Remote Sensing and GIS Approach to Assess Landform Changes in Kaduwela Divisional Secretariat Area and its Impacts to the Environment

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Abstract

Land use/land cover (LULC) change plays one of the major key roles in environmental impacts, and it is common to all nations. Monitoring this LULC change together with quantifications of environmental changes is an important concept in the Sustainable Development process. Therefore, remote sensing and geographic information system technique (RS & GIS) was used to exploit the variation of the LULC pattern, and satellite images of five years between 1997 and 2019 were used in this research. LULC changes in the Kaduwela Divisional Secretariat area were analysed using the Maximum likelihood supervised classification method and found that there was a significant decrease in vegetation cover due to rapid urbanisation. To assess landform changes and their impacts on the environment, normalised difference vegetation index (NDVI), normalised difference built-up index (NDBI), and land surface temperature (LST) were used. Further, relationships in-between them were used to analyse the correlations between NDVI and LST, NDBI and LST, and NDVI and NDBI, and it was noticed that negative, positive, and negative correlations respectively among them. It indicates that healthy vegetation can decrease the land surface temperature, whereas built-up will enhance land surface temperature. More than 70% of overall accuracy for LULC classification was able to achieve in this study.

Keywords: LST, LULC, NDBI, NDVI, Supervised classification

1. Introduction

Land Use/Cover change is one of the major influencing factors in this developing world and to be analysed in a proper way. The rapid growth of population, expansion of urban centres, scarcity of land and development activities are some driving factors. So to do the development activities in a sustainable manner, monitoring these changes in land-use patterns and the related environmental impacts are crucial. Therefore, for landform change analysis, Remote Sensing is a useful technique to achieve the data about ongoing situations and can be used to calculate the change detection, which is proven by many researchers [1]; [2]. The advantages of using remote sensing and geographic information system are large and inaccessible areas can be covered by Remote Sensing, data can be acquired at relatively low cost, long-term time-series analysis can be performed as Remote Sensing has historical digital data available for decades and also the spatial resolutions of remote sensing are suitable for environmental applications [3]. Areas of change in a region can be identified using temporal information on land use/cover [1]. Continuous removal of the vegetation cover may lead to an increase in the surface temperature, and this has the possibility to initiate drought around the area. The expansion of urban centres and the same runoff of vegetation may increase the waterproofing ability of the ground and may lead to problems related to flooding [4]. The resource extraction activities have the chance to cause geological and environmental changes mainly due to ground movements, collision with mining cavities and deformation of aquifers in the nearby areas [5].

In the mining industry also, it is important to assess the environmental impacts due to mining activities such as underground and open cast mining. Mining activities leads to environmental degradation as it is amongst the anthropogenic factor. Continuous observations are required for monitoring these activities, which leads to environmental degradation using automated techniques such as Remote Sensing [6]. There are significant environmental impacts due to the unsystematic surface and subsurface mining activities such as reduction of forest cover, soil erosion, pollution of land, air and water and reduction in biodiversity [7].

In Sri Lanka, the urban centres are clustered in the coastal belts and mainly in the Western and Southern parts of the country. Colombo is the metropolitan region of Sri Lanka and has a high growth rate of urbanisation. Thus the surrounding areas of Colombo, the rate of suburbanisation is very fast, and hence the rural land uses are converted into urban activities. Kaduwela Division is also located in the Colombo suburb area and experiencing rapid urbanisation similar to Colombo city.

2. Methodology

2.1 Study Area

Kaduwela divisional secretariat area is situated in Colombo district in the Western Province of Sri Lanka. The area extends over 87.7 km^2 between Northern latitude of 6°50′0″ N - 6°58′0″ N and Eastern longitude of 79°54′0″ E - 80°4′0″ E (Figure 1).

