Improved Land Cover Mapping Using Landsat 8 Thermal Imagery

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Abstract. Detection of land cover (LC) changes allows policymakers to recognize the complexities of environmental modification and change to achieve sustainability of economic growth. As a result, recognition of LC features has appeared as an essential research dimension and, consequently, an appropriate and reliable methodology for classifying LC is occasionally required. In this research, Landsat 8 satellite data captured by Operational Land Imager (OLI) and Thermal Infrared Scanner (TIRS) were utilized for the LC classification using the Support Vector Machine (SVM) classifier algorithm. The aim of the study is to enhance classification accuracy by integrating the use of data from satellite thermal and spectral imaging. Land Surface Temperature (LST) is sensitive to the soil surface characteristics, therefore, it may be used to gather LC feature information. The classification accuracy was designed to enhance the integration of thermal information from Landsat 8’s thermal band TIRS and Landsat 8 OLI’s spectral data. In this study, Advanced Thermal Integrated Vegetation Index (ATLIVI) and Thermal Integrated Vegetation Index (TLIVI) established and revealed fairly strong correlations with the related surface temperature (Ts) by $R^2=0.7$ and 0.65 respectively. The relationship between Ts and the other vegetation indices based on the empirical parameterization demonstrate that these two indices showed an improvement of almost 6% in the overall accuracy of the LC classification results compared to the Landsat 8 Standard False Colour Composite image as an input data using SVM algorithm.

1. Introduction

Land Cover (LC) trends are the key parameters of current approaches and policies for controlling and managing natural resources. At present, the world has seen the significance of LC variations in global environmental transformation that could lead to detrimental impacts [1, 2]. Changes in LC represent changes in the environment caused by natural or anthropogenic consequences [3]. This provides a significant element in the assessment, monitoring, and conservation of the Earth's resources needed for sustainable development and the economic distribution of the area [4]. Appropriate utilization accessible land is the essential element for the feasible protection of the environment that will eventually enhance the economic status of alleviating poverty. It requires an accurate measurement of present and historical LC fundamentals. The development and enhancement of Remote Sensing (RS), Geographic Information Systems (GIS), Global Positioning System (GPS) and advanced geospatial approaches, the classification of spatial-temporal LC trends has become appropriate, simple, pay-effective and accurate [5-8]. Using multi-temporal or multi-spectral satellite imageries through digital image classification processing have significant ability for LC classification.
systems, landscape interactions and change detection assessments. Digital classification algorithms involve unsupervised, supervised and objective-based classification techniques. The supervised classification system is most commonly utilized technique [5, 9-12]; however the object-based and supervised classification techniques have shown greater accuracy [13-16]. In addition, the utilization of high spatial resolution satellite imagery may be employed to classify LC targets. In the case of spectral mixtures, hybrid classification is also employed to distinguish LC features [17]. But at the other side, the precision of classification can indeed be improved through the incorporation of multi-source data [18-22].

LST provides a particular response to landscape dynamics, such as LC modification and LC categorization typically when it is measured from the remotely sensed thermal band [23-26]. Thermal Infrared imagery can indeed determine the quantitative details of Ts across various LC groups [17, 27]. There are complex interactions between the LST and many physicochemical and biological structures on Earth [28, 29]. As a result, LST serves as the primary measure in the physicochemical and biological of land surface structures, energy flows and Earth-atmosphere interactions among the planet and the atmosphere as part of the energy balance [30]. It can therefore provide vital description of the physical and climatic properties of the surface, which play a critical role across several environmental procedures [31, 32]. Thus, it is a great importance variable in the climatological and meteorological studies using RS data. On the other hand, climate change is associated with increases in LC and anthropogenic activities. The dynamics detailed and the theory explanation behind the LST is conceptualized in [33, 34]. In reality, spacecraft satellite imagery is the best method to obtain LST parameter, both internationally and regionally, owing to the accessibility of high resolution, continuous and revisited coverage and the capacity to measure Earth's surface requirements [35]. A comprehensive overview of the task of remote sensing approaches for meteorology and climate change in the LST has been established as well as a guide to the various thermal remotely sensed sensors that generate large, genuinely valuable datasets for LST measurement [36]. LST is responsive to vegetation and soil moisture; it may be adapted to identify patterns and changes in LC features [37]. Experiments conducted using MODIS for LST retrieval show significant results for small scale global environments [38-42]. A number of studies have been implemented to obtain LST from Landsat 5 and 7 thermal data, which are best suited for regional and national mapping scale [24, 37, 38, 43].

Previously, two thermal infrared bands (band 10 TIRS 1 (10.6-11.19 μm) and band 11 TIRS 2 (11.5-12.51 μm) in Landsat 8 (L8) Thermal Infrared Scanner (TIRS) with a high spatial resolution of 100 m are very useful for regional and national thermal infrared research.

For achieving high precision L8 thermal data with less parameters in the LST prediction, new techniques that are robust and easy to apply need be developed. Surface emissivity is indeed one of the critical elements of radiance transfer and balance. The Earth surface comprises of complex and varied LC features, and the surface emissivity accurate estimation of LC features is not simple. Relying on the conventional LC description, involving complex and seasonal variables. In the study [44] provided a description of the emissivity estimation by using MODIS thermal infrared bands. Vegetation Indices (VIs) such as the Soil Adjusted Vegetation Index (SAVI), Normalized Difference Vegetation Index (NDVI), the and the Leaf Area Index (LAI) are utilized as alternatives method for assessing the land surface temperature [45]. There is an evident correlation among both LST and NDVI [43, 46] and it differs with variations in land cover [47]. The correlations among both LST and NDVI differ on a diurnal and seasonal basis [48]. LAI, being one of the main significant biochemical and biophysical indicators of LC, already has a correlation with Ts [49]. A new Light Use Efficiency (LUE) estimation model was implemented utilizing SAVI, NDVI, and EVI2 in combination with the scaled LST, with moderate LUE assessments employing MODIS data [50]. The advent of new climate agreements such as REDD (Reducing Emissions from Deforestation and Degradation), there has been a growing demand for effective forest monitoring approaches [42, 51]. L 8 Thermal data could have been used to calculate temperatures inside the forest which cannot be reached by traditional techniques. It can be used to assess the surface temperature of the forest. Differences in thermal behaviour of the forest trees are the result of biophysical vegetation properties [52]. This paper discusses the index generated
utilizing both thermal band 10 data and spectral L8 satellite imagery for LC Image classification and mapping. Spatial assessment was done by creating models of spectral VIs with surface emissivity to calculate Ts and two thermal vegetation indices established in this research by integrating L8 TIR band 10 with NDVI, LAI and EVI2 VIs data. Thermal data of L 8 was utilized with the highest spatial resolution (100 m) presently accessible by space remote sensing. There was a possible interrelation between the surface features of the LC and the LST [17, 27, 51]. Appropriate studies have been performed employing a combination of Ts and VIs, primarily NDVI for LC visualization and mapping [47, 53-55].

