ASSESSMENT OF LAND SURFACE TEMPERATURE IN DRY AND WET SEASON USING SENTINEL IMAGERIES IN CAMERON HIGHLANDS, MALAYSIA

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ABSTRACT: Land Surface Temperature (LST) is a fundamental aspect of climate and ecosystems from local to global scales. LST and its spatial variations are the main parameters of highland climate and human-environment interactions study. Agricultural activities in high topographic elevation influence climate change, where without proper land cover (LC) planning of agriculture activities have resulted in various environmental issues such as soil erosion and muddy flood, water quality, and rising LST. Due to weather suitability, Cameron Highlands has extensive agriculture activities which resulted in rising LST variation. Thus, this study was carried out to investigate the relationship between LST and Land Cover (LC) in Cameron Highlands based on Normalized Difference Vegetation Index (NDVI), Normalized Difference Build-Up Index (NDBI), and Modified Normalized Difference Water Index (MNDWI) qualitatively from Sentinel Imageries over the dry and wet monsoon seasons in Malaysia. The results of the study show that the accuracy of LC and LST output is better than 90%. As the impervious surface increases, the surface temperature of the area increase, whereas decreased in the vegetated areas. The quantitative relationship between LST and NDVI, NDBI, and MNDWI are then analyzed using a linear regression model to find the impact of LC on LST. It is found that the satellite-derived emissivity values are in the acceptable range with the vegetation indices (VI) and fractional vegetation cover is effective in deriving surface emissivity. LST is also highly dependent on seasonal radiation conditions, especially during the monsoon season and its effects, resulting in an excessive estimation of cooling values. This study is crucial for land planning and environmental care on the climate impacts of land-use change for appropriate policy measures for sustainable agriculture management in Cameron Highlands.

1. Introduction

Land Surface Temperature (LST) is an essential part of the climate system, whereby the interaction between the land surface and the atmosphere involves multiple processes and feedback, all of which may vary simultaneously. It is frequently stressed that the changes of vegetation type can modify the characteristics of the regional atmospheric circulation and large-scale external moisture fluxes (Darren, et.al., 2020). In the past years, climate change has attracted increasing global attention, particularly amongst governments and scientists. Several studies have applied the use of LST from Sentinel-3 Sea and Land Surface Temperature Radiometer (SLSTR). (Sobrino and Irakulis, 2020) shows the retrieval of land surface temperature (LST) from satellite data allows the estimation of surface urban heat island (SUHI) as the difference between the LST obtained in the urban area and the LST of its surroundings, while (Yanga, et al., 2020) investigated and validated algorithm for six globally distributed sites estimating LST from Sentinel -3.

This paper investigates the relationship between LST and Land Cover (LC) in Cameron Highlands, and analyze the LST correlation based on Normalized Difference Vegetation Index (NDVI), Normalized Difference Build-Up Index (NDBI), and Modified Normalized Difference Water Index (MNDWI) qualitatively derived from Sentinel Imageries over the South West Monsoon (SWM) and North East Monsoon (NEM). The SWM is a drier period for the whole country. The results of this study can be used to monitor and predict the drought phenomenon in Malaysia.

LST values were much higher at the end of the dry season period, as discovered by a recent study (Nguyen, et al., 2019). Some studies have implied NDVI as an indicator in the study of the relationship between LST and vegetation using remote sensing and ground-based observation data (Mallick, et.al., 2008), (Subhanil, et al., 2018). Due to highland characteristics, the study area has an average daily temperature of 15.6-19.9°C in year 2021 (Nasional, 2021). Hence, agricultural cultivation becomes the main human activity in Cameron Highlands (Aminuddin, et al., 2005). Previous studies using satellite observations indicate that tropical deforestation results in warmer and drier conditions at the local scale (Darren, et al., 2020). LST is sensitive to vegetation and soil moisture, so it can be used to detect land cover changes, e.g. tendencies towards urbanization and desertification

(Mallick, et al., 2008). Extensive agricultural activities have possibly contributed to the warming and increased LST in Cameron Highlands. Significant studies about water quality affected by the widespread use of chemical fertilizer in large-scale agriculture have been made by (Khalik, et al., 2013), (Gasim, et al., 2009) and (Gasim, et al. 2009). They all agreed that the water quality in Cameron Highlands contains a high sedimentation rate resulting in water turbidity.