This division consists of three regions such as Battaramulla, Kaduwela and Athurugiriya. It is located 15 km away from Colombo city and comprises 57 Grama Niladari Division. This is in the fifth urban hierarchy place of Sri Lanka. According to the Census and Statistics data, the total population in 1981 of Colombo district was 1,699,241 and got increased to 2,251,274 in 2001. Also, in Kaduwela divisional secretariat area, the total population in 2001 was 209,741, which is 9% out of the total population [8].

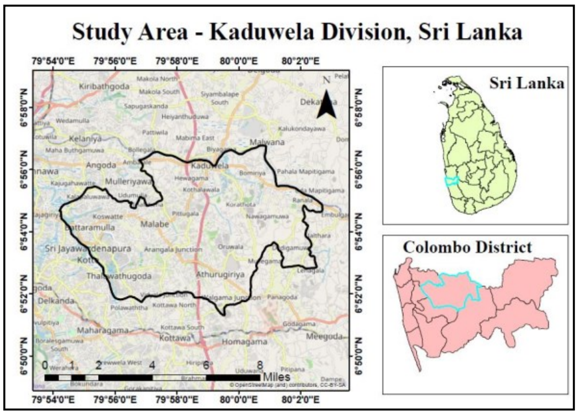

Figure 1: Study Area, Kaduwela Division.

2.2 Data Sources

Almost cloudless 5 Landsat satellite images of 2 different satellite sensors; Landsat 5 Thematic Mapper (TM), Landsat 8 Operational Land Imager and Thermal Infrared Sensor (OLI/TIRS), which has the spatial resolution of 30m each and already georeferenced to UTM coordinate system of Zone 44N taken on 07 February 1997, 02 January 2007, 21 January 2014, 13 January 2017 and 03 January 2019 were used in this study, as shown in Table 1. The specific years were chosen by mainly considering the cloud cover above the study area.

Table 1: Characteristics of Landsat 5TM, Landsat 8 OLI / TIRS.

Acquisition Date	Time (GMT)	Satellite Type	Cloud Cover (%)	Path	Row	Sun Elevation (Degree)
1997/02/07	4:18:24	Landsat 5 TM	8.00	141	55	45.93449564
2007/01/02	4:48:29	Landsat 5 TM	24.00	141	55	49.09226815
2014/01/21	4:54:48	Landsat 8 OLI / TIRS	10.83	141	55	51.05153600
2017/01/13	4:53:49	Landsat 8 OLI / TIRS	2.86	141	55	50.29800365
2019/01/03	4:53:31	Landsat 8 OLI / TIRS	16.94	141	55	50.00682176

2.3 LULC Classification

Land use/land cover classification was done to analyse the change detection over the concerned period, 1997 – 2019. Firstly, the single-band images were combined with multiple-band images using a composite band tool representing the years 1997, 2007, 2014, 2017 and 2019 to produce RGB colour composite images. Then image classification was done using the Maximum likelihood supervised classification technique for the composite images. Finally, the images were classified into four Land-cover classes, namely Water bodies, Vegetation, Barren Land and Built-up areas.

2.4 Normalised Difference Vegetation Index (NDVI)

NDVI is one of the most commonly used vegetation indexes to analyse the change detection of vegetation cover [9]. Depending on the features, absorption and reflection capacity can vary in Near Infrared (NIR) and visible radiation. In the electromagnetic spectrum, green vegetation can strongly reflect the NIR wavelength range (0.64 – 0.67 μm) and strongly absorb by Red portion range (0.85-0.88 μm). The NDVI was calculated using the following Equation (1);

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (1)$$

Landsat 5; NDVI = (Band 4 – Band 3) / (Band 4 + Band 3)

Landsat 8; NDVI = (Band 5 – Band 4) / (Band 5 + Band 4)

2.5 Normalized Difference Built-up Index (NDBI)

NDBI is one of the most widely used built-up indexes to analyse the change detection of built-up cover. When comparing the other land use/land cover surfaces, Build-up areas have typically higher reflectance in the Short Wave Infrared (SWIR) band range (1.57-1.65 μm) than that of Near-Infrared (NIR) band range (0.85-0.88 μm) [10]. For a proper mapping of urban areas, NDBI is a very effective tool and can be expressed and calculated using the following Equation (2);