2. Materials and Methods

2.1. Study Area and datasets
Kuala Krai District (coordination is 5°30′N 102°10′E as case study was chosen and is revealed in Figure 1. It is a densely populated district in the center of the state of Kelantan in the northeast of Malaysia. The terrain is hilly, and before the 20th century, nearly the entire area was a tropical rainforest. The territory contains the convergence of two main rivers, the Lebir and the Galas, to create the Kelantan River that mostly passes some 70 km north through one of the most thickly urbanized flood plains on the Malay Peninsula to its estuary in the South China Sea, near the State capital of Kota Bharu. Satellite data of L8 held on board two instruments: the Operational Land Imager (OLI) and the Thermal Infrared Scanner (TIRS). L8 OLI and TIR of 2014 data have been obtained from USGS freely (http://earthexplorer.usgs.gov). Malaysian sample topo sheets were also utilized to classify the LC base on satellite imagery. The study area in this research covers an area of almost 2329 km2 [56-58].

2.2. Landsat 8 Image Pre-processing
L8 OLI imagery was analyzed by utilizing ENVI image processing software (v5.1). Pre-processing of the L8 OLI imagery consists of two-steps; first, radiometric and atmospheric corrections [59, 60] through applying the latest radiometric calibration coefficients published (http://landsat.usgs.gov) and geometric correction and image registration as second step. Top of the atmosphere (TOA) is described as the radiance measured near the sensor according to [61]. In our study, we used the Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercube (FLAASH) radiative transfer model with radiometric rescaling coefficients in the product metadata file regarding the method specified on the USGS website to perform atmospheric correction of L8 OLI image to surface reflection. The data was then saved in the normal ENVI format and a single scale factor value (1000) was utilized for all bands to transform the [(W/m2 μm sr)*100] input radiance image to normal FLAASH input radiance units.
(μW/cm² μm sr). Reflectance values in FLAASH images were doubled by 10,000 so the resulting value ranged from 0 to 1. The next phase is the correction of geometry. Utilizing the WGS 84 reference ellipsoid, L8 image acquired from the United States Geological Survey (USGS) is based on the UTM projection, Level 1 T. The positional precision in x and y image directions as Root Mean Square Error (RMSE) was 0.07 using Fifteen excellently-distributed ground control points (GCPs), well below standard requirements of less than 1 pixel [62-64]. Then the sub-set image was re-projected to UTM (Universal Transverse Mercator), Datum WSG-1984, zone 48 N and resampled to a spatial resolution of 30 m, then use it as a dataset to perform classification methods and subsequent processes.

2.3. LC Image Interpretation

The L8 spectral details were used to compare image characteristics and ground features. Spectral signatures for various LC classes have been identified and the False-Color Composite (FCC) defined on the basis of imaging elements. Textural and Tonal variations owing to altitude-dependent vegetation and topo sheet contour data was utilized in the description analysis. For supervised classification, the Support Vector Machine (SVM) classifier base on Radial Base Function RBF kernel function was chosen [65, 66]. The penalty value C and the kernel parameter γ were the two variables used for the RBF kernels laid at 120 and 0.15, respectively. During the implementation SVM classifier, sets have been selected for FCC images of three bands (band 2 as green, band 3 as red and band 4 as near-infrared) depend on the training sample data as points obtained for the corresponding LC categories [67, 68]. Training points for the LC classification have been established on the basis of information acquired through a detailed ground survey and a thorough field analysis of the region; the topographical sheets and the Spot 5 (2.5 m) of the study region have also been put into consideration. Substantially selected training sites were made up of pure training pixels. 100 random points were generated as sample training points, which were cross-checked by utilizing GPS in the study area. Figure 1 represents the LC classification map for the proposed study area.

2.4. Landsat 8 Spectral VIs

LAI and NDVI indices were measured through visible and near-infrared L8 OLI imaging bands that follow Eqs. 1-3. The SAVI was first calculated using Eq. 2 in order to evaluate and retrieve the LAI image. In formula 2, L is a constant and 0.5 value used. The LAI is equivalent to SAVI [45] and it is derived from the empiric equation as indicated in Eq. 3. The formula of the EVI, SAVI and EVI2 index are indicated in Eq. 4, 3 and 5 respectively in which L is a canopy background enhancement that behaves as a soil-adjusted variable; G is gain factor; C1 and C2 are aerosol resistance coefficients; and R, B and NIR are reflectors in Red, Blue, and Near-Infrared spectral channels. The value varies from L in SAVI owing to the confluence of soil-adjusted appearance and aerosol resistance factors [69, 70].

