Spatial assessment of land surface temperature and land use/land cover in Langkawi Island

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Abstract. This study investigates the relationship between Land Surface Temperature and Land Use/Land Cover in Langkawi Island by using Normalized Difference Vegetation Index (NDVI), Normalized Difference Build-Up Index (NDBI) and Modified Normalized Difference Water Index (MNDWI) qualitatively by using Landsat 7 ETM+ and Landsat 8 (OLI/TIRS) over the period 2002 and 2015. Pixel-based classifiers Maximum Likelihood (MLC) and Support Vector Machine (SVM), has been performed to prepare the Land Use/ Land Cover map (LU/LC) and the result shows that Support Vector Machine (SVM) achieved maximum accuracy with 90% and 90.46% compared to Maximum Likelihood (MLC) classifier with 86.62% and 86.98% respectively. The result revealed that as the impervious surface (built-up/roads) increases, the surface temperature of the area increased. However, land surface temperature decreased in the vegetated areas. Based from the linear regression between LST and NDVI, NDBI and MNDWI, these indices can be used as an indicator to monitor the impact of Land Use/Land Cover on Land Surface Temperature.

1 Introduction

Rapid urbanization has caused significant changes in Land Use/Land Cover [1, 2], and this process especially affect urban heat island [3-5]. As cities grow, changes occur in the physical landscape, roads, building and other infrastructures thus replacing open land and vegetation [6-8]. Previous researches has shown that integration of remote sensing and geographic information system (GIS) can be used as a tool to estimate the impact of land surface temperature with the rapid urban growth development [9].

Human activity is massively altering the Earth’s vegetative cover where it directly contributes to climate change through a variety of processes. These include the growth or degradation of surface vegetation and changes in the land surface, which affect regional and global climate by producing changes in the surface energy budgets. This concern leads to an increasing research effort to understand the complex interactions between both urban and rural land surfaces and their atmospheric boundary layers. It also leads to efforts towards developing techniques for monitoring spatial and temporal land surface climate processes [10, 11].

Land Surface temperature can be obtained from direct ground measurement [12]. With the availability of satellite remote sensing, thermal band retrieved from the satellite can be used to estimate surface temperature. Several researches have been carried out to estimate land surface temperature by using split-window algorithms in Landsat 8 using band 10 and 11 [13]. The work demonstrates that linear regression method (LST vs NDVI) has negative correlation since the district consists of more vegetative cover in hilly regions. Raja et al. [14] investigates the spatial analysis of land surface temperature in Dhaka area by using the linear correlation between LST and NDVI and LST and NDBI which indicates the positives relationship with NDBI due to the urban growth. Yusuf
et al. [6] assessed the spatio-temporal of Urban Heat Island effects in Kuala Lumpur metropolitan city by using Landsat Images. This work demonstrates the use of mono-window algorithm using band 6 ETM+. The results revealed that remote sensing satellite image can be used to estimate the LU/LC changes and urban heat island around Kuala Lumpur metropolitan city. Chen et al. [15] stated that appropriated indices such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Build-Up Index (NDBI) and Modified Normalized Difference Water Index (MNDWI) can be used to classify land use/land cover.

The current study aims to estimate the relationship between land surface temperature and LU/LC in Langkawi Island, Malaysia. Therefore, the objectives of this study are (1) to estimate land surface temperature for the study area during years 2002 to 2015; (2) to generate LU/LC map using pixel based approach and finally (3) to analysis the relationship between LST and LU/LC using linear regression between LST and NDVI, NDBI and MNDWI.

2 Study area and data sets

2.1 Study area
The study area is in Langkawi Island, Kedah, Malaysia. Langkawi is located between longitude 99° 51´ 03´´E and latitude 06° 18´ 19´´N. The study area is characterized by a variety of agricultural fields, residential areas, and water body. Langkawi and its 99 islands were declared as a Geopark by the United Nations Educational, Scientific and Cultural Organization (UNESCO) in 2007.

Figure 1. Study area showing the site location on Google Map.