Malaysia's climate is described by 2 seasons, The South West Monsoon (SWM) so-called Dry Monsoon occurs from May-September while North East Monsoon (NEM) from November-March. The Northeast Monsoon brings in more rainfall compared to the Southwest Monsoon, originating in the South China Sea and the North Pacific (https://www.met.gov.my)

2. Study Area

Cameron Highlands is a well-known agricultural place and tourism destination in Malaysia but sensitive to environmental disturbance (Kok and Chee, 2015). Situated on the main range of Peninsular Malaysia with an estimated area of 712 km^2 (Muaz, et al., 2020) and altitude altitude of 1829 meters above mean sea level (Gasim, et al., 2009). The highland climate is suitable for agricultural cultivation, and Cameron Highlands is a major highland vegetable producer in Malaysia (Nurzawani and Norida, 2009). The coordinate position is at 4°20'N - 4°37'N and 101°20' - 101°36'E (Figure 1), which consists of three major sub-districts of Telom, Ringlet, and Tanah Rata.

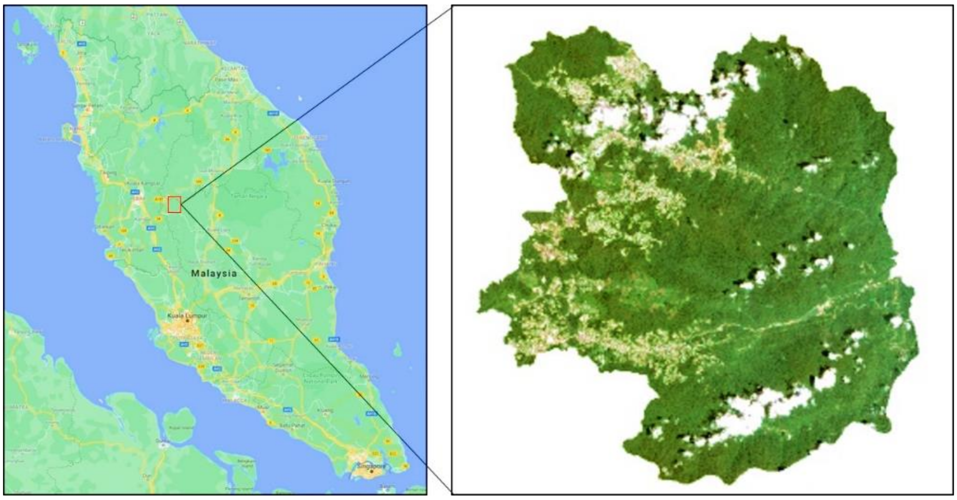


Figure 1: Study site of Cameron Highlands in Malaysia.

3. Materials and Methods

Figure 2 illustrates the data processing workflow which starts with pre-processing of Sentinel 2 and Sentinel-3 respectively. Then followed by image pre-processing, image classification, classification accuracy assessment, vegetation indices, land surface temperature calculation, linear correlation, and finally results and discussion.