2.5. Ts and Related Parameters Retrieval

Calibration for thermal band 10 data is conducted using a Double-step process [71, 72]. The first step involves converting the band to 10 digital number (DN) values Lλ (W m⁻² sr⁻¹ μm⁻¹). Second, this is converted into a Tb in Kelvin [17, 27, 45, 52, 73, 74]. After that, an emissivity change is made using the surface emissivity for identified LCs calculated from the LAI and NDVI indices values [45, 75] as indicated in Eq. (6). Albedo was measured using the L8 reflectance spectral bands referring to the transformation equation in question Eq. (7). The Fractional Vegetation Cover (Fc) is likewise main element in Ts and it calculated by employing Eq. (8). Ultimately, the identified thermal and spectral L8 OLI bands were integrated to obtain two new indices that were utilized for the LC classification. The new indices are based on three main key factors NDVI, EVI2, and LAI, along with DN band 10 of L8 data identified as TLIVI indicated in Eq. (9), and ATLIVI as indicated in Eq. (10). The ATLIVI and TLIVI are combined with the spectral NIR and Red L8 OLI bands to demonstrate an FCC that is used as input variables for the SVM classification. The elements of the whole procedure are seen in Figure 2. All equations described and utilized for the analysis are presented in Table 1.
Table 1. Equations utilized for the estimation of spectral indices from remote sensing.

| Eqs. | Formula | Comments |
|------|---------|----------|
| 1    | NDVI=(NIR-R)/(NIR+R) | Red (R) and Near-infrared (NIR) spectral reflectance band. |
| 2    | SAVI=(NIR-R)*(1-L)/(NIR+R+L) | L is a constant value and relies on the soil properties. |
| 3    | LAI = 2.3689*SAVI +0.7877 | |
| 4    | EVI=G *(NIR_R)/NIR+C1R-C2B+L | Blue spectral band (B), C1 =6, G=2.5, L =1, and C2 =7.5. |
| 5    | EVI2 = 2.5 *(NIR-R)/ (NIR+2.4*R+1) | |
| 6    | e = 0.047*ln(NDVI) +1.009 | |
| 7    | e = 0.003 *(LAI)+ 0.97; for LAI<3.0 | |
| 8    | αshort = 0.3*α2 + 0.277 *α3+ 0.233*α4+0.143*α5 +0.036*α6+0.12*α7 | α short is shortwave broadband albedo, and α1, . . ., α7 are the reflectance of the respective band number of L8 |
| 9    | Fc = 1 _ (NDVIsc max-NDVIi / NDVIsc max-NDVIsc min)0.625 | NDVIscmax and NDVIscmin are the maximum and minimum NDVI values from the L8 scene and NDVIi is the NDVI value of ith pixel |
| 10   | TLIVI = (DN L8 (band10)-NDVI-LAI)/(DN L8 (band10)+NDVI+LAI) | Current research |
|      | ATLIVI = (DN L8 (band10)-NDVI-LAI-EVI2) / (DN L8 (band10) + NDVI + LAI + EVI2) | Current research |

3. Results and Discussions

3.1. Interpretation of the LC feature

Figure 1 demonstrates the following categorized LC features, notably, Water Bodies (WB), Residential Area (RA), Primary Forest (PF), Secondary Forest (SF), Swamp Forest/Mangrove Swamp (SWF), Oil Palm (OP), Rubber (R), Others Crops (OC), Marshland (ML), Scrub Area (SA) and Cleared Land (CL). These variations in the specific features of the land responded to the L8 thermal 10 bands solely because of the variance in emissivity characteristics. It was determined by the relative
proportion of chlorophyll, soil and moisture content of the related LC properties. As a consequence, the indices used throughout the research did indeed respond appropriately and demonstrated various reactions relaying on the diverse LC characteristics; because all indices have been established utilizing L8 thermal and optical spectral data. The findings of study [52] mentioned a number of examples within which the LST data and thermal VIs indicate a relationship to earth surface biophysical characteristics, usually VIs that further differ with various LC features.

3.2. Ts Parameters Retrieval.
NDVI, LAI, SAVI, EVI2, LST, Surface Emissivity and LC maps as spatial parameters connected to the study area at heterogeneous tropical forests in the Kuala Krai district as seen in Figures 1, 3 and 4. The accuracy evaluation carried out for LC map (Figure 1) demonstrated by 93.57% of Overall Accuracy (OA) and 0.92 of Kappa Coefficient (K). The spatial variance of the NDVI map (Figure 3a) varied from values less than 0 (0 to-0.7) in areas with water bodies and no vegetation cover to 0.8 in areas with a high vegetation cover density. The LAI spatial variance (Figure 3b) indicated that the values ranged from the negative values -2.25 in the water bodies to 1.9 as high positive values for areas defined by vegetation. Directly the emissivity values are correlated to LAI and NDVI values and have similar trends in spatial distribution as NDVI and LAI (Figure 3d). In the spatial sense (Figure 3c), EVI2 revealed an average higher value of almost 0.8 for heavily vegetated areas, whereas an average value of-0.18 for cleared land was received. The spatial pattern of Ts in the Kuala Krai district and surrounding areas ranged between almost 18°C in the water bodies and 19°C in the primary forest at a minimum to a maximum of 30.5-31.9°C in the scrub and residential areas (see Figure 4). The temperature difference between the various groups of LC was almost 16°C. Kuala Krai forests were heterogeneous tropical forests with dry, deciduous and Open forests involving the highest size and small heterogeneous clusters of villages with minimal anthropogenic activities as a result of alteration of natural surface characteristics.

**Figure 3.** Heat flux radiation and related vegetation variables: (a) NDVI map, (b) LAI map, (c) EVI2 map, (d) Surface emissivity.
Various agricultural regions have been spread throughout the surrounding area. Owing to the severe vegetation abundant supply in the region, which decreased the radiation heat flow of the earth's surface by absorbing a significant amount of radiation energy during the evapotranspiration process, maximum Ts were decreased relative to cleared land and residential areas. Ts for water bodies have been expanded to a relative high value as opposed to vegetation regions. As settlements were divided into heterogeneous clusters with forest regions, the Ts reduced due to the effect of vegetation coverage. Univariate statistics, such as the minimum, average, mean and standard deviations were measured of various LC categories radiation factors of the study area and recorded in Table 2. Many other related parameters, such as normalized LST, albedo and fractional vegetation cover have often been identified. Albedo extraction with Eq.7 higher mean values for cleared land and residential areas have been shown; low mean values for vegetation land are usually primary forests, but for water bodies are the least. Fractional vegetation as calculated by Eq.8 relies on NDVI and estimated mean value of further than 0.8 for three forest-type areas, 0.7 for cleared land and residential sites, however water bodies class had an overall value of 0.7, even lower than the cleared land and residential places classes as they had overall values in excess of 0.7. As a result, the water features were clearly separated.