2.2 Data used
In this study LANDSAT 8 (OLI) and Landsat ETM+ imagery was utilized. The multispectral Landsat 8 image was acquired on January 13, 2015, local time overpasses was GMT 03:34:01, while Landsat 7 ETM+ was acquired on January 17, 2002, local time overpasses was GMT 03:22:46. Both data were downloaded from Earth Resources Observation and Science Center of the US Geological Survey, where the data were geometrically and radiometrically corrected. The Landsat 8 image consists of 11 spectral bands, 30m except 15m for panchromatic band and 100m for TIRS band. The bands are Coastal (0.43–0.45 µm), Blue (0.00–0.51 µm), Green (0.53–0.59 µm), Red (0.64–0.67 µm), Near-IR (0.85–0.88 µm), SWIR 1 (1.57–1.65 µm), SWIR 2 (2.11–2.29 µm), Panchromatic (0.50 – 0.68 µm), Cirrus (1.36 – 1.38 µm). TIRS 1 (10.6 – 11.19 µm) and TIRS 2 (11.5 – 12.51 µm) both are at 100m
but have been resample to 30m to match with multispectral data. Landsat 7 ETM+ consists of 8 spectral bands, 30m except 15m for panchromatic band and 60m for TIR band. The bands are Blue (0.45 – 0.52 µm), Green (0.52 – 0.60 µm), Red (0.63 – 0.69 µm), Near-IR (0.77 – 0.90µm), SWIR 1 (1.55 – 1.75µm), and SWIR 2 (2.09 – 2.35µm), Panchromatic (0.52 – 0.90 µm). TIR band (10.40 – 12.50 µm) is 60m but has been resampled to 30m to match with multispectral data.

3 Methodology

Figure 2 and 3 illustrate the data processing workflow which starts with preprocessing of Landsat 7 ETM+ and Landsat 8 respectively. This is followed by image preprocessing, image pan-sharpening, image classification, accuracy assessment for LU/LC, employing indices, land surface temperature estimation, linear correlation and finally result and discussion.

Figure 2. Data processing workflow for Landsat 7 ETM+.
3.1 Land use / land cover classification

First, the Landsat 7 ETM+ and Landsat 8 data were corrected for radiometric and atmospheric correction (Internal Average Reflectance) in ENVI 5.1. After that both Landsat imagery with spatial resolution of 30m were pan-sharpened using Gram-Schmidt method with the 15m panchromatic band to improve the spatial resolution for better LU/LC classification. The study area was then subset from the preprocessed datasets. By using pixel-based classification methods such as Maximum Likelihood and Support Vector Machine classifiers, the LU/LC map were produced for the year 2002 and 2015. Marino et al. [16] stated that pixel-based classification methods extract information from images based on pixels which rely on prior knowledge of the diverse land classes in the image, which can be known through field surveys, laboratory measurements, or from any existing source of information. The knowledge of these features was used to select training pixels for classification into seven different
land cover classes which are forest, built-up/roads, water, grassland, vegetation, cultivated land, and bare land.

3.2 Computation of land surface temperature from landsat 7 ETM+

The atmospheric correction of thermal band 61 has been performed using ENVI 5.1 Software. The purpose of atmospheric correction is to remove the atmospheric contributions from thermal infrared data.

i) Conversion of Digital Number to Spectral Radiance: According to Amiri et al. [17] and Coll et al. [18], the method has been taken from USGS Landsat User handbook:

\[ L_\lambda = \frac{L_{\text{MAX} \lambda} - L_{\text{MIN} \lambda}}{Q_{\text{CALMAX} \lambda} - Q_{\text{CALMIN} \lambda}} \times (Q_{\text{CAL}} - Q_{\text{CALMIN}}) + L_{\text{MIN} \lambda} \] (1)