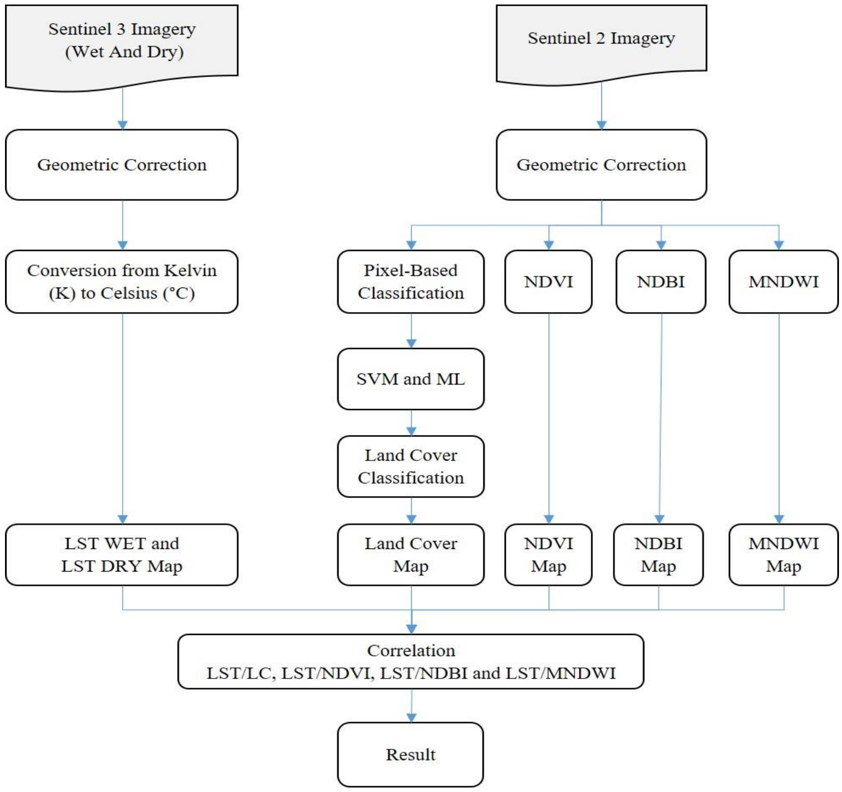


Figure 2. Data processing workflow.

3.1. Image Acquisition

3.1.1. Sentinel-2B Image Data

Sentinel-3 SLSTR data products have three processing levels (Level-0, Level-1, and Level-2) of which Level-1 and Level-2 are publically available (https://schihub.copernicus.eu). Level-1 products consist of calibrated radiances and brightness temperatures (RBT) for each channel at the instrument grid for nadir and oblique view, as well as some ancillary data. Among others, Level-2 products include Sea Surface Temperature (SST), LST, and fire radiative power (Yanga, et al., 2020). Hence, we use two (2) sets of Sentinel 2 data for dry (SWM) and wet (NEM) seasons that were downloaded from the Copernicus Open Access Hub. The data dated 09 March 2021 and 02 June 2021 were in Level 2A, which provides Bottom of Atmosphere (BOA) reflectance. Ten (10) bands (band 2, band 3, band 4, band 5, band 6, band 7, band 8, band 8A, band 11, and band 12) were resampled to 10 meter resolution and stacked to create a multispectral image. These imageries were then reprojected to Malaysian Rectified Skew Orthomorphic (RSO) projection.

Table 1: Band parameter of the Sentinel-2B MSI imagery

Band	Name	Wavelength range/μm	Resolution/m
1	Coastal aerosol	0.433-0.453	60
2	Blue	0.458-0.523	10
3	Green	0.543-0.578	10
4	Red	0.650-0.680	10
5	Vegetation red-edge	0.698-0.713	20
6	Vegetation red-edge	0.733-0.748	20
7	Vegetation red-edge	0.773-0.793	20
8	Near-infrared	0.785-0.900	10
8A	Near-infrared narrow	0.855-0.875	20
9	Water vapor	0.935-0.955	60
10	Shortwave infrared- Cirrus	1.360-1.390	60
11	Shortwave infrared	1.565-1.655	20
12	Shortwave infrared	2.100-2.280	20

3.1.2. Sentinel-3 SLSTR Image Data

Sentinel-3 SLSTR Level-2 provides five different product packages which include LST products generated in a 1 km pixel spacing grid. The LST dated 09 March 2021 and 02 June 2021 are the same as Sentinel-2 image data were downloaded from the Copernicus Open Access Hub (https://schihub.copernicus.eu) for further analysis.

3.2. Methodology

3.2.1. Land cover (LU) classification

Sentinel 2 imageries were classified into Urban, Water, Forest, Vegetation, Bare Land, Market Gardening, Cloud, and Shadow using pixel-based Support Vector Machine (SVM) and Maximum Likelihood (ML) classification methods. Training samples for all eight (8) classes were selected to represent each class.

3.2.2. Land surface temperature (LST)

LST data extraction from Level 2 Sentinel-3 SLSTR data is done using ESA SNAP software and converted from Kelvin to Celsius using ArcGIS.

3.2.3. Vegetation Indices

The Vegetation Indices was calculated in ArcGIS using the formula as shown below:

NDVI = [NIR-RED] / [NIR+RED] (1)