The simple demarcation of the forested areas (primary forest and secondary forest) was indeed demonstrated in the statistics. Almost all LC features have validated the variability of the univariate statistical values of the radiant thermal flux factors (Figures 3 and 4) just like correctly presented in Table 2, because these are the spatial sampling parameters identified by the crustal change of values for every data set. Table 2 displays the broader variety of every parameter under evaluation with its standard and average variance values.

![Figure 4. LST map in Kelvin.](image)

**Table 2.** Heat flux radiation univariate statistics and related parameters for LC categories.

| LC classes | WB | RA | PF | EF | SWF | OP | R | OC | ML | SA | CL |
|------------|----|----|----|----|-----|----|---|----|----|----|----|
| **TLIVI**  |    |    |    |    |     |    |   |    |    |    |    |
| Minimum    | 8.33 | 8.80 | 8.19 | 8.39 | 8.85 | 8.60 | 8.31 | 8.29 | 8.48 | 8.39 | 8.73 |
| Maximum    | 10.09 | 10.58 | 10.19 | 10.08 | 9.02 | 10.29 | 10.24 | 10.31 | 10.05 | 10.38 | 10.05 |
| Mean       | 9.11 | 9.56 | 9.13 | 9.32 | 8.93 | 9.39 | 9.30 | 9.38 | 9.34 | 9.51 | 9.41 |
| Standard Error | 0.04 | 0.04 | 0.01 | 0.01 | 0.00 | 0.01 | 0.01 | 0.02 | 0.01 | 0.01 | 0.02 |
| **ATLIVI** |    |    |    |    |     |    |   |    |    |    |    |
| Minimum    | 8.59 | 9.08 | 8.32 | 8.65 | 9.11 | 8.83 | 8.63 | 8.59 | 8.91 | 8.70 | 8.99 |
| Maximum    | 10.13 | 10.77 | 10.18 | 10.27 | 9.27 | 10.35 | 10.28 | 10.39 | 10.09 | 10.50 | 10.19 |
| Mean       | 9.38 | 9.80 | 9.42 | 9.65 | 9.20 | 9.69 | 9.60 | 9.65 | 9.61 | 9.76 | 9.69 |
| Standard Error | 0.03 | 0.03 | 0.01 | 0.01 | 0.00 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.02 |
| **ST in c°** |    |    |    |    |     |    |   |    |    |    |    |
| Minimum    | 18.48 | 19.01 | 15.63 | 17.52 | 19.60 | 19.40 | 17.37 | 18.11 | 19.78 | 19.16 | 18.67 |
| Maximum    | 28.28 | 31.99 | 26.95 | 27.09 | 20.18 | 29.34 | 28.73 | 29.98 | 27.96 | 30.55 | 27.24 |
| Mean       | 21.87 | 24.33 | 21.38 | 22.67 | 19.93 | 23.09 | 22.58 | 23.15 | 22.83 | 23.97 | 22.96 |
| Standard Error | 0.17 | 0.26 | 0.08 | 0.05 | 0.01 | 0.04 | 0.04 | 0.10 | 0.09 | 0.06 | 0.10 |
3.3. LC Classification of Thermal VIs

LC is dynamic in nature and has a dynamic effect on many parameters [76]. It is therefore noted that Ts are unique characteristics of each class of LC. Therefore, it was possible to create the LC classification much more precise when considering the Ts parameter. Figure 4 shows the trend of the Ts pattern for the LC groups; all forest types (primary, secondary and swamp forest / mangrove swamp forest) had a broad ST variety that could not be appropriately distinguished for classification on the premise of the Ts patterns. On the other hand, the water bodies and the residential area had comparable Ts ranges. This was primarily due to the reality that the residential areas were not reasonably spread in areas close or within the forest. Therefore, perhaps the influence of the low Ts of the forests had an impact on the Ts of the settlement regions. Residential areas were indeed tiny town villages with the largest regions occupied by humid or dry soil via limited sources of water, therefore, the road network and concrete structures were inaccurate. At the same time, cultivated land and degraded forests showed similar behaviors and trends. Different pixels boundary for various categories have therefore been established during the extraction process. Higher resolution images could mitigate this issue to some degree. These analyses suggested that the DN thermal band of the L8 could not defeat the function of the LC classification alone. Figure 5a and b demonstrates thermal VIs maps of TLIVI and ATLIVI respectively.

![Figure 5. Thermal VIs maps: (a) TLIVI map. (b) ATLIVI map.](image)

The same number of training samples of the various LC features were utilized for the classification and mapping procedure employing two FCC images; the first Red, NIR and ATLIVI implemented as RGB imagery and TLIVI, Red, and NIR assembled as second FCC imagery. Accuracy evaluation of LC classification results through utilizing ATLIVI as additional FCC band performed better to determine map the OA of 93.57% and K of 0.92, compared to 84.15 % and 0.81, respectively, with the FCC standard (Figure 1); also marginally better than that achieved by utilizing TLIVI as extra band to the FCC imagery 91.32 % of OA and 0.87 of k as seen in Table 3. Various patterns of bands were assessed, nevertheless the relationship of the ATLIVI provided the better reliability with respect to the accuracy of the LC classification. Table 3 provides a comparison of the accuracy of the user and producer for each LC class for the classifications using FCC with TLIVI showing a comparative improvement in accuracy for all LC categories, excluding water bodies and secondary forests categories, many of which display decrease in performance of classification. From all LC categories, water bodies’ class have been specifically oppressed towards the standard FCC imagery owing to lack of LC features spectral mixtures. The highest output of study region was conquered by primary and secondary forest as LC features with small portion of spectral mixtures present; therefore, the findings of the classification did not indicate any variations in this situation. Highest enhancement in classification accuracy for cleared land, oil palm and rubber was accomplished. Other crop areas, marshlands and residential areas have shown a slight increase in the accuracy of classification.
### Table 3. Accuracy of LC classification imagery.

