Mapping land use land cover (LUCL) and its influence on land surface temperature (LST): A case study in Dau Tieng district at Binh Duong province

Ha Phuong Tran 1*, Tuan Cuong Ha 2,6*, Thi Thuy Huong Nguyen3, Ngoc Thy Nguyen4, Ba Man Duong5, Mon Danh5, Tuan Nhi Pham2

1Institute of Applied Mechanics and Informatics, Vietnam Academy of Science and Technology
2Southern Sub-Institute of Forest Inventory and Planning
3Institute of Biotechnology, Vietnam Academy Science & Technology
4Nong Lam University
5Ho Chi Minh City Institute of Resources Geography
6Postgraduate of Resource and environmental management major, Faculty of Geography, University of Social Sciences and Humanities (HCMUSSH) - HCMC National University
*Email: phuonghatran76@yahoo.com; tuancuongdialyk38@gmail.com

Abstract. At present, land surface temperature (LST) is an important index in monitoring the urban heat is-land phenomenon and changes in local climate, as well as global climate. By analyzing the variation in land use land cover (LUCL), we can see how changes in LUCL will lead to changes in LST and understand the expansion of urbanization related to LST. This study used Landsat 8's thermal infrared band to extract and calculate LST values in Dau Tieng district in the period 2015-2022. In addition, this study also classified LUCL by using the Support Vector Machine algorithm, then evaluated changes in LST on cropland, forest, water surface, and impervious surface areas. The results showed that in places with dense vegetation cover, LST value was low, whereas when moving to areas with low density of vegetation and residential areas, industrial parks,... LST value gradually increased. In general, changes in LUCL are important factors that cause LST to increase or decrease, thereby suggesting solutions to minimize high-temperature areas.

Keywords: Land surface temperature, land use land cover, Landsat 8, support vector machine

1 Introduction

The urbanization process is a driving force for socio-economic development, population growth and environmental change. Urbanization changes agricultural land, vegetation, and water surface to built-up land. Establishing land use land cover (LUCL) maps is a necessity in monitoring changes in land use cover and the impact of this change on the environment, especially land surface temperature (LST) monitoring [1, 2]. The temperature difference between urban and rural areas could fluctuate from 3-6 oC, sometimes up to 11-12 oC [3]. The appearance of erratic high-temperature values compared to the surrounding temperature, forms the urban heat island (UHI) effect, due to impervious surfaces. LST can be estimated from radiance measurements by meteorological stations. However, this method does not generally allow large-scale monitoring since it is a point-based measurement and it costs a lot [4]. With the advent of satellites and air-craft, thermal infrared remote sensing has provided new developments for LST as well as UHI research. Thermal remote sensing from satellites to determine LST has a long history that can be traced back to the TIROS-II satellite, which was launched in the early 1960s [5]. Nowadays, there are many image datasets used to calculate LST, for example, the medium spatial resolution data from Landsat or MODIS images. In particular, the Landsat 8 image has a TIRS sensor with the thermal infrared band used to calculate LST. In particular, the Landsat 8 image has a TIRS sensor with the thermal infrared band used to calculate LST. The current studies focus on analyzing and evaluating the relationship between LUCL and LST, such as: From the vegetation index images we could assess the relationship between LST and the density of vegetation [6]; LUCL from one type to another, especially from agricultural land to urban land/built-up area, affects the energy exchange between the earth's surface and atmosphere, causing LST to vary from the city centre to the peri-urban area [7, 8];

In this study, we chose Dau Tieng district of Binh Duong province, which is considered the green lung of this province. The main objectives of this study include: (1) Assess LST changes in the period 2015-2022; (2) Extract LST values from Landsat from LUCL, then evaluating the spatial trend of LST fluctuations over the past 7 years; (3) Investigate the correlation between LST and LUCL indices.
2 Study area

Dau Tieng is a northern district of Binh Duong province, about 50 km from the administrative centre of Binh Duong province. The North borders Binh Long district (Binh Phuoc province), the East and Southeast borders Ben Cat town (Binh Duong province), the Northwest and Southwest border Duong Minh Chau district (Tay Ninh province), the South borders Cu Chi district (Ho Chi Minh City). Natural area is about 720 km², of which people living in urban areas account for 20.6 % and people living in rural areas account for 79.4 %. The economic strength of Dau Tieng district is agriculture.

