Detection of Land Use/Land Cover Change and Land Surface Temperature in the Eastern Part of Batna City (North East Algeria) Using Remote Sensing Data and GIS.

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Abstract. The present paper aims to evaluate the accuracy of classifying Land Use /Land Cover (LULC) types and assesses the trends of their changes in the Eastern Part of Batna City (Northernf Algeria) using remote sensing and GIS. The accuracy of image Land Satellite (Land Sat) was evaluated using the supervised classification technique, it’s applied in multi spectral and multi temporal satellite data acquired in 2000,2010,2022 and assessed with GOOGLE EARTH PRO and IMAGERY Land Use and topographical map. The second part focused on extraction of LST in three phases and explored the relationship between two land cover indices (NDVI, NDBI) and LST.LU/LC detected, quantified, and statistically analyzed, the result indicate that from 2000-2022 the built-up areas increased by 0.34% (6.638km^2), the forest area increased by 1.8% (35.144km^2), agricultural land cover increased by 1.12% (21.867km^2), while bare land decreased by 2.17% (42.368km^2). The conversions of areas from bare land to urban land represent the most significant Land Cover changes. The accuracy assessment and correlation coefficient R^2 analysis in this study affirms the previous research findings. Even a single land use unit like built-up area, bare land and vegetation also create differences in LST (R^2 of NDBI vs. LST ranges from 0.64 to 0.79; NDVI vs. LST ranges from -0.73 to -0.82). With the change of the LU/LC style, its imprint is reflected on the LST. Therefore, immediate reflection on new urbanism must be adopted, initiated and implemented to stop the warming that contributes to climate change in the study area.

Keywords: Supervised classification, Land Use Land Cover, land surface temperature, remote sensing & GIS, Batna.

Встановлення землекористування/зміни ґрунтового покриву та температури поверхні землі у східній частині міста Батна (північний схід Алжир) за допомогою даних дистанційного зондування та ГІС

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Анотація. Ця стаття має на меті оцінити точність класифікації типів землекористування/ґрунтового покриву (LULC) і оцінити тенденції їх змін у східній частині міста Батна (північ Алжир) за допомогою дистанційного зондування та ГІС. Точність зображення Land Satellite (Land Sat) було оцінено за допомогою методу контролюваної класифікації, його застосували до багатоспектральних і багаточасових супутникових даних, отриманих у 2000, 2010, 2022 роках і оцінених за допомогою GOOGLE EARTH PRO і IMAGERY Land Use та топографічних карт. Друга частина була зосереджена на вилученні LST у три фази та дослідженні зв’язку між двома індексами ґрунтового покриву (NDVI, NDBI) і LST.LU/LC, виявленням, кількісною та статично-проаналізованням. Площа зрошеної 0,34% (6,638 км²). Площа лісів збільшилася на 1,8% (35,144 км²), рослинний покрив збільшився на 1,12% (21,867 км²), а площа гіллях земель зменшилася на 2,17% (42,368 км²). Перетворення територій із гіллях земелю на міську землю є найбільш суттєвими змінами земельного покриву. Оцінка точності та аналіз коефіцієнта кореляції R^2 у цьому дослідженні підтверджують результати попередніх досліджень. Найвища точність землекористування, як-от забудована територія, оголена земля та рослинність також створюють відмінності в LST (R^2 NDBI проти LST коливається від 0,64 до 0,79; NDVI проти LST коливається від -0,73 до -0,82). З ізміною стилю LU/LC його відбітком відображається на LST. Таким чином, необхідно негайно здатисяся на новий урбанізм, розпочати та реалізувати його, щоб зупинити потепління, яке сприяє зміні клімату в досліджуваній території.

Ключові слова: контролювана класифікація, землекористування, земельний покрив, температура поверхні землі, дистанційне зондування та ГІС, Батна.
Introduction

Land use/land cover represents an important factor in geographical studies, environmental analysis and spatial planning approaches. It is a dynamic variable because it reflects the interaction between socio-economic activities and regional environmental change, and for this reason, it needs to be updated frequently (Marina and al., 2016).