| LC Categories                | Data Used        | Standard FCC | +TLIVI | +ATLIVI |
|------------------------------|------------------|--------------|--------|---------|
|                              |                  | UA%          | PA%    | UA%     | PA%     |
| Water Bodies                 |                  | 74.11        | 90.62  | 83.67   | 88.76   | 82.12   | 90.20   |
| Residential Area             |                  | 86.03        | 92.16  | 92.03   | 96.30   | 92.87   | 95.42   |
| Primary Forest               |                  | 91.06        | 92.32  | 90.13   | 90.32   | 91.35   | 91.47   |
| Secondary Forest             |                  | 76.12        | 84.06  | 99.92   | 92.74   | 92.88   | 92.74   |
| Swamp Forest / Mangrove Swamp|                  | 98.10        | 98.81  | 69.17   | 98.29   | 98.63   | 98.12   |
| Oil Palm                     |                  | 64.11        | 60.93  | 76.93   | 61.82   | 69.25   | 72.19   |
| Rubber                       |                  | 76.77        | 71.52  | 56.27   | 87.33   | 78.32   | 93.21   |
| Others Crops                 |                  | 46.92        | 51.58  | 93.62   | 82.36   | 68.02   | 78.49   |
| Marshland                    |                  | 92.87        | 76.97  | 92.18   | 86.35   | 93.61   | 87.91   |
| Scrub Area                   |                  | 90.19        | 75.23  | 89.74   | 87.36   | 86.26   | 89.71   |
| Cleared Land                 |                  | 82.33        | 76.28  | 87.68   | 79.92   | 87.95   | 88.65   |
| OA (%)                       |                  | 84.15        | 91.32  | 93.57   |         |         |         |
| K                            |                  | 0.8103       | 0.8727 | 0.9203  |         |         |         |

*Note: User Accuracy (UA), Producer Accuracy (PA), Overall Accuracy (OA), Coefficient Kappa (k)*

3.4. Statistical Assessment

The average value of the each LC classes in the research area referring to TLIVI and ATLIVI were graphical form displayed in Figures 6a and b. This indicates the variability of the various types of LC in comparison to the newest indices under examination. This provides the possibility of the two indices in the outcomes of the classification. Average, minimum, maximum, and standard variance values for each parameter are shown in Table 2. Various differences in the parameters relying on the LC classes illustrates in Figure 6. Correlation among derived Ts and other related parameters was determined in terms of $R^2$ values Table 4. The results indicate a fairly good correlation between LST and EVI2 ($R^2=0.68$) compared to NDVI, SAVI, and LAI ($R^2=0.55-0.65$). Thus, TLIVI created using NDVI and LAI reveals a lower Ts correlation of 0.82 as opposed to ATLIVI ($R^2 = 0.88$) established with an extra EVI2 parameter other than LAI and NDVI. As demonstrated in Table 4, the ATLIVI index has a significant correlation with to every variables in this investigation. The fractional vegetation cover has often delicate correlation coefficients with every one of the parameters described previous section, such as the thermal VIs parameters.

### Table 4. Correlation ($R^2$) statistics.

| LST in K | LAI  | SAVI | NDVI | FC  | TLIVI | EVI2 | ATLIVI |
|----------|------|------|------|-----|-------|------|--------|
| LST in K | 1    |      |      |     |       |      |        |
|          | LAI  | 0.554|      |     |       |      |        |
|          | SAVI | 0.592| 0.626|     |       |      |        |
|          | NDVI| 0.653| 0.574| 0.943| 1     |      |        |
|          | FC  | 0.359| 0.574| 0.543| 0.887 | 1    |        |
|          | TLIVI| 0.825| 0.508| 0.614| 0.758 | 0.652| 1      |
|          | EVI2| 0.681| 0.601| 0.997| 0.918 | 0.918| 0.577  | 1      |
|          | ATLIVI| 0.887| 0.461| 0.796| 0.681 | 0.581| 0.759  | 0.530  | 1      |

This research identified primarily surface emissivity because it's such an essential factor influencing the extraction of Ts using thermal satellite data and can be efficiently assessed by remote sensing. Throughout that analysis, the surface-specific emissivity was described in terms of NDVI and LAI, which were then determined using satellite observations. The surface emissivity selected mainly since this is a vital variable that affects the extraction of Ts from thermal satellite data and thus can be reasonably calculated by remote sensing. Throughout the analysis, the emissivity of surface-specific was measured using NDVI and LAI then determined utilizing satellite interpretations. The water bodies’ class further significantly reduce the heat flow of radiation. Findings showed significantly
better production of Ts relative to barren fields. Since urbanized small towns were small-scale in and across forest land, the temperatures values were not high. Thus, the region is not financially sensible, so there is an absence of advancement in aspects of roads or concrete buildings. Enough that, evidently, the Ts will be small, as they are described by the current surface features. From now on, Ts was high in the fallow and barren areas. Typically, there was an inverse relationship among surface albedo and LAI caused by increased absorption of the canopy and reduced reflection from the relatively lighter soil below the vegetation. Nevertheless, this has not been strongly noticed in this paper. Fractional vegetation coverage was associated fairly well with all related parameters, such as Ts. The Soil Moisture Index is an LST variable that includes minimum and maximum Ts for established NDVI values, the variety is from 0 for dry side to 1 for the humid side.