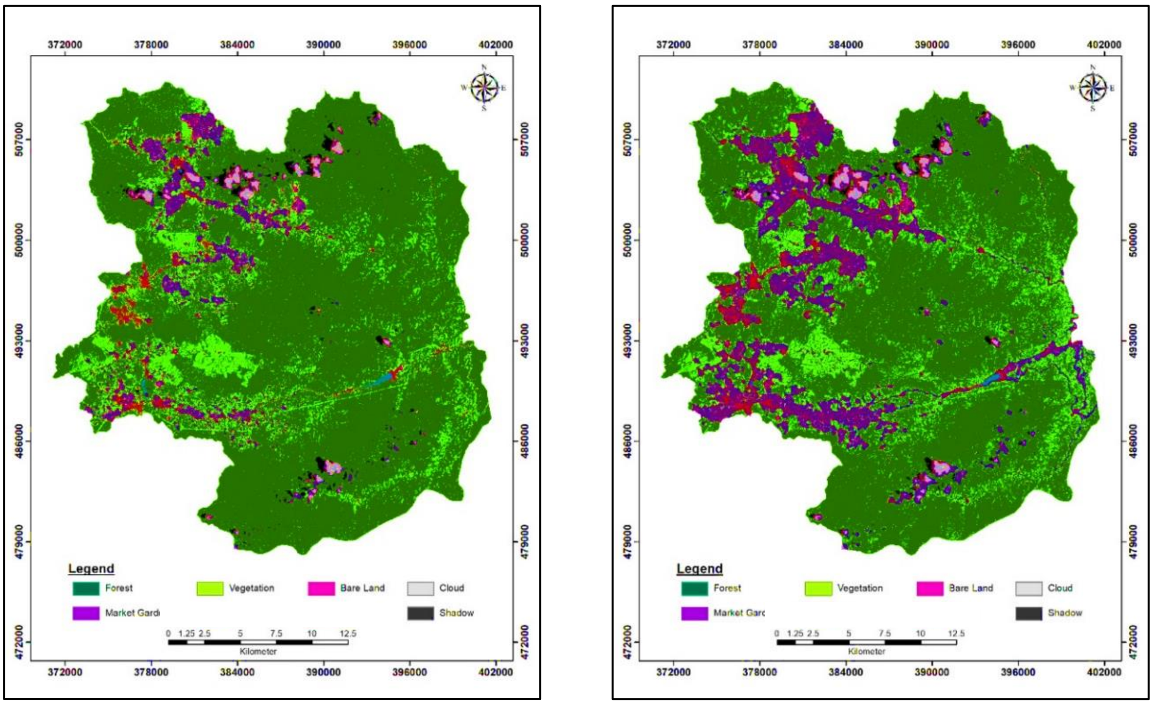
NDBI = [MID-NIR] / [MID+NIR] (2)

MNDWI = [Green –SWIR] / [Green + SWIR] (3)

4. Results and discussion

4.1. Land Cover (LU) classification

Land cover classification of Sentinel-2 was carried out using Maximum Likelihood (MLC) and Support Vector Machine (SVM) as shown in Figure 3 to find out which method gave the best result. The result of the SVM classifier is 92% with a kappa coefficient of 0.85, while the MLC is 79% with a kappa coefficient of 0.66. This result showed that the SVM classification method gives better LU result accuracy than MLC.



(a) Support Vector Machine (SVM) (b) Maximum Likelihood (MLC)

Figure 3: Classification Output of Sentinel Imagery using SVM and MLC Classifier.

Table 2: SVM Overall Classification Accuracy of Sentinel-2.

Sentinel 2B (9 March 2021) : **Support Vector Machine Classifier (SVM)**
Overall Accuracy : **92%**
Kappa Coefficient : **0.85**

LU	Cloud	Shadow	Forest	Water	Bare land	Urban	Vegetation	Market Gardening	Total	User Accuracy
Cloud	9.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	10.00	0.90
Shadow	0.00	10.00	0.00	0.00	0.00	0.00	0.00	0.00	10.00	1.00
Forest	0.00	1.00	206.00	0.00	0.00	0.00	1.00	0.00	208.00	0.99
Water	0.00	0.00	0.00	10.00	0.00	0.00	0.00	0.00	10.00	1.00
Bare land	0.00	0.00	0.00	0.00	8.00	0.00	0.00	2.00	10.00	0.80
Urban	2.00	0.00	0.00	0.00	0.00	6.00	0.00	2.00	10.00	0.60
Vegetation	0.00	0.00	4.00	0.00	0.00	0.00	24.00	4.00	32.00	0.75
Market Gardening	7.00	0.00	0.00	0.00	0.00	1.00	0.00	13.00	21.00	0.62
Total	18.00	11.00	210.00	10.00	8.00	7.00	25.00	22.00	311.00	0.00
Producer Accuracy	0.50	0.91	0.98	1.00	1.00	0.86	0.96	0.59	0.00	0.92