Land use/Land cover (LU/LC) change play a major role in the study of global change, Land use/Land cover and human/natural modifications have largely resulted in deforestation, biodiversity loss, global warming and increase of natural disaster- flooding, these environmental problems are often related to LULC change (Selçuk, 2008).

Remote Sensing (RS) and Geographical Information System (GIS) based Change Detection (CD) studies have focused on providing the knowledge of what type, where and how much LULC change has occurred (Haruna. A., 2018). Remote sensing has become an important tool applicable for developing and understanding the global, physical processes affecting the earth. A recent development in the use of satellite data is to take advantage of increasing amounts of geographical data available in conjunction with GIS to assist in interpretation (Praveen and al., 2013).

Over the earlier few decades, our interdependence of the understanding between LU/LC, socio-environmental and ecological systems has increased. There is a need for more accurate, timely information on land change science (LCS) to understand the spatial-temporal dynamics of nature in several landscapes (Siddi Raju and al., 2018). The current research delivers the spatio-temporal LU/LC over two decades (2000-2010 and 2010-2022), and the relationship between LST and LULC in which an increase in land surface temperatures (LST) is considered one of the main effects of LULC changes especially in urban areas. The relationship between LST, Normalized Difference built-up Index (NDBI), and Normalized Difference Vegetation Index (NDVI) was established using linear regression (Guechi and al., 2021), other studies examined the classification of the area study and the temporal changes of LULC for the years 2000, 2010, 2022.

This research assessed the accuracy of classification and analysed the trends of changes in LULC from PC of Landsat images for a period of 3 decades (2000, 2010, and 2022) to provide a reliable database for sustainable management of resources. This analysis will make it possible to identify urban sprawl, as well as changes in forest and agricultural cover. The produced results will make an essential contribution to decision-making in the fields of environmental management and future planning (El Adnani and al., 2019).

Material and Methods

Study Area and Data Used. The study area is situated in the Eastern part of Batna city (North East Algeria), located between 35°24′00″ and & 35°42′00″N latitudes, and 5°42′00″ and & 6°18′00″ E longitudes (Fig. 1), this region covers an extent of about 1952.465km².

Geographically, the study area is dominated by the mountainous Massifs of the Aures with high elevation (+2000 m of altitude), and has a semi-arid climate with cool winter, an average annual temperature of 20°C, and the average annual rainfall between 1970-2014 is about 450mm/year. In the study area, there are two periods in the year, eight months of cold and wet weather from October to May and four months of hot and dry weather from June to September (Guchi and al, 2021). The forest areas cover most parts of the study area from East to West, natural vegetation cover was represented by dense forests such as the Belazma Massifs (Cedrus atlantica and Quercus ilex) in the western part of the study area, and the mountains of Bouaarif and Ich Ali in the Eastern part, and open forests. The hill slopes are occupied by orchards, shrub lands and pasture while in the depression and at the contact with the plain areas, the agricultural crop area extends (cereals, vegetables).

Fig. 1. Location of the study area

Three Landsat images were selected to map and assess the LULC change and LST over the last twenty two years (2000-2022), the Landsat image was geo-referenced (Universal Transverse Mercator UTM, WGS 84), the scenes are available with a spatial resolution of 30m and acquired during the summer
period in July (dry season) depending on availability, and have been used to avoid coinciding with extreme conditions and heat waves for the years 2000, 2010, and 2022 (Table 1).

The times series of Land sat image have been captured by Landsat TM, ETM+ and Landsat OLI (operational land image) and TIRS (thermal infrared sensor). All the datasets have been downloaded from the website of the United States Geological Survey (USGS) (https://earthexplorer.usgs.gov). The image processing software ArcGIS Spatial Analyst (version 10.6), Environment for Visualizing Image ENVI version 5.3 and excel were used for conducting the statistical analysis.

In this study, atmospheric analysis of hypercube (FLAASH Method) was utilized for atmospheric correction in ENVI 5.3 software.