Where \( L_\lambda \) is cell value as radiance in W/(m\(^2\)*sr*μm), \( L_{\text{MAX} \lambda} \) is spectral radiance that is scaled to \( Q_{\text{CALMAX} \lambda} \) in W/(m\(^2\)*sr*μm) and \( L_{\text{MIN} \lambda} \) is Spectral radiance that is scaled to \( Q_{\text{CALMIN} \lambda} \) in W/(m\(^2\)*sr*μm). \( Q_{\text{CALMAX}} \) is a maximum quantized calibrated pixel value (corresponding to \( L_{\text{MAX} \lambda} \)) in DN: 255 and \( Q_{\text{CALMIN}} \) is a minimum quantized calibrated pixel value (corresponding to \( L_{\text{MIN} \lambda} \)) in DN: 1.

| Table 1. LMAX\(_\lambda\) and LMIN\(_\lambda\) of Band 61 (Landsat 7 ETM+). |
|------------------|----------|
| LMAX\(_\lambda\)  | 17.040   |
| LMIN\(_\lambda\)  | 0.000    |

ii) Conversion of Spectral Radiance (\( L_\lambda \)) to Kelvin with emissivity value:

\[ T_B = \frac{K_2}{\ln\left(\frac{L_\lambda}{\varepsilon + 1}\right)} \] (2)

Where \( T_B \) is value at satellite brightness temperature (K), \( L_\lambda \) is a cell value as radiance in W/ (m\(^2\)*sr*μm). \( \varepsilon \) is emissivity value (typically 0.95) for Landsat TM and ETM+ and \( K_1 \) and \( K_2 \) are band specific thermal conversion constant from the metadata of band 61(low gain).

| Table 2. K\(_1\) and K\(_2\) Constant value of Band 61 (Landsat 7 ETM+). |
|------------------|----------|
| Thermal Constant | Band 61   |
| \( K_1 \)        | 666.09   |
| \( K_2 \)        | 1282.71  |

iii) Conversion of Kelvin to Degree Celsius:

\[ T_C = T_B - 273.15 \] (3)

Where \( T_B \) is value at satellite brightness temperature (K) and \( T_C \) is temperature in Degree Celsius.

3.3 Computation of Land Surface Temperature from Landsat 8
The atmospheric correction of thermal band 10 has been performed using ENVI 5.1 Software in order to remove the atmospheric contributions from thermal infrared data.

i) Top of Atmospheric Spectral Radiance:

\[ L_\lambda = ML \times Q_{cal} + A_L \]  

Where \( L_\lambda \) is top of Atmospheric Radiance in watts/ \((m^2 \cdot sr \cdot \mu m)\), ML is band specific multiplicative rescaling factor (band 10), \( Q_{cal} \) is band 10 image. \( A_L \) is band specific additive rescaling factor band 10.

Table 3. \( Q_{cal} \) and \( A_L \) of Band 10 (Landsat 8).

| \( Q_{cal} \)  | \( A_L \) |
|-------------|-------|
| 0.00033420  | 0.1   |

ii) Normalized Difference Vegetation Index (NDVI) and Fractional Vegetation Cover (FVC): In this study NDVI has been used as an index to estimate vegetation cover and Fractional Vegetation cover has been calculated to calculate the amount of vegetation distribution on the flat background.

\[ NDVI = \frac{NIR - RED}{NIR + RED} \]  

\[ f_v = \frac{NDVI_{(x,y)} - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \]  

iii) Surface Emissivity

Sobrino et al. [19] stated that surface emissivity can be obtained from the surface mixture of bare soil and vegetation as in the equation 7 as below:

\[ \varepsilon = \varepsilon_s \cdot f_v + \varepsilon_v (1 - f_v) \]  

Where \( f_v \) is fractional vegetation cover and emissivity of vegetation (\( \varepsilon_v \)) is 0.985 and emissivity of soil (\( \varepsilon_s \)) is 0.96.

iv) Conversion of Spectral Radiance (\( L_\lambda \)) to Kelvin with emissivity value: Similar to equation (2), \( T_B \) is value at satellite brightness temperature (K), \( L_\lambda \) is a cell value as radiance in W/ \((m^2 \cdot sr \cdot \mu m)\). \( \varepsilon \) is emissivity value (typically 0.945) and \( K1 \) and \( K2 \) are band specific thermal conversion constant from the metadata of band 10.