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \quad (2)$$

Landsat 5; NDBI = (Band 5 – Band 4) / (Band 5 + Band 4)

Landsat 8; NDBI = (Band 6 – Band 5) / (Band 6 + Band 5)

2.6 Land Surface Temperature (LST) retrieval

Here, for the LST analysis radiometrically corrected bands were used. For Landsat 5 TM, Band 3, 4 and Band 6 (Thermal infrared) and for Landsat 8 OLI / TIRS, Band 4, 5 and Band 10 (Thermal infrared) were used. To evaluate the LST, there are some specific steps involved [9].

2.6.1 Convert the satellite Digital Number (DN) into spectral radiance

Initially, from the Digital Number (DN) values, the thermal infrared pixels were converted into spectral radiance. For Landsat 5 TM, Equation (3) and Landsat 8 OLI / TIRS, Equation (4) was used, and the equations are as follows;

$$L\lambda = \left[\frac{LMAX\lambda - LMIN\lambda}{QCALMAX - QCALMIN}\right] \times [QCAL - QCALMIN] + LMIN\lambda \quad (3)$$

$$L\lambda = ML \times QCAL + AL - Oi \quad (4)$$

Where; L_λ is Top of Atmosphere (TOA) spectral radiance (Watts/ (m^2.Srad.µm)), QCAL is quantised calibrated pixel value in DN, LMAX λ and LMIN λ are the maximum and minimum spectral radiance (Watts/ (m^2.Srad.µm)), QCALMAX & QCALMIN are maximum and minimum quantised calibrated pixel value in DN (corresponding to LMAX λ & LMIN λ), ML is Band-specific multiplicative rescaling factor, AL is Band-specific additive rescaling factor and Oi is the correction value for Band 10. All values can be obtained from the metadata.

2.6.2 Convert the spectral radiance into at-sensor brightness temperature

Sensor temperature will be derived [9] from spectral radiance values which represents the black body temperature.

$$BT = \frac{K2}{\ln\left(\frac{K1}{L\lambda} + 1\right)} - 273.5 \quad (5)$$

Where; BT is effective at satellite temperature in Kelvin, and K1 and K2 are Band specific thermal conversion constants that could be obtained from metadata.

2.6.3 Convert the brightness temperature into LST

Equation (6) was used to retrieve the emissivity corrected LST value.

$$Ts = \frac{BT}{1 + \left(\lambda \times \frac{BT}{\rho}\right) \ln(\varepsilon\lambda)} \quad (6)$$

Where; Ts is the LST in Celsius (°C), λ is the wavelength of emitted radiance (λ=11.5 µm for Band 6 and λ=10.8 µm for Band 10) and ελ is Emissivity and ρ = h(c/σ) = 1.438 ×10^{-2} mK where; h= Planck's constant (6.626×10^{-34} Js), c = Velocity of light (2.998 × 10^{8} m/s) and σ = Boltzmann constant (1.38 × 10^{-23} J/K). For this conversion, emissivity (e or Ɛλ) and proportion of vegetation (Pv) is required and can be calculated from NDVI using the following Equations (7) and (8);

$$e = 0.004\,Pv + 0.986 \quad (7)$$

$$Pv = \left(\frac{NDVI - NDVImin}{NDVImax - NDVImin}\right)^2 \quad (8)$$

2.7 Statistical Analysis of NDVI, NDBI and LST

For the analysis, scatter plots were created first. Then correlation and regression analysis were done to find out the relationship in-between NDVI and LST, NDBI and LST and NDVI and NDBI. To plot the graph, 2000 random spatially unbiased points belonging to all Land Use/Cover classes were selected using the systematic sampling method. The points were extracted from NDVI, NDBI and LST maps using Arc GIS software.

3. Results and Discussion

3.1 LULC Distribution (1997-2019)

The Land Use/Cover classification map of the Kaduwela Division for the years 1997 and 2019 are shown in Figure 2. A similar kind of analysis was done to the years 2007, 2014 and 2017.