Methods. Land Use/ Land Cover Mapping. LULC maps of the study area were produced for the years 2000, 2010 and 2022, using a supervised classification technique for classification of Maximum Likelihood (MLC); MLC is the most used method of supervised classification in a variety of applications, following a meticulous selection of pixel samples, based on the spectral variation of each class. The generalized images were reclassified into four categories (Table 2).

Generally, a supervised classification requires learning samples as well as the definition of the size and the number of learning samples to achieve a specific result (Chi, M and al., 2008), which is one of the most critical problems of the supervised classification (El Adnani and al., 2019).

The flowchart in Fig. 2 summarizes the methodology used for this study.

In the supervised classification of Maximum Likelihood (MLC) technique, three images with different dates are independently classified; accurate classifications are imperative to insure a precise change detection. The purpose was to validate and compare the Change detection analysis, which describes and quantifies the differences between images of the same region at different times. For improving the quality of Land Use/Land Cover maps, ground verification was done with GOOGLE EARTH PRO and IMAGERY for doubtful areas and misclassified areas were corrected.

Image Processing. LST Estimation. There are several ways of calculating and estimating land surface temperature (LST), different algorithms to do that like Split-Window (SW), Dual-Angle (DA), and Single-Channel (SC) (Majed and al., 2018), in this study LST was calculated by applying a structured mathematical algorithm viz., Split-Window (SW) algorithm. It uses brightness temperature of two bands of TIR, mean and difference in land surface emissivity for estimating LST of our area. The equation of LST is:

$$LST = BT/1 + (W \times BT/P \times \ln(e))$$

Where:
- LST: Land Surface Temperature.
- BT: Brightness Temperature.
- W: Wavelength.
- P: 1438.
- e/LSE: Land Surface Emissivity

Brightness Temperature (BT). Brightness temperature (BT) is the microwave radiation radiance traveling upward from the top of Earth’s atmosphere (Rajeshwari and al., 2014), it is the temperature T that had been received by the satellite landsat at the time that the image was taken. Therefore, this is not the real temperature on the ground; it is the temperature at satellite (Alipour and al., 2003). TIRS band data

<table>
<thead>
<tr>
<th>Landsat Scene Id</th>
<th>Spacecraft Id</th>
<th>Acquisition Date</th>
<th>UTM Zone</th>
<th>Spatial Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>LT51940352000210FU100</td>
<td>L5_TM</td>
<td>28/07/2000</td>
<td>31</td>
<td>30m</td>
</tr>
<tr>
<td>LT51940352010189MPS00</td>
<td>L5_TM</td>
<td>08-07-2010</td>
<td>31</td>
<td>30m</td>
</tr>
<tr>
<td>LC08L1TP194035202207252022072502RT</td>
<td>LANDSAT8</td>
<td>25-07-2022</td>
<td>31</td>
<td>30m</td>
</tr>
</tbody>
</table>

Table 1. Datasets used in the analysis and their characteristics

<table>
<thead>
<tr>
<th>LAND COVER CLASSES</th>
<th>DESCRIPTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>SHRUBS AND FOREST LAND</td>
<td>Areas dominated by forest (dense and clear forests) and covered by herbaceous plants such as grass and shrubs</td>
</tr>
<tr>
<td>AGRICULTURAL LAND</td>
<td>Areas of land prepared for agricultural activity, including areas currently under cultivation and land under preparation, and greenhouse</td>
</tr>
<tr>
<td>BARE LAND</td>
<td>Unvegetated land</td>
</tr>
<tr>
<td>URBAN AREA</td>
<td>Residential, commercial, industrial, transportation, and facilities</td>
</tr>
</tbody>
</table>

Table 2. The identified LULC types in the study area.
can be converted from spectral radiance to brightness temperature using the thermal constants provided in the metadata file (Majed and al., 2018), the (Equation (2)) was used to convert from spectral radiance (TOA) to brightness temperature (TB).

\[
T = K_f \ln (k_1 L_{\lambda} + 1) - 272.15
\]  

(2)

Where:

- \(K_f\): Thermal constant.
- \(L_{\lambda}\): Top of Atmospheric spectral radiance (TOA).