Table 4. \( K_1 \) and \( K_2 \) Constant value of Band 10 (Landsat 8).

| Thermal Constant | Band 10 |
|-----------------|---------|
| \( K_1 \)       | 774.8853|
| \( K_2 \)       | 1321.0789|
v) Rescale of Land Surface Temperature: In order to make a comparison of the data at different times, the parameter of LST were used to rescale the data using minimum and maximum values as in equation 8, 9 [20]:

\[
LST\ 2002 = \frac{LST - LST_{\text{min}}}{LST_{\text{max}} - LST_{\text{min}}}
\]

\[
LST\ 2015 = \frac{LST - LST_{\text{min}}}{LST_{\text{max}} - LST_{\text{min}}}
\]

3.4 Indices
In order to find the relationship between land surface temperature, the NDVI, NDBI and MNDWI has been employed on Landsat 7 ETM+ and Landsat 8 based on the equation (5). The normalized difference vegetation index (NDVI) (Rouse et al., 1974) has been extensively used to monitor and identify vegetation and land cover changes. NDVI is expressed by the following formula based on Near-infrared and Red bands.

The Normalized Difference Build-Up Index has been developed by Zha et al. (2003) in order to identify the built-up areas. NDBI is expressed by the following formula based on Mid-infrared and Near-infrared bands:

\[
NDBI = \frac{MID - NIR}{MID + NIR}
\]

Xu [21] developed the Modified Normalized Difference Water Index (MNDWI) in order to identify the water purity degree and the matter content of water due its dynamic range. MNDWI is expressed by the following formula based on Green and Mid-infrared bands:

\[
MNDWI = \frac{GREEN - MIR}{GREEN + MIR}
\]

3.5 Accuracy assessment
Finally accuracy assessment was performed to evaluate the quality of classification output [22]. Error matrix [23, 24] based on assessment of the overall accuracy, producer’s accuracy, user’s accuracy, and kappa coefficient [25, 26] was utilized to evaluate the pixel-based classification output for LU/LC classification.

4 Results and discussion
4.1 Land surface temperature emissivity for Landsat 7 ETM+ and Landsat 8
Figure 4 shows the Land Surface Temperature Emissivity extracted from Landsat 7 ETM+ of the year 2002 and Landsat 8 of the year 2015. From the result, it can be concluded that the minimum temperature of the year 2002 was 14 degree Celsius and maximum temperature was 32 degree Celsius. However, land surface temperature emissivity of the year 2015 shown a minimum temperature of 15 degree Celsius and maximum temperature of 34 degree Celsius.
4.2 Pixel-based classification results for land use / land cover classification 2002
The Landsat 7 ETM+ has been classified using Maximum Likelihood (MLC) and Support Vector Machine (SVM) classifier. From the result, it can be observed that water and vegetation classes have been mixed with forest class. The SVM classifier (90%) with kappa coefficient 0.735 provided the highest result, followed by the MLC (86.62%) with kappa coefficient 0.746.
Table 5. Overall classification accuracy of Landsat 7 ETM+.

| Landsat 7 ETM+: Maximum Likelihood | Overall Accuracy = (7914/9136) 86.6243%; Kappa Coefficient = 0.7464 |
|------------------------------------|-------------------------------------------------------------------|
| Forest                             | Water | Built-Up/Road | Grassland | Vegetation | Cultivated Land | Bare Land |
| 5935                               | 41    | 4             | 166       | 0          | 0               |
| 28                                 | 156   | 20            | 0         | 9          | 0               |
| Built-Up/Road                      | 6     | 7             | 612       | 5          | 15              | 1          |
| Grassland                          | 2     | 4             | 79        | 19         | 100             | 1          |
| Vegetation                         | 83    | 5             | 60        | 22         | 719             | 9          |
| Cultivated Land                    | 0     | 0             | 14        | 0          | 402             | 301        |
| Bare Land                          | 0     | 0             | 14        | 1          | 49              | 56         |
| Total                              | 6054  | 172           | 840       | 51         | 1460            | 368        |