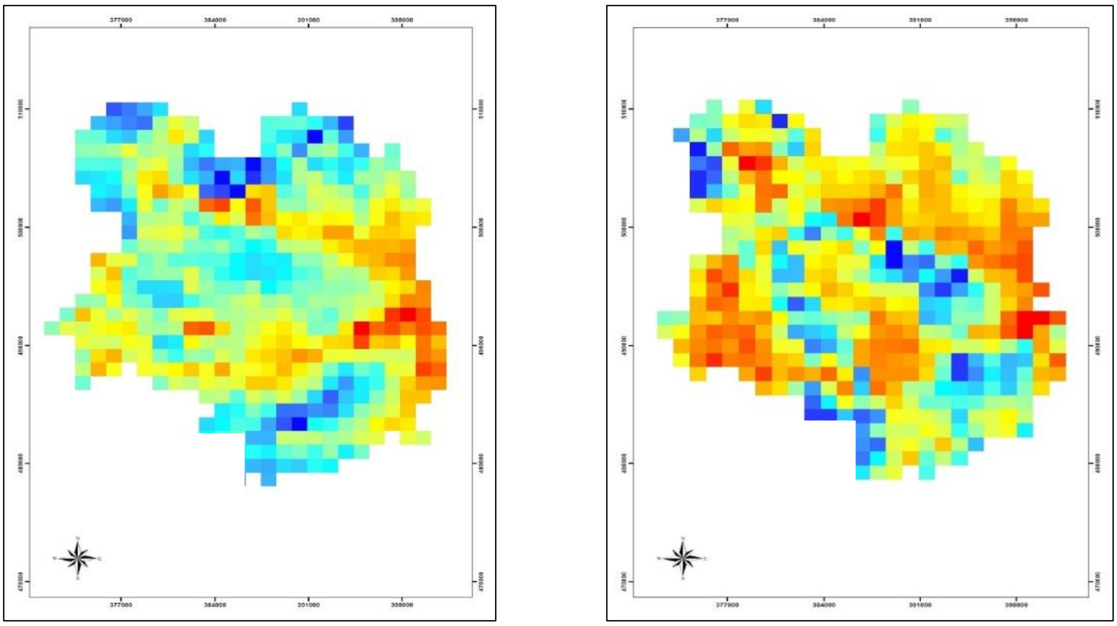
Table 3: ML Overall Classification Accuracy of Sentinel-2.

Sentinel 2B (9 March 2021) : **Maximum Likelihood Classifier (MLC)**
Overall Accuracy : **79%**
Kappa Coefficient : **0.66**

LU	Cloud	Shadow	Forest	Water	Bare land	Urban	Vegetation	Market Gardening	Total	User Accuracy
Cloud	9.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	10.00	0.90
Shadow	0.00	10.00	0.00	0.00	0.00	0.00	0.00	0.00	10.00	1.00
Forest	0.00	0.00	170.00	0.00	0.00	0.00	9.00	0.00	179.00	0.95
Water	0.00	0.00	0.00	10.00	0.00	0.00	0.00	0.00	10.00	1.00
Bare land	0.00	0.00	0.00	0.00	8.00	0.00	0.00	2.00	10.00	0.80
Urban	0.00	1.00	0.00	0.00	2.00	5.00	0.00	2.00	10.00	0.50
Vegetation	0.00	0.00	22.00	0.00	0.00	0.00	13.00	0.00	35.00	0.37
Market Gardening	5.00	0.00	7.00	0.00	1.00	3.00	9.00	22.00	47.00	0.47
Total	14.00	11.00	199.00	10.00	12.00	8.00	31.00	26.00	311.00	0.00
Producer Accuracy	0.64	0.91	0.85	1.00	0.67	0.63	0.42	0.85	0.00	0.79