![Figure 6. Differences in the mean value for TLIVI and ATLIVI per each LC classes (a) TLIVI (b) ATLIVI.](image)

### 4. Conclusions

In conclusion, the approach utilized to obtain LST can be used to accomplish rapid LST predictions from L8 data employing fewer parameters with reasonable certainty. L8 is probably the better option for local LST investigations. In addition to the determination of the LST, thermal L8 data could further be utilized to assess temperatures inside the forest that would be challenging with conventional methods. The categorization precision of the maps is assessed in the research paper employing thermal and spectral data generated via the satellite L8 imagery. TLIVI and ATLIVI as Thermal VIs recommended as assistance to define LC more accurately by 9% than the standard satellite image of the FCC. EVI2 has a higher correlation with the LST derived than the other spectral VIs introduced in the research. Thus, ATLIVI generates using EVI2 with LAI and NDVI data provides an enhanced ST association than the TLIVI index, which includes simply LAI and NDVI. These associations will keep increasing if the values for the water bodies’ class do not fluctuate significantly in the study region. As a consequence, the above indices show a lower reaction to water body’s class. This study findings suggest that utilize of both NDVI and LAI improve the classification of Ts and LC mapping process instead of NDVI. This further improves though the implementation of EVI2 along with LAI and NDVI. Sequential improvements of this study results demonstrated that the NDVI, SAVI, LAI and EVI2 increase the classification accuracy significantly, potentially whilst analysing the issue of saturation addressed separately. The use of thermal data further improved the accuracy of the SVM classifier and highlighted the rule of the integration process of thermal data with vegetation and soil analysis parameters. The classification performance is more meaningful in the regions of PF, SF, SWF, OP, R, and OC classes owing to a higher percentage of soil content that is not present in water bodies’ class. This might indeed be suggested that the thermal indices of TLIVI and ATILVI can either differentiate between soil or cleared land and vegetation, and thus the indices of vegetation-soil interrelationships contribute to an enhancement in the reliability of classification results. Thus the research proposes the use of satellite L8 thermal and spectral data integration to improve the automated LC classification.
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References
[1]. Mucova SAR, Leal Filho W, Azeiteiro UM, Pereira MJ. Assessment of land use and land cover changes from 1979 to 2017 and biodiversity & land management approach in Quirimbas National Park, Northern Mozambique, Africa. Global ecology and conservation. 2018;16:e00447.
[2]. Iqbal MF, Khan IA. Spatiotemporal land use land cover change analysis and erosion risk mapping of Azad Jammu and Kashmir, Pakistan. The Egyptian journal of remote sensing and space science. 2014;17(2):209-29.
[3]. Nuttall M, Callaghan TV. The Arctic: environment, people, policy: Routledge; 2019.
[4]. de Bremond A, Ehrenesperger A, Providoli I, Messerli P. What role for global change research networks in enabling transformative science for global sustainability? A Global Land Programme perspective. Current Opinion in Environmental Sustainability. 2019;38:95-102.
[5]. Abburu S, Golla SB. Satellite image classification methods and techniques: A review. International journal of computer applications. 2015;119(8).
[6]. Elbeih SF. An overview of integrated remote sensing and GIS for groundwater mapping in Egypt. Ain Shams Engineering Journal. 2015;6(1):1-15.
[7]. Asokan A, Anitha J. Change detection techniques for remote sensing applications: a survey. Ain Shams Engineering Journal. 2015;6(1):1-15.
[8]. Rawat J, Kumar M. Monitoring land use/cover change using remote sensing and GIS techniques: A case study of Hawalbagh block, district Almora, Uttarakhond, India. The Egyptian Journal of Remote Sensing and Space Science. 2015;18(1):77-84.
[9]. Al-Doski J, Mansorl SB, Shafri HZM. Image classification in remote sensing. Department of Civil Engineering, Faculty of Engineering, University Putra, Malaysia. 2013.
[10]. Blaschke T, Burnett C, Pekkarinen A. Image segmentation methods for object-based analysis and classification. Remote sensing image analysis: Including the spatial domain: Springer; 2004. p. 211-36.
[11]. Dhoke SN, Sir JA, Sir R. Satellite Image Classification Methods and Techniques: A Review. International Journal of Research. 2018;5(13):380-5.
[12]. Du P, Xia J, Zhang W, Tan K, Liu Y, Liu S. Multiple classifier system for remote sensing image classification: A review. Sensors. 2012;12(4):4764-92.
[13]. Cai S, Liu D. A comparison of object-based and contextual pixel-based classifications using high and medium spatial resolution images. Remote sensing letters. 2013;4(10):998-1007.
[14]. Ma L, Li M, Ma X, Cheng L, Du P, Liu Y. A review of supervised object-based land-cover image classification. ISPRS Journal of Photogrammetry and Remote Sensing. 2017;130:277-93.
[15]. Siregar VP, Agus SB, Jhonnerie R, editors. An object-based classification of mangrove land cover using Support Vector Machine Algorithm. IOP Conference Series: Earth and Environmental Science; 2019: IOP Publishing.
[16]. Xu S, Zhao Q, Yin K, Zhang F, Liu D, Yang G. Combining random forest and support vector machines for object-based rural-land-cover classification using high spatial resolution imagery. Journal of Applied Remote Sensing. 2019;13(1):014521.
[17]. Sinha S, Sharma LK, Nathawat MS. Improved Land-use/Land-cover classification of semi-arid deciduous forest landscape using thermal remote sensing. The Egyptian Journal of Remote Sensing and Space Science. 2015;18(2):217-33.
[18]. Chen B, Huang B, Xu B. Multi-source remotely sensed data fusion for improving land cover classification. ISPRS Journal of Photogrammetry and Remote Sensing. 2017;124:27-39.
[19]. Li J, Wu W, Xue D, Gao P. Multi-Source Deep Transfer Neural Network Algorithm. Sensors. 2019;19(18):3992.
[20]. Nizalapur V. Land cover classification using multi-source data fusion of ENVISAT-ASAR and IRS p6 LISS-III Satellite data: A case study over tropical most deciduous forested regions of Karnataka, India. Int Arch Photogramm Remote Sens Spat Inf Sci. 2008:329-34.
[21]. Tuominen S, Pekkarinen A. Performance of different spectral and textural aerial photograph features in multi-source forest inventory. Remote sensing of Environment. 2005;94(2):256-68.
[22]. Zhang J. Multi-source remote sensing data fusion: status and trends. International Journal of Image and Data Fusion. 2010;1(1):5-24.

[23]. El-Zeiny AM, Elfat HA. Environmental monitoring of spatiotemporal change in land use/land cover and its impact on land surface temperature in El-Fayoum governorate, Egypt. Remote Sensing Applications: Society and Environment. 2017;8:266-77.