| Landsat 7 ETM+: Support Vector Machine | Overall Accuracy = (7220/8028) 90 %; Kappa Coefficient = 0.7335 |
|----------------------------------------|-------------------------------------------------------------------|
| Forest                                 | Water | Built-Up/Road | Grassland | Vegetation | Cultivated Land | Bare Land |
| 6031                                  | 3     | 20            | 0         | 458        | 0               | 0          |
| Water                                  | 0     | 156           | 0         | 0          | 0               | 0          |
| Built-Up/Road                         | 0     | 2             | 397       | 18         | 0               | 0          |
| Grassland                              | 0     | 0             | 2         | 4          | 0               | 0          |
| Vegetation                            | 23    | 0             | 23        | 33         | 237             | 0          |
| Cultivated Land                       | 0     | 0             | 35        | 6          | 75              | 359        |
| Bare Land                             | 0     | 0             | 23        | 2          | 0               | 36         |
| Total                                  | 6054  | 161           | 500       | 63         | 770             | 359        |

4.3 Pixel-based classification results for land use / land cover classification 2015

The Landsat 8 has been classified using Maximum Likelihood (MLC) and Support Vector Machine (SVM) classifier. From the observation, it is obvious that vegetation class has been mixed up with forest class. The SVM classifier (90.4574 %) with kappa coefficient 0.8068 achieved a better result compared to MLC (86.9779 %) with kappa coefficient 0.8045.
Table 6. Overall classification accuracy of Landsat 8.

| Landsat 8: Maximum Likelihood | Overall Accuracy = (4956/5698) 86.9779 ; Kappa Coefficient = 0.8045 |
|--------------------------------|---------------------------------------------------------------------|
| Forest                        | 2713                                                                |
| Water                         | 0                                                                  |
| Built-Up/Road                 | 0                                                                  |
| Grassland                     | 3                                                                  |
| Vegetation                    | 350                                                                |
| Cultivated Land               | 0                                                                  |
| Bare Land                     | 0                                                                  |
| Cloud/Shadow                  | 35                                                                  |
| Total                         | 2815                                                               |

| Landsat 8: Support Vector Machine | Overall Accuracy = (8247/9117) 90.4574 %; Kappa Coefficient = 0.8068 |
|-----------------------------------|-----------------------------------------------------------------------|
| Forest                            | 6007                                                                 |
| Water                             | 1                                                                  |
| Built-Up/Road                     | 25                                                                  |
| Grassland                         | 2                                                                  |
| Vegetation                        | 560                                                                |
| Cultivated Land                   | 0                                                                  |
| Bare Land                         | 0                                                                  |
| Cloud/Shadow                      | 2                                                                  |
| Total                             | 6054                                                               |

4.3.1 Area changes of LU/LC between year 2002 and year 2015

Table 7 shows a statistical analysis of LU/LC area changes from year 2002 and 2015. From the observation, it can be concluded that there was drastic change in built-up/roads, forest. Built-Up/Roads has been increased by percentage from 4.746% to 8.297% and forest has been decreased from 80.927% to 78.04% respectively. Total vegetation and cultivated land from the year 2002 with 11.421% has been decreased by 9.527% corresponding to the loss of 61.782 km$^2$ to 51.537 km$^2$ respectively. The rapid changes have been detected due to tourism factor and the conversion of vegetated and cultivated land to water due to soil digging activities.