After being recognized as a new rural district, Dau Tieng district, Binh Duong province continues to make efforts to plan, build and develop a number of localities with rapid and strong growth to become urban areas. That is one of the stepping stones to gradually realize this locality's determination to become a green urban area. The economic strength of Dau Tieng district is agriculture. Therefore, Dau Tieng also determined a plan to develop a high-tech agricultural economy associated with eco-tourism.

3 Materials and Methods

3.1 Data base

This article used Landsat 8 OLI/TIRS and Landsat 9 for calculating LST, with a focus on cloud cover less 10 %, and images data acquired in dry season for 2015, 2018 and 2022, and downloaded from https://earthexplorer.usgs.gov/.

<table>
<thead>
<tr>
<th>Scene ID</th>
<th>Acquisition time</th>
<th>Cloud cover (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LC08_L1TP_125052_20150209_20200909_02_T1</td>
<td>09/02/2015</td>
<td>0.09</td>
</tr>
<tr>
<td>LC08_L1TP_125052_20200207_20200823_02_T1</td>
<td>07/02/2020</td>
<td>2.03</td>
</tr>
<tr>
<td>LC09_L1TP_125052_20220204_20230429_02_T1</td>
<td>04/02/2022</td>
<td>1.3</td>
</tr>
</tbody>
</table>

3.2 Retrieval of land surface temperature (LST) from thermal band

3.2.1 Convert Digital number into top of atmosphere spectral

The first method is to convert the DNs to spectral radiance using bias and gain values. The other longer method uses $L_{\text{Min}}, L_{\text{Max}}$ spectral radiance scaling factors [9]. This step was performed by the following formula [10]:

$$ L_\lambda = M_\lambda Q_{\text{cal}} + A_\lambda $$

where: $L_\lambda$ is the spectral radiance expressed in W/(m².sr.μm);
$M_\lambda$ is $3.342 \times 10^{-4}$ W/(m².sr.μm) – band specific multiplicative rescaling factor;
$Q_{\text{cal}}$ is the digital value of the bands that varies in a range from 0 to 255 and;
$A_\lambda$ is band-specific additive rescaling factor.
3.2.2 Brightness temperature (B_T)  
The equation for calculating the brightness temperature for Landsat OLI/TIRS [11]:  
\[ T = \frac{K}{\log\left(\frac{T}{T_0} + 1\right)} - 273.15 \]  
where:  
- B_T - brightness temperature (oK);  
- K - thermal constants (W/(m².sr.μm)) and K is found in metadata file.

3.2.3 Normalized difference vegetation index (NDVI)  
NDVI is an index that describes the vegetation proportion by measuring the difference in the near-infrared portion of electromagnetic spectrum which is strongly reflected by green vegetation and red portion of the spectrum which is absorbed by vegetation [12].  
\[ \text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} \]  

3.2.4 Proportion of vegetation (PV)  
PV is defined as the percentage of vegetation occupying the ground area in vertical projection [13]. Changes in vegetation cover directly impact surface water and energy budgets through plant transpiration, surface albedo, emissivity, and roughness [12].  
\[ P_v = \left[ \frac{\text{NDVI} - \text{NDVI}_{\text{max}}}{\text{NDVI}_{\text{max}} - \text{NDVI}_{\text{min}}} \right]^2 \]

