Time series analysis of urban temperature in Kandy city, Sri Lanka with the use of satellite remote sensing

***Abstract*— Nowadays Rapid urbanization is the foremost swelling problem in society. The building layer growth and the vegetation layer reduction lead to acceleration of urban temperature within the time. This increasing phenomena identified as an Urban Heat Island (UHI) effect in most of the suburb areas.*

In Sri Lanka, there are several identical cities that affect UHI effect and Kandy city noted as one of highly affected area. Urban population increase, vehicle traffic growth, development of the building layer and industrialization which leaded to the urbanization in Kandy.

Most of the major Sri Lankan rivers starting from this central fragile area and it's well-known as the highly environmentally sensitive area. Nonetheless with the increase of urban population along with building and other infrastructure facilities it leads for high temperature surge. Due to the recent development projects in Kandy city, it missing green colour layer and in the other hand rapidly rise the brown colour layer.

Remote sensing is the best platform for monitoring environmental sensitive problems time series and the Landsat satellite program is the most appropriate, reliable data source. Therefore in this study Landsat 8 images of 2015, 2016 and 2017 was used as the data sources. With use of Infra-Red (IR) band temperature analysed and Normalized Difference Vegetation Index (NDVI) and Normalized Difference Building Index (NDBI) indices provide information of decrease of vegetation and increase of building layer correspondingly.

Rendering to the study, it reveals that temperature increase in each year and it has directly relationship with building layer.
***Keywords*— NDBI, NDVI, Temperature, UHI, Urbanization**

I. INTRODUCTION

Over half of the total populace presently live in urban regions, and this number will keep on expanding, especially in developing nations (united nation, 2008).

Remotely detected thermal infrared (TIR) information have been generally used to recover land surface temperature (LST) (Weng et al., 2004). A progression of satellite and airborne sensors have been created together TIR information from the earth surface, for example, HCMM, Landsat TM/ETM+, AVHRR, MODIS, ASTER, and TIMS. Notwithstanding LST estimations, these TIR sensors may likewise be used to acquire emissivity information of various surfaces with different characteristics. LST and emissivity information is utilized in an urban atmosphere and ecological investigations, principally for breaking down LST examples and its association with surface attributes, for surveying urban heat island (UHI), and for relating LSTs with surface vitality motions so as to describe scene properties, examples, and procedures (Quattrochi and Luvall, 1999).

In this study, the phenomenon of an urban heat island is investigated by the use of Landsat/Thematic Mapper (TM) data collected seasonally over metropolitan Kandy.

Kandy is the most sacred city of Sri Lanka and also it is the largest city in the central province. It's set on a plateau surrounded by mountains, which are home to tea plantations and biodiversity rainforest. Kandy is both an authoritative and religious city and is likewise the capital of the Central Region. Kandy is the home of the temple of the Tooth Relic (Sri Dalada Maligawa), a standout amongst the most hallowed spots of love in the Buddhist world. It was announced a world legacy site by UNESCO in 1988.

Kandy city limit selected as the study area because of the growing importance and recent pollution that arise in this area. The issue of traffic and urbanization in Kandy City has been become as the major problems over the past few decades. And also according to the recent studies which conducted around the study area have been highlighted the air pollution, traffic jam, urbanization growth and the environmental pollutions in different aspects.

Temperature rises noticed as the leading problem of the Kandy in recent years. According to the experienced from the people around city limit, truly it's difficult to be there during daytime because of this high temperature rises.

This attempt to analysis and identify the pattern and causes for temperature change around the city limit using satellite remote sensing.

II. METHODOLOGY AND EXPERIMENTAL DESIGN

Thermal infrared (TIR) remote sensing lets for the gathering, investigation, and modelling of environmental parameters. It allows to calculating land surface temperature (LST) which is an important factor in many environmental processes including global warming or urban heat islands.

The surface temperature is of actual importance to the examination of urban air, not simply in procuring limit conditions of the atmosphere, yet likewise in understanding the environmental conditions essential for people. Satellite TIR sensors measure top of the Atmosphere (TOA) radiances, from which quality temperatures can be resolved using Planck's law. (Dousset and Gourmelon, 2003).

The Landsat program is the longest-running innovativeness for acquisition of satellite imagery of Earth. It provide greater platform to remote sensing applications in medium resolution scale. In this study Landsat-8 data used as the data source which downloaded from U.S. Geological Survey (USGS) using Earth Explorer (http://earthexplorer.usgs.gov).