Landsat 8 provides some constant to estimate LST such as thermal constant and rescaling factor; it found it in metadata file of Landsat satellite images (Table 3).

We can find the Brightness Temperature (BT); the Top of Atmospheric spectral radiance (TOA) is acquired. The Equation (3) states:

\[
L_\lambda = ML \cdot Q_{cal} + AL
\]  

(3)

Where:

- \(ML\): Band specific multiplicative rescaling factor (radiance_mult_band_10/11).
- \(AL\): Band specific additive rescaling factor (radiance_add_band_10/11).
- \(Q_{cal}\): band 10/11 image.

**Land Surface Emissivity**

There are many methods to estimate land surface emissivity, One of them is the Normalized Difference Vegetation Index (NDVI) method (Equation (4)), taking into account the proportion vegetation \(P_v\) (Majed and al., 2018), then LST in Kelvin to Celsius is determined. The formula of LSE is equation (5).

\[
e = 0.004 \cdot P_v + 0.9
\]  

(4)

\[
P_v = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \cdot 2
\]  

(5)

Table 3. Landsat 8 Metadata base of the study area

<table>
<thead>
<tr>
<th>SENSOR</th>
<th>Optical Land imager</th>
<th>Thermal Infrared Sensor</th>
</tr>
</thead>
<tbody>
<tr>
<td>PATH/ROW</td>
<td>194/35</td>
<td></td>
</tr>
<tr>
<td>BANDS</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RADIANCE MULT-BAND-10</td>
<td>/</td>
<td>3.3420</td>
</tr>
<tr>
<td>RADIANCE MULT-BAND-11</td>
<td>/</td>
<td>3.3420</td>
</tr>
<tr>
<td>RADIANCE ADD-BAND-10</td>
<td>0.10000</td>
<td>0.10000</td>
</tr>
<tr>
<td>RADIANCE ADD-BAND-11</td>
<td>0.10000</td>
<td></td>
</tr>
<tr>
<td>(K_f) FOR BAND 10</td>
<td>774.89</td>
<td></td>
</tr>
<tr>
<td>(K_f) FOR BAND 11</td>
<td>480.89</td>
<td></td>
</tr>
<tr>
<td>(K_f) FOR BAND 10</td>
<td>1321.08</td>
<td></td>
</tr>
<tr>
<td>(K_f) FOR BAND 11</td>
<td>1201.14</td>
<td></td>
</tr>
</tbody>
</table>
Where:
e/LSE: Land Surface Emissivity.
P.: Proportion of vegetation.
NDVI: Normalized Differences Vegetation Index.

**Estimation of Normalized Indexes: Estimation of Normalized Difference Vegetation Index (NDVI).**
The NDVI index is a measure of the surface vegetation quantity and vigor, given that vegetation is well reflected in the near infrared part of the spectrum, Normalized Difference Vegetation Index has become a simple graphical indicator for assessing target vegetation cover. Several researches focused on understanding the LST-NDVI relationship (Guechi and al., 2021). The NDVI index is calculated by the equation (6)

\[
\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}}
\]

Where:
NIR, Red are the spectral reflectance of vegetation in the near infrared and Red Bands.

**Estimation of Normalized built-up Index (NDBI).** In addition, the Normalized Difference Build-up Index value lies between -1 to +1. Negative value of NDBI index represents water bodies, whereas higher value represents built-up lands. NDBI value for vegetation is low. The NDBI index is calculated by the equation (7)

\[
\text{NDBI} = \frac{\text{SWIR} - \text{NIR}}{\text{SWIR} + \text{NIR}}
\]

For Landsat 5 and 7 data: 
\[
\text{NDBI} = \frac{\text{Band 5} - \text{Band 4}}{\text{Band 5} + \text{Band 4}}
\]

For Landsat 8 data: 
\[
\text{NDBI} = \frac{\text{Band 6} - \text{Band 5}}{\text{Band 6} + \text{Band 5}}
\]

**Results and discussion**

**Land Use/Land Cover Change Analysis.** Supervised classification is a well-known and the most acceptable classification algorithm used for image classification (Siddi Raju and al., 2018), hence the MLC algorithm in Landsat image software is used to evaluate LU/LC change in the study area. The ultimate classification products provide an impression of the major LULC features of the Eastern part of Batna city, massifs and urban center and its periphery for 2000, 2010, and 2022 (Figure. 3). Tabulations and area calculations offer a comprehensive data set of the area under different LULC, spatial and temporal transformation of LULC, transformation rate, increasing or decreasing pattern of LULC in terms of the overall landscape (Swades et al., 2017) (Table 4).