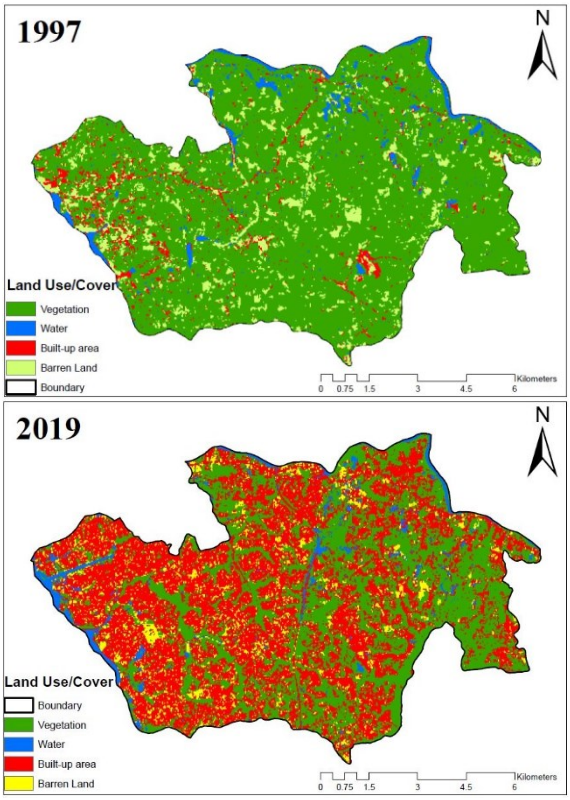

Figure 2: LULC Distribution.

From the statistical data, Figure 3 was generated.

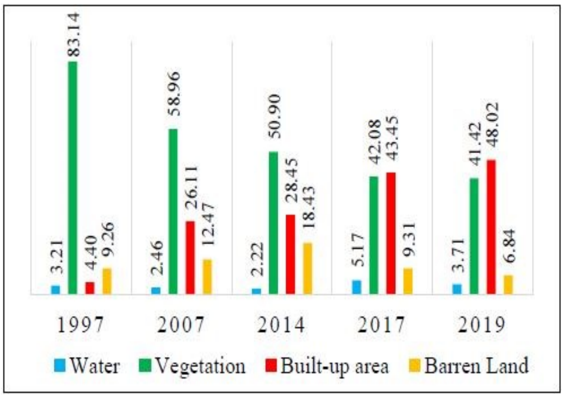

Figure 3: Statistical data of LULC.

According to the results, from 1997 to 2019, there is no significant change in barren land and water cover as they change only 2.42% and 0.5%, but when considering the vegetation cover and built-up area, the changes are 41.72% and 43.62%.

So it can be seen that Kaduwela Division has undergone urbanisation from 1997 to 2019, and especially since 2007, there is rapid urbanisation can be seen. Also, Figure 2 clearly shows that most of the vegetation covers are occupied by the built-up areas, and this may be due to the development activities.

3.2 NDVI Distribution (1997-2019)

NDVI Distribution of Kaduwela Division for the year 2019 is shown in Figure 4. A similar kind of analysis was done to the years 1997, 2007, 2014 and 2017 as well.

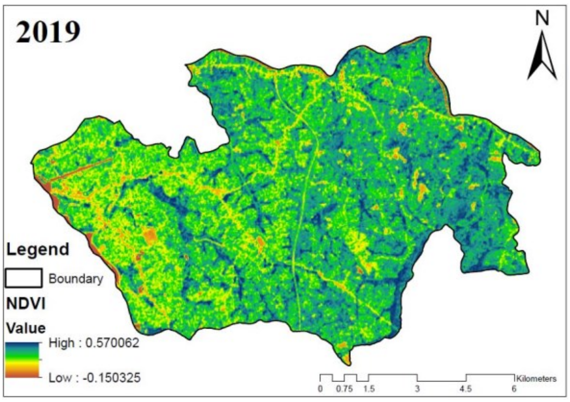

Figure 4: NDVI Distribution, 2019.