Initially data corrected from the atmosphere and sun angle. Then completed several analysis separately with different band combinations.

Using thermal bands analysed the LST and with red, NIR (Near Infrared) and SWIR (Short Wave Infrared) bands calculated the vegetation indices, such as NDVI and NDBI. Finally calculated the correlation coefficients among the LST values and vegetation indices.

The following diagram describe the entire workflow of the study.

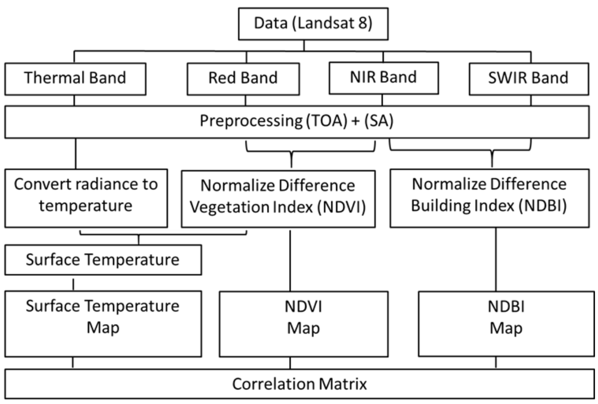

Figure 1 methodology applied in the study

OLI and TIRS at Sensor Spectral Radiance

Images are processed in units of absolute radiance using 32-bit floating-point calculations. These values are converted to 16-bit integer values in the finished Level 1 product. They can then be converted to spectral radiance using the radiance scaling factors provided in the metadata file:

$$L\lambda = ML * Qcal + AL$$

Where:

Lλ = Spectral radiance (W/(m2 * sr * µm))

ML = Radiance multiplicative scaling factor for the band (RADIANCE_MULT_BAND_n from the metadata)

AL = Radiance additive scaling factor for the band (RADIANCE_ADD_BAND_n from the metadata)

Qcal = Level 1 pixel value in DN 5

Correction for solar elevation angle(Pλ)

$$P\lambda = L\lambda / \mathrm{Sin}\ (\mathrm{Sun\ Elevation})$$

Where:

Lλ = Spectral radiance (W/(m2 * sr * µm))

TIRS Top of Atmosphere Brightness Temperature

$$T=K_2/\ln\ (K1/L_\lambda + 1)$$

Where:

T = Top of atmosphere brightness temperature (K)

Lλ = TOA spectral radiance (Watts/ (m2 * srad * µm))

K1 = Band-specific thermal conversion constant from the metadata (K1_CONSTANT_BAND_x, where x is the thermal band number)

K2 = Band-specific thermal conversion constant from the metadata (K2_CONSTANT_BAND_x, where x is the thermal band number)

Conversion of degree kelvin into Fahrenheit (TF)

$$TF=T-273.15$$

Where:

T = Top of atmosphere brightness temperature (K)

Computing NDVI

Landsat noticeable and close infrared groups were utilized for ascertaining the NDVI. The significance of assessing the NDVI is fundamental since the measure of vegetation present is a significant factor and NDVI can be utilized to induce general vegetation condition.

$$NDVI= (NIR-RED)/ (NIR+RED)$$

Where:

NIR= Near Infrared Band

RED= Red Band

Proportional vegetation (Pv)

This proportional vegetation gives the estimation of area under each land cover type.

$$Pv= ((NDVI-NDVI_{min})/ (NDVI_{max}-NDVI_{min}))^2$$

Emissivity

$$e = 0.004*(Pv) + 0.986$$

Where:

e =emissivity

(Pv)= Proportional vegetation

Conversion of Satellite Brightness Temperature into LST

The final step is to calculate LST using satellite brightness temperature (BT) of band 10 and LSE derived from Pv and NDVI.

LST can be retrieved using the equation

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

Where,

BT= satellite brightness temperature

W=wavelength of emitted radiance

P= 14380

P= h*c/s

h= Plank's constant (6.626 x 10-34)

s= Boltzmann constant (1.38 x 10-23 J/K)

c=Velocity of light (3 x 108 m/s).