The spatial distribution and patterns of Land Use/land cover changes and persistence are shown in (Fig. 3). Over the entire study period, agricultural land was the predominant land use type (4.62%) (90.203km2) during 2000, it declined at an annual rate of -1.11%(-21.672km²) during 2010 and it increased 1.12%(21.867km²) in 2022. Forest (Belezma and Aures Massifs) was the predominant land cover type in the study area, (20.96%) (409.23km²) during 2000, although it showed a decrease of 17.9%(349.490km2) since 2000-2010 with an annual decrease of -3.06% (-59.745km²), but in period of 2010-2022 forest land shown a significant increase 22.76% (444.379km²) with an annual increase of 1.8%(35.144km²) (Table.4).

An urbanization trend enhanced the growth of the Urban Area between 2000 and 2022; recorded areal expansion was 1.92% to 2.26% with an increasing rate of 0.34% (6.638km²). In the Urban Area, positive change of land use during the study period is highly detected indicating increasing intensity of built up areas and extension of them. However, steady urban growth also captured Bare Land, it decreased significantly (72.49% to 70.32%) over the twenty-two years of the study period, at an annual rate of -2.17% (-42.368km²).

The overall accuracies of the classified images (2000, 2010, and 2022) were respectively 91.50%, 88%, and 97% with Kappa coefficients of 88.67%, 84%, and 96%, (Table 5). Note that the Kappa coefficient is a measure of the proportional (or percentage) improvement by the classifier over a purely random assignment to classes (Ahmed and al., 2013). In 2000, and 2022 classification, User’s accuracies of individual class were extremely high, ranging between 74% and 94%.

<table>
<thead>
<tr>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Forest Land</td>
<td>409.33</td>
<td>20.96</td>
<td>349.53</td>
<td>17.9</td>
<td>-3.06</td>
<td>444.52</td>
<td>22.76</td>
<td>4.86</td>
</tr>
<tr>
<td>2</td>
<td>Agriculture Land</td>
<td>90.19</td>
<td>4.62</td>
<td>68.63</td>
<td>3.51</td>
<td>-1.11</td>
<td>90.54</td>
<td>4.63</td>
<td>1.12</td>
</tr>
<tr>
<td>3</td>
<td>Urban Area</td>
<td>37.48</td>
<td>1.92</td>
<td>41.88</td>
<td>2.14</td>
<td>0.22</td>
<td>44.26</td>
<td>2.26</td>
<td>0.12</td>
</tr>
<tr>
<td>4</td>
<td>Bare Land</td>
<td>1415.46</td>
<td>72.49</td>
<td>1492.42</td>
<td>76.43</td>
<td>3.94</td>
<td>1373.15</td>
<td>70.32</td>
<td>-6.11</td>
</tr>
</tbody>
</table>
Table 5. Details of overall accuracy and Kappa Coefficients.

<table>
<thead>
<tr>
<th>Year</th>
<th>Overall accuracy</th>
<th>Kappa coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>28-07-2000</td>
<td>91.5</td>
<td>88.67</td>
</tr>
<tr>
<td>8-07-2010</td>
<td>88</td>
<td>84</td>
</tr>
<tr>
<td>25-07-2022</td>
<td>97</td>
<td>96</td>
</tr>
</tbody>
</table>