3.2.5 Land Surface Emissivity (LSE or ε)  
Valor and Caselles [12] proposed a theoretical model that relates the emissivity to the NDVI of a given surface by:  
\[ \varepsilon = \varepsilon_0 + (1 - \varepsilon_0)P_v + 4\beta_P(1 - P_v) \]  
As Valor and Caselles [12] suggested, ε0 and ε as 0.985 and 0.960, respectively, for unknown emissivity and vegetation structures. Besides, they calculated the mean value for ε0 term as 0.015. The final equation of the LSE model can be given by:  
\[ \text{LSE} = 0.985 \times P_v + 0.960 \times (1 - P_v) + 0.06 \times (1 - P_v) \]  

3.2.6 Calculating the land surface temperature (LST)  
Land surface temperature is the temperature at the interface of earth’s surface with its atmosphere. The last step of retrieving emissivity-corrected LST:  
\[ \text{LST} = \frac{B_T}{\varepsilon^4} - 273.1 \]  
where:  
- LST in Celsius (oC);  
- B_T is brightness temperature of the Landsat (oK);  
- ε is the land surface emissivity;  
- 273.1: Conversion value from oK to oCelsius

3.3 Calculating NDBI index  
Normalized Difference Built-Up Index is derived from the spectral reflectance values captured by the satellite sensors in the near-infrared and shortwave infrared [13]:  
\[ \text{NDBI} = \frac{\text{SWIR}_2 - \text{NIR}}{\text{SWIR}_2 + \text{NIR}} \]  

3.4 Classification of LULC Classes  
This study used the Support Vector Machine (SVM) method for overlay classification in ArcGIS Pro. SVM uses a binary classification algorithm to determine an optimal and most accurate boundary to divide data points into two different categories. This classification method is considered to have high accuracy in addition to commonly used classification methods [14]. In this study, we classified LULC into 6 main cover types: Natural forest, rubber tree, annual tree, built-up area, bare land with grass, and water bodies. After classifying images, we used the kappa index to evaluate accuracy. The kappa index result was relatively high, at 0.7 over the years.  

<table>
<thead>
<tr>
<th>LULC</th>
<th>General description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Natural forest</td>
<td>Rough structure, dark green color, relatively rugged compared to other plant objects.</td>
</tr>
<tr>
<td>Rubber tree</td>
<td>Dark green color, relatively smooth structure, contrast between surrounding objects, signs of row distribution of crops in the image.</td>
</tr>
<tr>
<td>Annual tree</td>
<td>Dark green to light green, fragmented structure</td>
</tr>
</tbody>
</table>
4 Results

4.1 States of LULC and LULC change detection

The results showed that the rubber tree and natural forest (mainly in the Dau Tieng lake area, partly in Long Tam and Minh Thanh communes) occupied the majority of Dau Tieng district. For the rubber tree area, depending on the time of collecting satellite images and the time of rubber tree exploitation, this cover can easily change to bare land with grass. But in general, the area of rubber trees accounts for most of the current LULC of Dau Tieng district, specifically 42,089.67 ha in 2015, 41,206.51 ha in 2020 and 44,263.92 ha in 2022. The natural forest area was maintained at > 70,000 ha, however this object is easily confused with mature rubber trees, causing in 2020, the natural forest area decreased by nearly 300 ha compared to the other two times. Bare land with grass, this is the type of land that appears after exploiting rubber trees. The impervious surface area only accounted for the third largest area compared to other types of LULC, but from 2015 to 2020, the impervious surface area increased from 7,285.73 hectares in 2015, increasing by more than 1,000 hectares in 2020 and by 2022, the area was the largest compared to other types of LULC (9,624.41 hectares). The water surface in Dau Tieng area mainly comes from Dau Tieng lake and Can Nom lake, and partly comes from Long Hoa dam. However, the area always fluctuates depending on the amount of rain in the month and the need for water supply for agricultural activities. The annual crop area in Dau Tieng district is mainly grapefruit, oranges, mangosteen and rice. Depending on the time of satellite image collection, the annual crop area always changes because it coincides with the time of harvest or the time when young trees have just been planted.