[24]. Hussain A, Bhalla P, Palria S. Remote sensing based analysis of the role of land use/land cover on surface temperature and temporal changes in temperature; A case study of Ajmer District, Rajasthan. The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences. 2014;40(8):1447.

[25]. Setturu B, Rajan K, Ramachandra T. Land Surface Temperature Responses to Land Use Land Cover Dynamics. Geoinfor Geostat: An Overview 1: 4. of. 2013;10:2.

[26]. Wang W, Huang D, Wang X-G, Liu Y-R, Zhou F. Estimation of soil moisture using trapezoidal relationship between remotely sensed land surface temperature and vegetation index. Hydrology and Earth System Sciences. 2011;15(5):1699-712.

[27]. Sinha S, Pandey PC, Sharma LK, Nathawat MS, Kumar P, Kanga S. Remote estimation of land surface temperature for different LULC features of a moist deciduous tropical forest region. Remote Sensing Applications in Environmental Research: Springer; 2014. p. 57-68.

[28]. Becker F, Li Z-L. Temperature-independent spectral indices in thermal infrared bands. Remote sensing of environment. 1990;32(1):17-33.

[29]. Li F, Jackson TJ, Schmugge TJ, French AN, Cosh MH, et al. Deriving land surface temperature from Landsat 5 and 7 during SMEX02/SMACEX. Remote sensing of environment. 2004;92(4):521-34.

[30]. Sobrino J, El Kharraz J, Li Z-L. Surface temperature and water vapour retrieval from MODIS data. International Journal of Remote Sensing. 2003;24(24):5161-82.

[31]. Weng Q. Advances in environmental remote sensing: sensors, algorithms, and applications: CRC Press; 2011.

[32]. Zhang H, Weng Q, Lin H, Zhang Y. Remote sensing of impervious surfaces in tropical and subtropical areas: CRC Press; 2015.

[33]. Dash P, Götttsche F-M, Olesen F-S, Fischer H. Retrieval of land surface temperature and emissivity from satellite data: physics, theoretical limitations and current methods. Journal of the Indian Society of Remote Sensing. 2001;29(1-2):23.

[34]. Dash P, Götttsche F-M, Olesen F-S, Fischer H. Land surface temperature and emissivity estimation from passive sensor data: Theory and practice-current trends. International Journal of remote sensing. 2002;23(13):2563-94.

[35]. Owen T, Carlson T, Gillies R. Remotely sensed surface parameters governing urban climate change. Int J Remote Sens. 1998;19:1663-81.

[36]. Tomlinson CJ, Chapman L, Thorne J, Baker C. Remote sensing land surface temperature for meteorology and climatology: a review. Meteorological Applications. 2011;18(3):296-306.

[37]. Mallick J, Kant Y, Bharath B. Estimation of land surface temperature over Delhi using Landsat-7 ETM+. J Ind Geophys Union. 2008;12(3):131-40.

[38]. Bayala MI, Rivas RE. Enhanced sharpening procedures on edge difference and water stress index basis over heterogeneous landscape of sub-humid region. The Egyptian Journal of Remote Sensing and Space Science. 2014;17(1):17-27.

[39]. Hachem S, Duguay C, Allard M. Comparison of MODIS-derived land surface temperatures with ground surface and air temperature measurements in continuous permafrost terrain. The Cryosphere. 2012;6(1):51-69.

[40]. Hanes JM, Schwartz MD. Modeling land surface phenology in a mixed temperate forest using MODIS measurements of leaf area index and land surface temperature. Theoretical and applied climatology. 2011;105(1-2):37-50.

[41]. Mildrexler DJ, Zhao M, Running SW. A global comparison between station air temperatures and MODIS land surface temperatures reveals the cooling role of forests. Journal of Geophysical Research: Biogeosciences. 2011;116(G3).

[42]. van Leeuwen TT, Frank AJ, Jin Y, Smyth P, Goulden ML, van der Werf GR, et al. Optimal use of land surface temperature data to detect changes in tropical forest cover. Journal of Geophysical Research: Biogeosciences. 2011;116(G2).
[43]. Yue W, Xu J, Tan W, Xu L. The relationship between land surface temperature and NDVI with remote sensing: application to Shanghai Landsat 7 ETM+ data. International Journal of Remote Sensing. 2007;28(15):3205-26.

[44]. Snyder WC, Wan Z, Zhang Y, Feng Y-Z. Classification-based emissivity for land surface temperature measurement from space. International Journal of Remote Sensing. 1998;19(14):2753-74.

[45]. Faris A, Reddy YS. Estimation of urban heat island using Landsat ETM+ imagery at Chennai city—A case study. Int J Earth Sci Eng. 2010;3(3):332-40.

[46]. Kaufmann R, Zhou L, Myeni R, Tucker C, Slayback D, Shabanov N, et al. The effect of vegetation on surface temperature: A statistical analysis of NDVI and climate data. Geophysical Research Letters. 2003;30(22).

[47]. Julien Y, Sobrino JA, Mattar C, Ruescas AB, Jimenez-Munoz JC, Soria G, et al. Temporal analysis of normalized difference vegetation index (NDVI) and land surface temperature (LST) parameters to detect changes in the Iberian land cover between 1981 and 2001. International Journal of Remote Sensing. 2011;32(7):2057-68.

[48]. Sun D, Kafatos M. Note on the NDVI-LST relationship and the use of temperature-related drought indices over North America. Geophysical Research Letters. 2007;34(24).

[49]. Jin M, Zhang D-L. Observed variations of leaf area index and its relationship with surface temperatures during warm seasons. Meteorology and Atmospheric Physics. 2002;80(1-4):117-29.

[50]. Wu C, Niu Z. Modelling light use efficiency using vegetation index and land surface temperature from MODIS in Harvard Forest. International journal of remote sensing. 2012;33(7):2261-76.

[51]. Sharma L, Sinha S. Investigations on potential relationship between biomass and surface temperature using thermal remote sensing over tropical deciduous forests. Research & Reviews: Journal of Space Science & Technology. 2019;2(3):13-8.

[52]. Weng Q. Thermal infrared remote sensing for urban climate and environmental studies: Methods, applications, and trends. ISPRS Journal of Photogrammetry and Remote Sensing. 2009;64(4):335-44.