According to the analysis, lands occupied by healthy vegetation covers like forest cover and grassland have high value for NDVI, whereas the areas with buildings show low value. For the duration 1997 to 2019, the NDVImax = 0.72 and NDVImin = -0.43.

3.3 NDBI Distribution (1997-2019)

NDBI Distribution of Kaduwela Division for the year 2019 is shown in Figure 5. The same kind of analysis was done to the remaining years too.

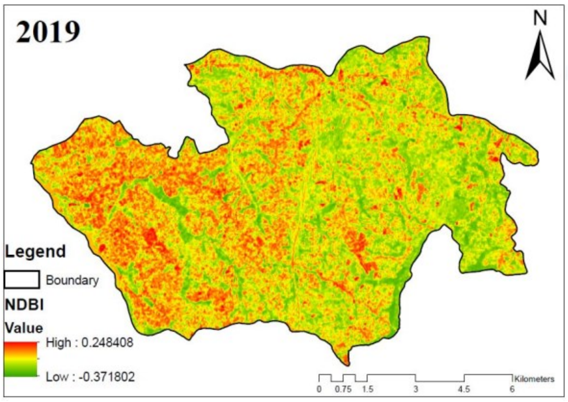

Figure 5: NDBI Distribution, 2019.

Generally, the area occupied by buildings shows a higher NDBI value. For the duration 1997 to 2019, the NDBImax = 0.44 and NDVImin = -0.45.

3.4 LST Distribution (1997-2019)

LST Distribution of the Kaduwela Division for the year 2019 is shown in Figure 6.

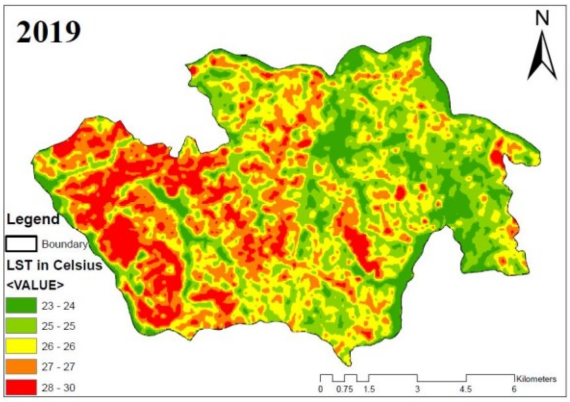

Figure 6: LST Distribution, 2019.

The same kind of analysis was done for the remaining years, and LST distribution maps were developed. The area occupied by buildings shows a higher LST value. For the duration from 1997 to 2019, the LSTmax = 32.46° C and LSTmin = 20.06° C. Due to the rapid development and urbanisation in Colombo suburb, the North-Western and South-Western part of Kaduwela Division shows a higher LST value as a result of the increment of buildings, roads, bridges, industries etc.