4.2. Land Surface Temperature (LST) analysis during the wet and dry seasons

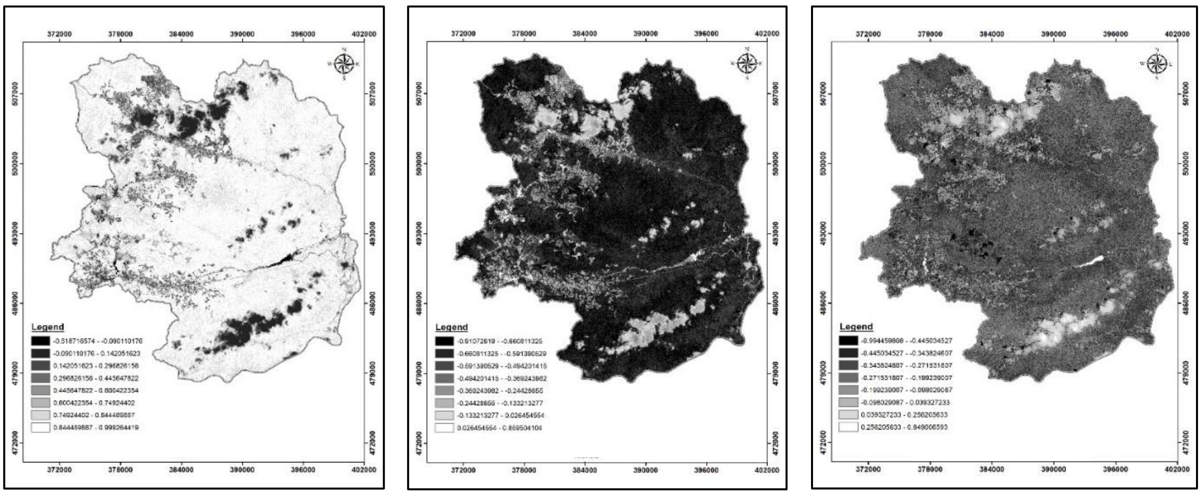
Figure 4 shows the LST map from Sentinel-3 during the wet season (LST WET) dated 09 March 2021 and dry season (LST DRY) dated 2 June 2021. The LST WET temperature ranges between 22.97^{0}C to 24.36^{0}C, while the temperature for LST DRY is slightly higher, between 24.28^{0}C to 26.14^{0}C in the sampling area. The presence of clouds especially in the middle, top left, and bottom left in the LST DRY image caused the inaccurate temperature in these areas. The LST DRY results show that the temperatures rise almost 2 degrees for the entire Cameron Highlands area. LST DRY image dated June 2021 was chosen, as it is near July which was reported as the hottest month for the dry season in the Monthly Global Climate Report (Gohd, 2021).



(a) LST WET dated 9 March 2021 03:11:14 GMT. (b) LST DRY dated 2 June 2021 03:07:37 GMT.

Figure 4. LST map of Cameron Highlands.

4.3 Vegetation Indices



(a) NDVI (b) NDBI (c) MNDWI

Figure 5: Vegetation Indices of NDVI, NDBI, and MNWI.

Vegetation indices result (Figure 5) shows that the minimum and maximum values for NDVI are -0.62 and 0.99, NDBI is -0.68 and 1.00 and MNDWI is -0.163 and 0.997.

4.4 Temperature comparison between wet and dry seasons

A summary of the two seasons temperature as demonstrated in Figure 6, shows the temperature variation of LU classes during wet and dry seasons (LST WET and LST DRY). The overall temperature has increased in all LU classes from wet to dry season except for market gardening. Market gardening is a covered greenhouse that is normally planted with vegetables, flowers, and fruits. Farmers have been applying temperature control in the greenhouse during the dry season to maintain the temperature within 24^{0}C. The temperature increased by about 2^{0}C for the urban and bare land areas while 3^{0}C for vegetation and forest areas. This result also shows that during dry seasons, the average temperature conditions in Cameron Highlands are around 26^{0}C (11:11:14 am Malaysian time) in all areas compared to wet seasons, where the temperature in vegetation and forest areas are cooler than in other areas. Water temperature (sampling taken in a dam) remains high (28^{0}C) in both seasons due to turbidity. Waterbodies with turbid areas show higher temperatures than clear surface water (Tanushri and Jhariya, 2020)