**Table 7. Area changes of LU/LC in year 2002 and 2015.**

| Types               | Year 2002 | Year 2015 |
|---------------------|-----------|-----------|
|                     | Total Area (km$^2$) | Percentage (%) | Total Area (km$^2$) | Percentage (%) |
| Forest              | 198,036   | 80.92     | Forest              | 182,472   | 78.04     |
| Water               | 11,025    | 2.03      | Water               | 11,262    | 2.08      |
| Built-Up/Road       | 25,674    | 4.74      | Built-Up/Road       | 44,884    | 8.29      |
| Grassland           | 1,067     | 0.19      | Grassland           | 6,338     | 1.17      |
| Vegetation          | 37,916    | 7.09      | Vegetation          | 46,935    | 8.67      |
| Cultivated Land     | 23,865    | 4.412     | Cultivated Land     | 4,601     | 0.85      |
| Bare Land           | 3,628     | 0.67      | Bare Land           | 1,357     | 0.25      |
4.4 Indices result of the years 2002 and 2015

From the observation of the year 2002, the minimum and maximum values of NDVI were -0.694147 and 0.450689, respectively. For NDBI, the minimum value was -0.489924 and maximum value was 0.468670. For MNDWI, the minimum and maximum values of the year 2002 were -0.460173 and 0.745609 respectively. In contrast, the observations of the year 2015 shown that, the minimum and maximum values of NDVI were -0.948714 and 0.582615, respectively. For NDBI, the minimum value was -1.00 and maximum value was 0.684669. For MNDWI, the minimum and maximum values of the year 2015 were -0.635346 and 1.000 respectively.

Figure 7. Indices outputs of Landsat 7 ETM + imagery by applying: (a) Normalized Difference Vegetation Index, (b) Normalized Difference Build-Up Index and (c) Modified Normalized Difference Water Index.

Figure 8. Indices outputs of Landsat 8 imagery by applying: (a) Normalized Difference Vegetation Index, (b) Normalized Difference Build-Up Index and (c) Modified Normalized Difference Water Index.
4.5 The relationship between Land Surface Temperature (LST) and land use/land cover 2002

4.5.1 Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI)

Table 8 shows a summary of the linear regression between Land Surface Temperature 2002 with Normalized Difference Vegetation Index (NDVI). 20 random samplings have been done in order to see the relationship. From the observation, it was obvious that the coefficients value between LST vs NDVI was good in forest with $R^2 = 0.548$. However, the coefficient value for water, built-up / roads, grassland, cultivated land, vegetation and bare land were small due to presence of water on the which lead to the negative values. The correlation between LST and NDVI of the year 2002 was $R^2 = 0.1524$.

| LU/LC          | Equations                        | $R^2$  |
|----------------|----------------------------------|--------|
| Forest         | $y = 16.353 \times \text{NDVI} + 15.459$ | 0.548  |
| Water          | $y = -3.1366 \times \text{NDVI} + 19.136$ | 0.0835 |
| Built-Up/Roads | $y = 0.9858 \times \text{NDVI} + 25.251$ | 0.0018 |
| Grassland      | $y = 3.0676 \times \text{NDVI} + 23.214$ | 0.0161 |
| Cultivated Land| $y = 9.9899 \times \text{NDVI} + 25.492$ | 0.101  |
| Vegetation     | $y = 11.076 \times \text{NDVI} + 18.778$ | 0.1021 |
| Bare Land      | $y = -5.2356 \times \text{NDVI} + 22.999$ | 0.0582 |

4.5.2 Land Surface Temperature (LST) and Normalized Difference Build-Up Index (NDBI)

Twenty random samplings have been performed on LST and NDBI data of the year 2002. From the observation, it is obvious that the correlation between LST and NDBI were significantly positive with $R^2 = 0.8137$ as can be seen from the Figure 9 below:

![Figure 9. LST vs NDBI](image-url)
4.5.3 Land Surface Temperature (LST) and Modified Normalized Difference Water Index (MNDWI)

Figure 10 shows that LST vs MNDWI has significantly negative correlation from 20 random samplings that has been made on the LST and MNDWI data of the year 2002. From the observation, it shown that LST and MNDWI have negative correlation implied that pure water decrease the surface temperature and polluted water increase the surface temperature.