### Table 3. Area statistics of LULC in 2015, 2020, and 2022

<table>
<thead>
<tr>
<th>LULC class</th>
<th>2015 Area in hectares</th>
<th>2015 Area in %</th>
<th>2020 Area in hectares</th>
<th>2020 Area in %</th>
<th>2022 Area in hectares</th>
<th>2022 Area in %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annual tree</td>
<td>2,862.73</td>
<td>3.97</td>
<td>3,920.30</td>
<td>5.43</td>
<td>6,540.40</td>
<td>0.91</td>
</tr>
<tr>
<td>Bare land with grass</td>
<td>7,713.29</td>
<td>10.69</td>
<td>6,184.53</td>
<td>8.57</td>
<td>4,526.37</td>
<td>6.27</td>
</tr>
<tr>
<td>Impervious surface</td>
<td>7,285.74</td>
<td>10.10</td>
<td>8,730.19</td>
<td>12.10</td>
<td>9,624.41</td>
<td>13.34</td>
</tr>
<tr>
<td>Natural forest</td>
<td>7,757.12</td>
<td>10.75</td>
<td>7,478.19</td>
<td>10.36</td>
<td>7,736.10</td>
<td>10.72</td>
</tr>
<tr>
<td>Rubber tree</td>
<td>42,089.67</td>
<td>58.33</td>
<td>41,206.52</td>
<td>57.10</td>
<td>44,263.92</td>
<td>61.34</td>
</tr>
<tr>
<td>Water</td>
<td>4,453.86</td>
<td>6.17</td>
<td>4,641.78</td>
<td>6.43</td>
<td>5,356.71</td>
<td>7.42</td>
</tr>
<tr>
<td>Total</td>
<td>72,162</td>
<td>100</td>
<td>72,162</td>
<td>100</td>
<td>72,162</td>
<td>100</td>
</tr>
</tbody>
</table>

Fig. 2. LULC of Dau Tieng district for the years (a) 2015, (b) 2020, (c) 2022

4.2 LST change analysis and the impact of LULC change on LST

The temperature threshold below 24 oC and from 24-26 oC coincided with the distribution of water surface and rubber forests in the mature stage. In 2020, the temperature was below 24 oC mainly in lakes and a very small part in rubber forests, and in this time, the LST value tended to increase, when looking at figure 3, the entire Dau Tieng district mainly had a temperature range of 26-28 oC, due to the cover of rubber forests and bare land. For the threshold value of 28-30 oC, from 2015 to 2022, the area increased by nearly 1,000 ha, due to the urbanization.

### Table 4. The changes in LST area for Dau Tieng district in 2015, 2020 and 2022

<table>
<thead>
<tr>
<th>LST range</th>
<th>2015 Area (hectare)</th>
<th>2020 Area (hectare)</th>
<th>2022 Area (hectare)</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 24 oC</td>
<td>7500.15</td>
<td>0.09</td>
<td>4383.09</td>
</tr>
<tr>
<td>24-26 oC</td>
<td>16507.4</td>
<td>4811.13</td>
<td>12570.7</td>
</tr>
<tr>
<td>26-28 oC</td>
<td>33312.1</td>
<td>15941.4</td>
<td>42076.4</td>
</tr>
<tr>
<td>28-30 oC</td>
<td>8927.55</td>
<td>39601.2</td>
<td>9176.76</td>
</tr>
<tr>
<td>&gt; 30 oC</td>
<td>5921.73</td>
<td>11815.1</td>
<td>3962.07</td>
</tr>
</tbody>
</table>
Impervious surfaces and bare land had the highest LST values, ranging from 28-30 oC and > 30 oC, of which, in 2020, bare land with grass had the highest temperature value (31.6 oC). Natural forests, rubber tree (in mature stage) and annual crop lands had temperature values ranging from 27-28 oC. For rubber forests, the value was almost as high as built-up land because it was affected by bare land after rubber exploitation. The water surface had the lowest LST value.