3.5 LULC Analysis around Quarry

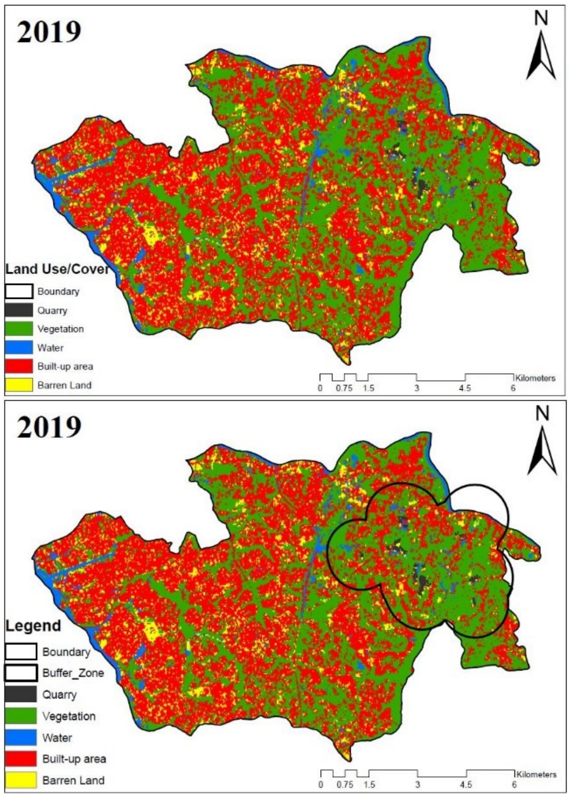

Figure 7: Map of the buffer zone, 2019.

Quarry boundaries were selected to overlay on the LULC classified map to analyse the distribution of the classes around the quarrying area. Even though the quarry site has been presented with minimal background in the study area, the major significance to give concern on this is to analyse whether the quarry development has any considerable effect on the classes concerned. Therefore, a 1 km buffer zone was created around the quarry boundary for this analysis. Figure 7 shows the created buffer zone for the year 2019, and the same kind of analysis was done to the remaining years 2007, 2014 and 2017.

From the statistical data derived from the analysis above, Figure 8 was generated.

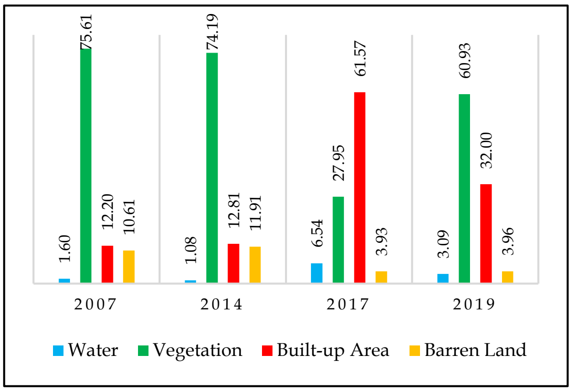

Figure 8: Statistical data of buffer map.

The statistical data shows that quarrying activities also have a certain impact on vegetation cover as they decrease the green cover up to some level. Especially in 2017, the major reason for decreasing the vegetation cover may be the combination of Quarrying activities and urbanisation.

3.6 Relationship between NDVI, NDBI and LST

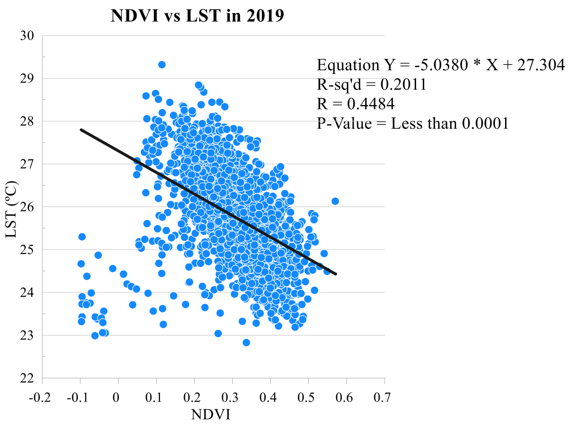

Figure 9: NDVI vs LST in 2019.

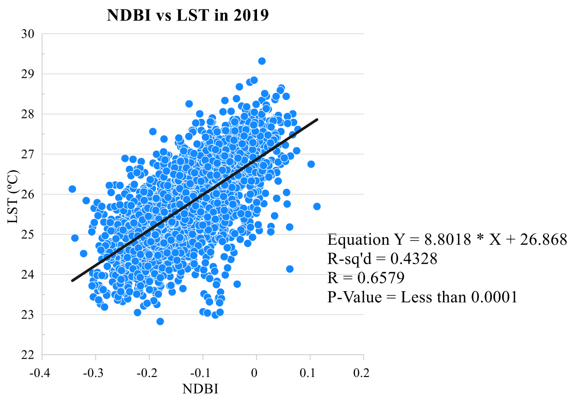

Figure 10: NDBI vs LST in 2019.

