore, this article also has carried out research on this issue in China cities. In comparison with past researches of the urban heat island phenomena of China cities, the similar conclusion was that the change of land use and land cover and urbanization are main causes causing the increase in land surface temperature, which further leads to heat island phenomena [17-20].

However, there are also some differences that might be considered as weaknesses for this paper compared with these researches. To some extent, these satellite data that processed and analyzed in this article are not a continuous and completely correct set of monitoring data, because of the nature of the temporal and spatial discontinuities of the satellite sensors and the availability of contemporaneous LST and air temperature data. Therefore, it might cause analysis error and incorrect prediction from a strictly scientific standpoint because the monitoring data is not continuous and accuracy [22]. In further study, it might be useful and power way to combine the site data from Network of weather stations and satellite thermal data from the short interval HJ-1 and MODIS satellite datasets.

In addition to this, the obvious weakness in this paper that might be further improved in the future is that the specific impact degree from one factor should be detailly studied for a specific region. The reason is that although the main reasons leading to city heat island phenomena have been detected from this research, this is not enough to give the policymakers of the Fuzhou city clear and enough direction controlling the problem of urban heat island. Therefore, the study might need to focus on more specific information about which factor is dominant to mitigate the effects of Fuzhou heat island and which one is unimportant relatively because of the uniqueness of the region, the certain urbanization processes and the different degree of city heat island [18]. This improvement might be important for government to predict and protect the eco-environment of the Fuzhou city.

6. Conclusion
In this paper, the phenomena of urban heat island and changes of the land-use pattern of Fuzhou city during the period from 1999 to 2019 have been analyzed using thermal remote sensing data. Moreover, the spatial distribution of the LULC and its effects on thermal environment of Fuzhou city have been studied by land surface temperature information processed from Landsat TM, ETM+ and 8 satellite data. The result is that the land use change resulted from urbanization is the main cause affecting spatial distribution of LST and the temperature in the central portion of Fuzhou city kept an increased trend from 1999 to 2019.

In addition, the NDVI change and its relationship with LST also have been studied. The result reveals that the falling trend in the natural vegetation have been observed from 1999 to 2019 and there is positive relationship between increased urban heat island and worst eco-environment. The similar result also was confirmed by the analysis of Urban Thermal Field Variance Index.

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Reference