![LST vs MNDWI](image)

**Figure 10. LST vs MNDWI.**

4.6 The relationship between Land Surface Temperature (LST) and Land Use/Land Cover 2015

4.6.1 Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI)

Table 9 shows a summary of the linear regression between Land Surface Temperature 2015 with Normalized Difference Vegetation Index (NDVI). 20 random samplings have been done in order to see the relationship. From the observation, it was obvious that the coefficients value between LST vs NDVI was good in forest, grassland and vegetation with $R^2 = 0.548$, $R^2 = 0.2655$ and $R^2 = 0.3406$ respectively. However, the coefficient value for water, built-up/roads, cultivated land, and bare land were small. The correlation between LST and NDVI of the year 2015 was $R^2 = 0.055$.

| LU/LC          | Equations                    | $R^2$  |
|----------------|------------------------------|--------|
| Forest         | $y = 6.0237 \times NDVI + 23.741$ | $R^2 = 0.4395$ |
| Water          | $y = -0.578 \times NDVI + 26.097$ | $R^2 = 0.0646$ |
| Built-Up/Road  | $y = -3.3429 \times NDVI + 29.318$ | $R^2 = 0.1151$ |
| Grassland      | $y = 6.4735 \times NDVI + 27.334$ | $R^2 = 0.2655$ |
| Cultivated Land| $y = 2.9025 \times NDVI + 28.519$ | $R^2 = 0.1092$ |
| Vegetation     | $y = 3.2486 \times NDVI + 25.42$ | $R^2 = 0.3406$ |
| Bare Land      | $y = -5.5912 \times NDVI + 30.289$ | $R^2 = 0.0684$ |

**LST vs NDVI**

$y = -1.0973 \times 28.195$

$R^2 = 0.055$

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4.6.2 Land Surface Temperature (LST) and Normalized Difference Build-Up Index (NDBI)

Figure 11 shows the significant positive correlation between LST and NDBI of the year 2015 with 20 random samplings of each class. Built-Up/ Roads indicates positives value while others features indicates negatives values. However, bare land/cultivated land (no Vegetation) also resulting in positive values in NDBI imagery. From the observation, LST would increase with the density of urban built-up, bare land and cultivated land (no vegetation) where the $R^2$ is 0.8419.

4.6.3 Land Surface Temperature (LST) and Modified Normalized Difference Water Index (MNDWI)

Figure 12 shows that LST vs MNDWI has significantly negative correlation from 20 random samplings that has been made on the LST and MNDWI data of the year 2015. From the observation, this index enhanced the water features in a MNDWI image. Water will indicates positives values while other features such as built-up area/roads, forest, vegetation, bare land, cultivated land and will have negative value. The correlation between LST and MNDWI is negatives with $R^2 = 0.1584$. 
4.7 Comparison of LST datasets (2002 and 2015)
Figure 13 shows the comparison of the dataset between the year 2002 and 2015. The rescale factor ranges between 0 and 1. From the observation, it was obvious that the temperature increase from 2002 to 2015 from all classes. The main reason that may support this result is due to the rapid urbanization from the tourism sector in Langkawi Island and the conversion of the cultivated land and vegetation area to water due to soil digging activities and residential areas.

![Comparison LST 2002 & LST 2015](image)

Figure 13. Comparison dataset of years 2002 and 2015.

5 Conclusion

In this study, pixel-based classifiers were used to classify seven land cover types: forest, built-up/roads, water, grassland, vegetation, cultivated land, and bare land. The analysis indicates that Support Vector Machine (SVM) is more efficient in mapping land cover features compared to Maximum Likelihood classifier. NDVI has been used widely as an indicator of vegetation abundance to estimate LST in studies of urban heat islands. However, for other LU/LC classes, it is not effective index to correlate with LST. By employing NDBI and MNDWI positive relationship were found on NDBI and LST. In addition, this process indicated that, land surface temperature increases in correlation to significant increase of impervious surface on the area. While MNDWI shows a negative correlation due to unpolluted water that significantly help to reduce the temperature. In conclusion, the correlations between land surface temperature with NDVI, NDBI and MNDWI can be used as an indicator in monitoring urban thermal environment.

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