Fig. 3. Land Use Land Cover maps of 2000, 2010, and 2022

Table 6. Accuracy Assessments of the Land Use/Land Cover types

<table>
<thead>
<tr>
<th>YEARS</th>
<th>Urban Area</th>
<th>Forest Land</th>
<th>Agricultural land</th>
<th>Bare Land</th>
<th>total accurate</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>0.96</td>
<td>0.94</td>
<td>0.76</td>
<td>1</td>
<td>194</td>
</tr>
<tr>
<td>2010</td>
<td>0.96</td>
<td>1</td>
<td>0.58</td>
<td>0.98</td>
<td>176</td>
</tr>
<tr>
<td>2022</td>
<td>0.94</td>
<td>1</td>
<td>0.94</td>
<td>1</td>
<td>183</td>
</tr>
</tbody>
</table>
The spatial Land Use Land Cover Maps of the study area are shown in Figure 3. It is clear that there have been a Forests and Urban expansion in the eastern part of Batna city in the last twenty two years. The urban expansion was in the inter-municipal grouping of Batna, this growth is concentrated in Batna municipality, which is very significant compared to the other municipalities. Batna is one of the Algerian cities which fulfills very important urban functions.

A very considerable growth in vegetation cover predominates, in particular, in the North West part of the study area, especially the forests Massif of Belezma, and lower slopes of Abdi in the North East part in the region of Oued Taga and Bouzina.

Fig. 4 illustrates that there was a high loss in the Agriculture and Forests land categories in period of 2000-2010. This means that some parts of the previously existing agriculture areas were converted into some other land cover classes. However, there has been a significant change in the Bare land class in both periods 2010-2022 and 2000-2022 and this category of Land Cover has lost areas in approximately equal quantity in each period. The report shows that Bare land has been a major contributor to the formation and expansion of built-up areas, and Agricultural areas and Forests have experienced significant expansion during the period 2010-2022, despite successive fire incidents in recent years.

**Fig. 4.** Gains and losses of the Land Use/Land Cover types (Unit %) in the study Area
**Land Surface Temperature Change.** Fig. 5 indicates the spatial pattern of Land Surface Temperature in three years e.g. 2000, 2010, and 2022. This analysis was also carried in the summer season (July month). These spatial patterns of LST concentration and temporal shift LST pattern actually highlight rapid change of Land Use/ Land Cover, which show a clear gradient between Forests Areas, Agriculture Lands, Urban areas, and Bare Lands from 2010 to 2022. The results show that the LST is confined within the range of 21°C to 44°C during July 2000 (Fig. 5), 17°C to 50°C, and 27°C to 50°C during July 2010 and 2022 respectively. Mean temperature of this study area in this time was 33°C. In next two phases (2010 and 2022), both maximum and minimum LST patterns have up heaved. Minimum LST since 2000–2010 and 2010–2022 have risen from 21.50°C to 17.93°C and from 17.93°C to 27.23°C respectively. Similarly, maximum temperature has also risen by 5.75°C since 2000–2020. This growth is entirely arithmetic but more realistic temperature growth calculated using spatial average indicates that LST has increased by about 2.75°C since 2000–2020 and the annual rate of increase is 0.114°C/year (Swades and al., 2017). LST in 2010 ranged from 17.93°C to 50.64°C, which increased its average temperature compared to 2000 to 34.28 °C, while the northwestern and southeastern parts of the study area show a relatively low temperature range because it is a forest area.

In 2010, the average temperature of urban settings was 34.28 °C, whereas, in 2022 it reached 38.71°C. Mean temperature values for every class has revealed that the lowest temperature values were observed in the Forests area, and the highest temperature values were observed in Bare land and Urban land.

![Fig. 5. Spatial distribution of Land Surface Temperature (LST).](image-url)
**Relationship between Temperature and land Cover Indices.** In the later section, it is to be investigated how a single LULC with different intensity can create variant land surface temperature? For example, built up areas retain maximum temperature but within built up land radiant surface is diversified as the intensities of the built up area vary in different parts of urban areas (Mallick et al., 2008). This association is also valid in case of Agriculture Land and intensity and canopy cover area of the Forests land. Keeping this fact in mind, LULC specific temperature analysis is also carried out (Swades and al., 2017). Tow land cover indices (e.g., NDVI, NDBI) were derived in order to establish quantifiable relationship between LST and the indices.