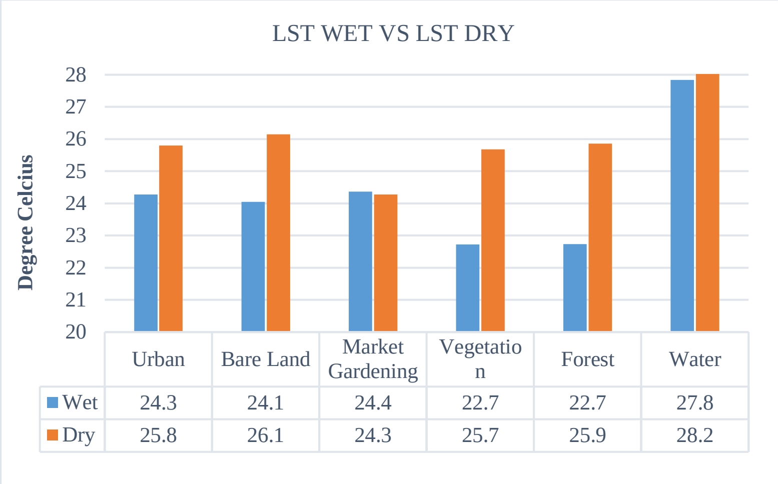


Figure 6: LST WET and LST DRY Temperature.

4.5 The relationship between LST and indices

Table 4 shows a summary of the linear regression value of vegetation indices for LU classes against LST during wet and dry seasons.

Table 4: Linear regression value of indices.

LAND COVER	NDVI	NDBI	MNDWI
Urban	R^2= 0.0973	R^2= 0.0034	R^2= 0.2003
Bare Land	R^2= 0.0022	R^2= 0.0008	R^2= 0.2067
Marker Gardening	R^2= 0.3832	R^2= 0.1560	R^2= 0.0692
Vegetation	R^2= 0.9311	R^2= 0.3194	R^2= 0.9663
Forest	R^2=0.0108	R^2= 0.0069	R^2= 0.0042
Water	R^2= 0.7073	R^2= 0.3843	R^2= 0.0033

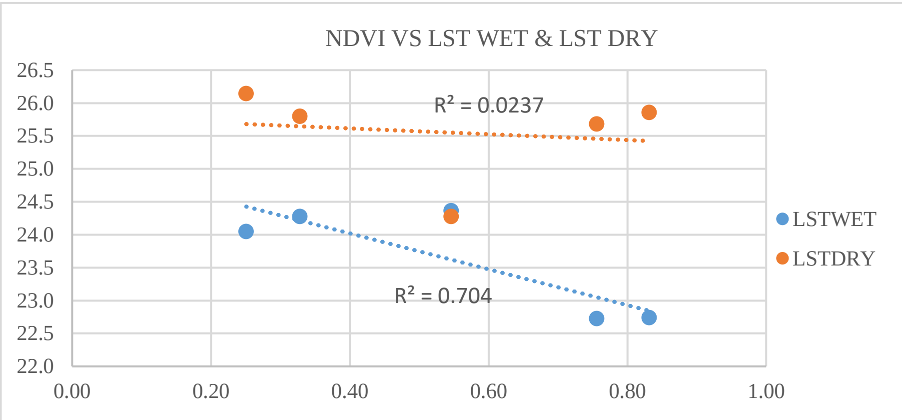


Figure 7: Temperature difference of NDVI between wet and dry.

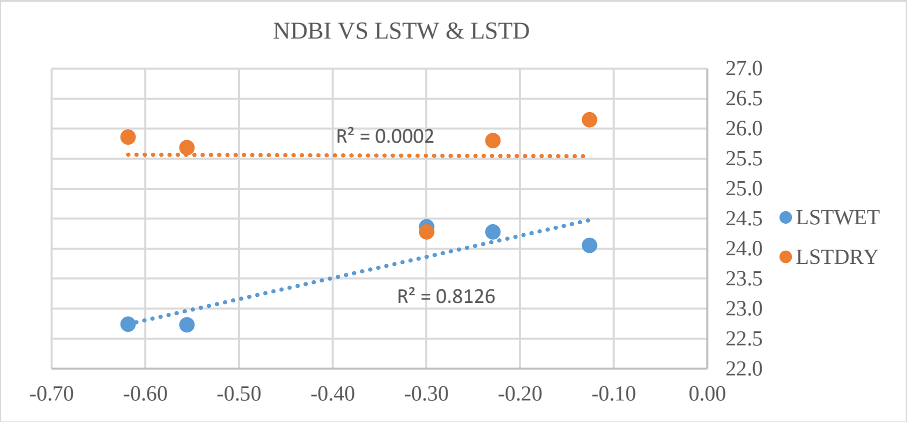


Figure 8: Temperature difference of NDBI between wet and dry.