[53]. Radoux J, Bassine C, Lennert M, Grippa T, Beaumont B, Van de Vyvere L, et al. Multiscale image fusion for submetric land cover mapping. 2019.

[54]. Sun D, Kafatos M. Note on the NDVI-LST relationship and the use of temperature-related drought indices over North America. Geophysical Research Letters. 2007;34(24).

[55]. Radoux J, Bassine C, Lennert M, Grippa T, Beaumont B, Van de Vyvere L, et al. Multiscale image fusion for submetric land cover mapping. 2019.

[56]. Wang Z, Wang P, Li X. Using MODIS land surface temperature and normalized difference vegetation index products for monitoring drought in the southern Great Plains, USA. International journal of remote sensing. 2004;25(1):61-72.

[57]. Al-Doski J, Mansor SB, Shafri HZM. NDVI differencing and post-classification to detect vegetation changes in Halabja City, Iraq. IOSR Journal of Applied Geology and Geophysics (IOSR-JAGG). 2013;1(2):01-10.

[58]. Hossain M, Bujang J, Zakaria M, Hashim M. Application of Landsat images to seagrass areal cover change analysis for Lawas, Terengganu and Kelantan of Malaysia. Continental Shelf Research. 2015;110:124-48.

[59]. Pour AB, Hashim M. Application of Landsat-8 and ALOS-2 data for structural and landslide hazard mapping in Kelantan, Malaysia. Natural Hazards and Earth System Sciences. 2017;17(7):1285.

[60]. Satyanarayana B, Mohamad KA, Idris IF, Husain M-L, Dahdouh-Guebas F. Assessment of mangrove vegetation based on remote sensing and ground-truth measurements at Tumpat, Kelantan Delta, East Coast of Peninsular Malaysia. International Journal of Remote Sensing. 2011;32(6):1635-50.

[61]. Bernstein LS, Adler-Golden SM, Sundberg RL, Levine RY, Perkins TC, Berk A, et al., editors. Validation of the QUick Atmospheric Correction (QUAC) algorithm for VNIR-SWIR multi-and hyperspectral imagery. Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspctral Imagery XI; 2005: International Society for Optics and Photonics.

[62]. Bernstein LS, Adler-Golden SM, Sundberg RL, Levine RY, Perkins TC, Berk A, et al., editors. Status of atmospheric correction using a MODTRAN4-based algorithm. Algorithms for multispectral, hyperspectral, and ultraspctral imagery VI; 2000: International Society for Optics and Photonics.

[63]. López-Serrano PM, Corral-Rivas JJ, Díaz-Varela RA, Álvarez-González JG, López-Sánchez CAJRS. Evaluation of radiometric and atmospheric correction algorithms for aboveground forest biomass estimation using Landsat 5 TM data. 2016;8(5):369.

[64]. Coppen P, Jonckheere I, Nackaerts K, Muys B, Lambin EJJIors. Review ArticleDigital change detection methods in ecosystem monitoring: a review. 2004;25(9):1565-96.

[65]. Mas J-FJIIors. Monitoring land-cover changes: a comparison of change detection techniques. 1999;20(1):139-52.
[64]. Huang C, Goward SN, Schleeweis K, Thomas N, Masek JG, Zhu ZJRsoE. Dynamics of national forests assessed using the Landsat record: Case studies in eastern United States. 2009;113(7):1430-42.

[65]. Jia K, Wei X, Gu X, Yao Y, Xie X, Li BJGI. Land cover classification using Landsat 8 operational land imager data in Beijing, China. 2014;29(8):941-51.

[66]. Kavzoglu T, Colkesen IJIjors. An assessment of the effectiveness of a rotation forest ensemble for land-use and land-cover mapping. 2013;34(12):4224-41.

[67]. Sinha S, Sharma L, Nathawat MS. Retrieving tiger habitats: Conserving wildlife geospatially. Applied Remote Sensing Journal. 2011;2(1):1-5.

[68]. Sinha S, Sharma L, Pandey P, Nathawat M, Kanga S. Impact of human intrusion on tiger habitat and conservation using integrated geospatial techniques. Int J Earth Sci Eng. 2011;4(3):39-45.

[69]. Jiang Z, Huete AR, Didan K, Miura T. Development of a two-band enhanced vegetation index without a blue band. Remote sensing of Environment. 2008;112(10):3833-45.

[70]. Liu HQ, Huete A. A feedback based modification of the NDVI to minimize canopy background and atmospheric noise. IEEE transactions on geoscience and remote sensing. 1995;33(2):457-65.

[71]. Forkuor G, Dimobe K, Serme I, Tondoh JE. Landsat-8 vs. Sentinel-2: examining the added value of sentinel-2’s red-edge bands to land-use and land-cover mapping in Burkina Faso. GIScience & remote sensing. 2018;55(3):331-54.

[72]. He J, Harris J, Sawada M, Behnia P. A comparison of classification algorithms using Landsat-7 and Landsat-8 data for mapping lithology in Canada’s Arctic. International Journal of Remote Sensing. 2015;36(8):2252-76.

[73]. Stathopoulou M, Cartalis C. Daytime urban heat islands from Landsat ETM+ and Corine land cover data: An application to major cities in Greece. Solar Energy. 2007;81(3):358-68.

[74]. Fan L, Liu S, Bernhofer C, Liu H, Berger F. Regional land surface energy fluxes by satellite remote sensing in the Upper Xilin River Watershed (Inner Mongolia, China). Theoretical and Applied Climatology. 2007;88(3-4):231-45.

[75]. Opoku-Duah S, Donoghue D, Burt T. Intercomparison of evapotranspiration over the Savannah Volta Basin in West Africa using remote sensing data. Sensors. 2008;8(4):2736-61.

[76]. Kidane M, Tolessa T, Bezie A, Kessete N, Endrias M. Evaluating the impacts of climate and land use/land cover (LU/LC) dynamics on the Hydrological Responses of the Upper Blue Nile in the Central Highlands of Ethiopia. Spatial Information Research. 2019;27(2):151-67.