![Fig. 3. The LST map in 2015 (a), 2020 (b) and 2022 (c).](image)

<table>
<thead>
<tr>
<th>Class</th>
<th>LST in 2015 (oC)</th>
<th>LST in 2020 (oC)</th>
<th>LST in 2022 (oC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annual tree</td>
<td>25.1</td>
<td>28.7</td>
<td>27.7</td>
</tr>
<tr>
<td>Bare land with grass</td>
<td>30.1</td>
<td>31.6</td>
<td>27.6</td>
</tr>
<tr>
<td>Impervious surface</td>
<td>28.2</td>
<td>29.41</td>
<td>27.4</td>
</tr>
<tr>
<td>Natural forest</td>
<td>25.98</td>
<td>27.7</td>
<td>26.5</td>
</tr>
<tr>
<td>Rubber tree</td>
<td>26.4</td>
<td>28.7</td>
<td>27.1</td>
</tr>
<tr>
<td>Water</td>
<td>23.1</td>
<td>25.6</td>
<td>24.4</td>
</tr>
</tbody>
</table>

### 4.3 The correlation LST with NDVI and NDBI index

The relationship between LST and NDVI was established from pixel value points extracted using random points. The result of correlation of coefficient of LST with NDVI showed a positive correlation of $R^2 = 0.01$ in 2015, $R^2 = 0.01$ in 2020 and $R^2 = 0.0024$ in 2022. According to the statistics, NDVI and LST were negatively correlated, was shown by the coefficient $r$ reaching a negative value: $r = -0.132$ in 2015, $r = -0.222$ in 2020 and $r = -0.049$ in 2022. Statistical analysis showed that LST and NDVI had an inverse relationship with each other. From there, it could be seen that as the impervious surface area increased, it would lead to an increase in LST and a decrease in vegetation cover area (shown through the NDVI index), which proved that the urbanization process has had an impact on the coating and directly affects LST.

![Fig. 4. Linear regression analysis between LST and NDVI.](image)

The NDBI indicates that the expansion of built-up areas was positively correlated with an elevation in LST values. The result of correlation of coefficient of LST with NDBI showed a positive correlation of $R^2 = 0.179$ in 2015, $R^2 = 0.19$ in 2020 and $R^2 = 0.039$ in 2022. According to the statistics, NDBI and LST were negatively correlated, were shown by the coefficient $r$ reaching a negative value: $r = 0.423$ in 2015, $r = 0.436$ in 2020 and $r = 0.199$ in 2022. That means that when the construction land area increased, it would change the LST value, causing the maximum LST value to increase and expand the spatial distribution.

![Fig. 5. Linear regression analysis between LST and NDBI.](image)
Acknowledgment

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5 Conclusion

From Landsat 8 image data, the study calculated land surface temperature (LST) in 2015, 2020, and 2022 in Dau Tieng district along with calculating NDVI and NDBI index. Based on the Landsat images of 1990, 2015, and 2020, LULC changes and its impact on LST was examined. The study area has been classified into six LULC types, for example natural forest, annual tree, rubber tree, impervious surface, bare land with grass, water surface. The results showed that, in places with natural forest cover (Dau Tieng lake area), rubber forest cover, and water surface, the LST value was only from 20 to 24 oC, while bare land had an LST value of 26-28 oC and construction land had a value above 28 oC.

The correlation between NDBI and NDVI to LST showed that most NDBI had a positive correlation with LST. Meanwhile, NDVI was negatively correlated. Meaning, that when the area of vegetation cover decreased, the area of bare land and construction land increased, and the LST value would increase and expand not only in space but also in value. The effects of LULC change on LST can be seen in the form of vegetation increase, deglaciation, changes in agricultural practices, and alteration of wet-lands. These changes in LST can have far-reaching effects on the local and regional climate, as well as on ecosystems and human communities.

References

3. T C Ha, T P C Nguyen, Application of Multi-Temporal Landsat Images to Analyze the Relationship Between the Land Surface Temperature (LST) and the Land Use Land Cover (LULC) in Ho Chi Minh City, IOP Conf. Ser.: Earth Environ. Sci.,1170 012017 (2022).