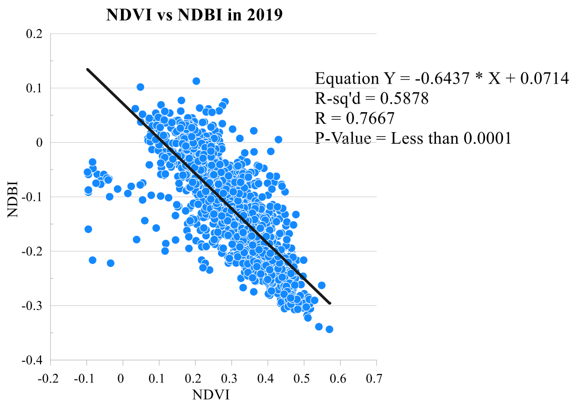

Figure 11: NDBI vs NDVI in 2019.

Scatter plots of NDVI vs LST, NDBI vs LST and NDBI vs NDVI are shown from Figures 9 to 11 for the year 2019 and show an inverse relationship among NDVI vs LST and NDBI vs NDVI and a positive relationship with NDBI vs LST. Similar kinds of graphs were plotted for the remaining years; 1997, 2007, 2014 and 2017. The correlation coefficient (R) of the scatter plots, NDVI vs LST, NDVI vs NDBI and NDBI vs LST, were -0.4484, -0.7667 and 0.6579, respectively. According to the R-Value, NDVI and NDBI and NDBI and LST are highly correlated, whereas NDVI and LST have a moderate correlation. Also, similar kinds of scatter plots were generated for a duration of 22 years (1997-2019), and it was observed that NDVI and LST values have a near-zero covariance, so it is obvious that the relationship is quite nonlinear, and this may be due to the heterogeneity in the land cover.

4. Conclusion

According to the analysis, it was found that there is a significant change in land use/cover pattern during the evaluated years; 1997-2019. Especially in vegetation cover and built-up areas as 41.72% and 43.62% respectively. Here vegetation cover decreased mainly due to urbanisation, quarrying and other industrial activities. Also, more than 70% of overall accuracy was achieved for the Land Use/Cover classification for this study.

As the major purpose of this study is to identify the environmental impacts due to landform changes, the correlation coefficient (R) of NDVI vs LST, NDBI vs LST and NDVI vs NDBI were calculated from the scatter plots and they indicated a negative, positive and negative correlations respectively. When there is an increase in built-up areas together with the decrease in vegetation cover, normally, the surface temperature will increase. However, the healthy vegetation cover will lower the surface temperature. Therefore, it was concluded that vegetation-cover and built-up areas have direct impacts on environmental changes like adverse weather conditions. Therefore, from this study, we found that in the Kaduwela Divisional Secretariat area also, there are temperature variations due to Land Use/Cover changes, especially in the North-Western and South-Western parts of the region due to rapid urbanisation as it locates close to Colombo city. Also, there are environmental issues related to significant climatic changes due to temperature variations, and sometimes it may lead to Urban Heat Island effect as well. Moreover, the decreasing pattern in vegetation cover may lead to not only the surrounding temperature increase but also widespread dust and particulate matter distribution in the study area as rapid urbanisation may cause to increase in the dust emission to the environment. Thus, vegetation cover and rainfall are the key important aspects for dust control in urban areas; in Kaduwela Division, through altering the vegetation cover to urban centres, the reducing regional rainfall pattern may be induced. As a result, deforestation and morphological changes may lead to severe climatic changes in this study area.

Landsat images with 30 m resolution were used in this study as they can be acquired free of charge. So the major limitation we faced was the resolution of the images; we found it difficult to mark the quarry boundaries and differentiate similar spectral classes during the classification due to the low resolution of the images. Landsat images can be acquired free of charge so that, mainly we have focused on Landsat images. Also, it is recommended to consider rainfall data, flood analysis data and socio-economic data for further studies like this one considered only the undesirable weather condition with the use of parameters such as NDVI, NDBI and LST,

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