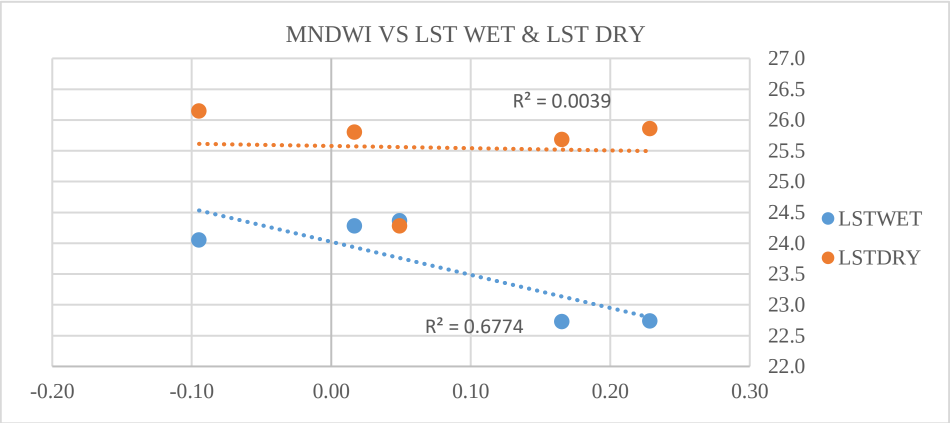


Figure 9: Temperature difference of MNDWI between wet and dry.

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

From the graph in Figure 7, the LST WET value decreased as NDVI increased in wet seasons. LST WET regression value, R^2 = 0.704 has a good relationship with NDVI. The major temperature decreased mostly in vegetation and forested area which reduces about 3^0C from dry to wet seasons. Meanwhile, the LST DRY regression value, R^2 = 0.0039 shows that there is no significant difference in temperature in dry seasons for all LU classes even for vegetation and forest. The temperature remains at about 25.5^0C.

4.6.2 *Land Surface Temperature (LST) and Normalized Difference Built-up Index (NDBI)*

The positive relationship (Figure 8) found between NDBI and LST indicates that built-up area is generating many surface temperature variations. The mean NDBI value for the urban class is -0.23 which was collected from 5 random samplings. Build-up area such as road and building indicates positives values, as well as bare land, where no surface vegetation. LST WET value increased as NDBI value increased with good correlation, R^2 = 0.8126 and R^2 = 0.0002 for LST DRY. This result revealed that LST in all areas during the dry season is almost the same even for vegetation and forest.

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

MNDWI graph during wet and dry season shows in Figure 9 with negative correlations were shown for both seasons. The wet season has a stronger relationship, R^2 =0.6774 compared to the dry season, R^2=0.0039. The water temperature range is 27.84 - 28.19^0C, where there is no significant difference because of turbid water in the sampling area. Sedimentation rate inside the water resulting in the same reflectance in both seasons. This study also found that the MNDWI has enhanced the water features. Positive values indicate water, while other land cover classes indicate negative values.

5. Conclusions

This study was conducted to assess the temperature variation in land use classified from Sentinel-2 during The Southwest Monsoon (SWM) and North East Monsoon (NEM) so-called dry and wet seasons using Sentinel-3 satellites LST data. Image classification was done using Maximum Likelihood (MLC) and Support Vector Machine (SVM). The classification accuracy of SVM is 92% with a kappa coefficient of 0.85, which is higher than MLC 79% accuracy with a kappa coefficient of 0.66. The Sentinel-2 image was also processed to generate NDVI, NDBI, and MNDWI vegetation indices. The first analysis is to assess temperature variation on seven different types of classified LU, namely plants, forests, urban, clear land, garden, and water during wet and dry seasons. The results show that the dry season temperature of vegetation and forest areas has increased higher than urban and bare land areas, which is 3^0C - 3.2 ^{0}C and 1.5^0C - 2^0C respectively. With the establishment of a linear correlation of NDVI, the R^2 value has a higher correlation in the wet season compared to the dry season, which indicates that the higher the NDVI value, the lower the temperature. The correlation of R^2 also reveals that during the dry season the temperature is almost the same in all types of land use. NDBI R^2 value has a positive correlation which shows that temperature increase in impervious areas. In conclusion, LST and vegetation indices have a good relationship for temperature assessment in Cameron Highlands. In the future study, many additional data may be included such as several years of land cover changes, ground temperature analysis with robust statistical methods instead of linear regression.

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