**Temperature change in Built up areas.** Fig. 6 depicts the extracted NDBI classes indicating intensity and spatial pattern of the Built up area for 2000, 2010, and 2022. Spatial extension and intensity have increased over the selected periods. According to Fig. 7, maximum values of NDBI varied between 0.26 in 2000, 0.54 in 2010, and 0.45 in 2022, while the minimum values varied between -0.38 in 2000, -0.84 in 2010, and -0.92 in 2022. Figure 6 show the correlations and linear regression equations of the LST and NDBI index from 2000 to 2022, the results of multiple correlation and regression analyses indicate that LST presents a positive correlation with NDBI, the coefficient of determination value generated for 28-07-2000 is 0.79, high decreased on 25-07-2022 and became 0.64. Both values strongly show that NDBI score correlates positively with LST, a similar fact and trend is found for the summer months. Such higher trend of $R^2$ value establishes the fact that high intensity Impervious land retains maximum LST (Swades and al., 2017).

**Temperature change in vegetated land.** Fig. 9. shows the spatial pattern of NDVI classes extracted from the multi temporal satellite images. This distribution map is compiled for making a relationship between NDVI of different intensity levels and LST. As documented in the literature, a higher level of LST is found to be associated with a lower NDVI in this research (Fig. 5 and 9). In 2000, the NDVI ranged between 0.019 and 0.69, which gradually increased between -0.55 and 0.98, in 2010. in 2022 NDVI increased between -0.52 and 0.95. Therefore, it can be said that the NDVI increased in the study area over time. The results of multiple correlation and regression analyses indicate that the relation between NDVI and LST is negative and $R^2$ value of July 2000 is -0.82, which gradually reduced to -0.77 in July 2010, and to -0.73 in the same month in 2022.

**Conclusion**
This is the first study, to the knowledge of the authors, that has demonstrated a method of deriving land surface temperature (LST) of the LU/LC areas based on the supervised classification of them from observed relationships between Land use/Land cover and LST changes in Eastern part of Batna city (North-western part of Aurès Massifs). In this study, we produced LULC and LST maps based on multi-temporal Landsat images from 2000, 2010 and 2022. They are used to assess the impact of Land Use and LST change over the last two decades in the study area, especially at the level of Forest land, Agriculture land, Bare land, and Built-up categories. Forests have decreased dramatically; Forests of (Belezma and Aures Massifs) are the predominant land cover type.
Fig. 7. NDBI classes of July 2000, 2010, and 2022

Fig. 8. Correlation between NDVI and LST
in the study area, although they showed a decrease of 17.9% since 2000-2010 with an annual decrease of -3.06%, but in the period of 2010-2022 forest land showed a significant increase of 22.76% with an annual increase of 1.8%. A distinct difference is identified in different LULC units and temperature rises gaining over time (Swades and al., 2017). Temperature variation is also detected within a single land use/land cover unit. Land use changes in terms of increasing areas of agriculture and forests, transforming of Bare land into Urban land, and exchange of land between fruit orchards and agricultural land.

In our study, the following conclusions were reached: (1) the amount of built-up areas have increased between 2000 and 2022, and is expected to double and triple by 2030 and 2040, respectively; (2) there was a significant negative association between NDVI and LST whereas a significant positive association between NDBI and LST exists, which suggests that vegetation reduces the LST and built-up areas increases LST. Changes to LULC have been followed by changes in LST. It is worth noting that urbanization is the main driving process of land cover changes and consequently rise of LST. (3) The study used two land cover indexes (e.g., NDVI, NDBI) and applied a simple regression equation for the derivation of LST over the study period.

We can conclude that surface temperature has been rising over advancing phases in all periods of the study and LST surface diversified due to positional influence of the existing LULC. In this research, we can say that Land Use/Land Cover mapping and documentation may not provide the ultimate explanation for all the problems associated with environmental change and degradation. They can provide a descriptive overview of the evolution of the causes of anthropogenic expansion; however, it is one of the most important steps for better understanding of trends and possible causes of this degradation in the study area.

Fig. 9. NDVI classes of jolly 2000, 2010, and 2022.
References