Computing NDBI

NDBI is Significant in Urban studies. It is a lengthy process to convert satellite imagery into land cover map using the existing methods of manual interpretation and parametric image classification digitally. NDBI automatically map urban built-up areas takes advantage of the unique spectral response of built-up areas and other land covers.

$$NDBI= (SWIR-NIR)/\,(SWIR+NIR)$$

Where:

NIR= Near Infrared Band

SWIR= Short Wave Infrared Band

III. Results

The temperature changes can be express as following graph with maximum and minimum temperature.

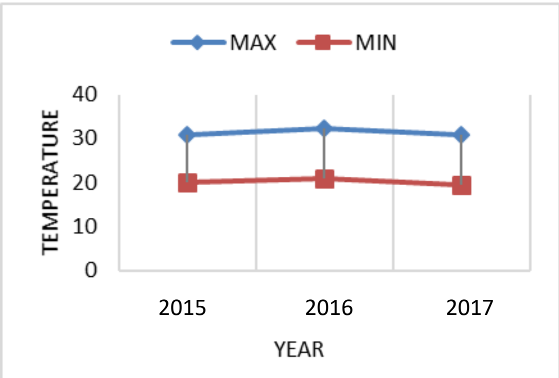

Figure 2. Maximum and minimum temperature fluctuation of in 2015, 2016 and 2017

According to this resulted graph there is no indistinguishable changes in the temperature of Kandy city limit. Because the maximum and the minimum temperature values didn't contain considerable amount of variation. It range in between 20 to 40 in average.

Even though there is no any identical difference in between maximum and minimum temperature values in recent years, we can identify some temperature changes occurred in between the maximum and minimum temperature vales conferring to the following maps. Which reflect that, the high temperature equivalent areas get growth with time.

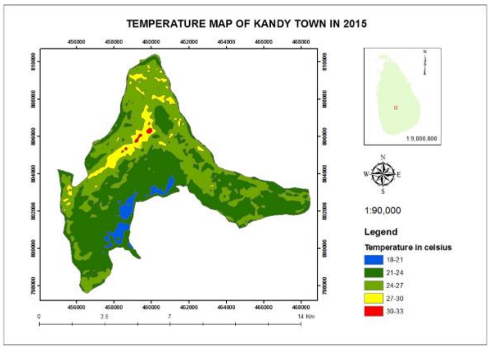

Figure 3. Temperature map of Kandy city limit in 2015

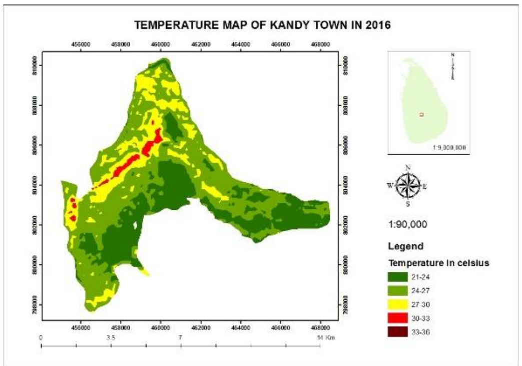

Figure 4. Temperature map of Kandy city limit in 2016

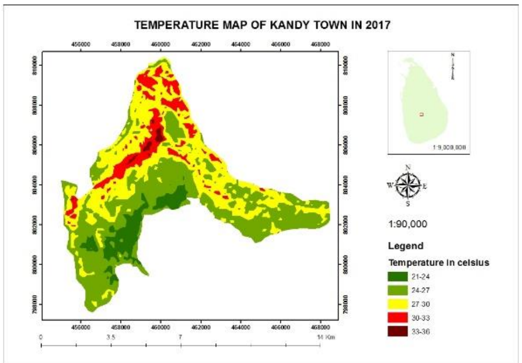

Figure 5. Temperature map of Kandy city limit in 2017

The computed LST maps of Kandy city limit in 2015, 2016 and 2017 are shown in figure 3, figure 4 and figure 5 respectively.

The red colour areas represent uppermost temperature areas and the green and yellow colour areas represent a lesser amount of temperature areas respectively.

The results in Figure 3, 4 and 5 suggest that the spatial pattern of the heat islands (areas with relatively high temperatures) has changed from a scattered pattern (bare land, semi-bare land and urban area were warmer than other areas) in 2015 to a more contiguous pattern of urban heat islands in 2016, along with the expansion of the regional urban system.

The centres of high temperature were consistent with built-up areas, which can be seen by comparing land use/cover with temperature maps. And also according to the maps we can identify the areas correspond to high temperature get enlarged and on the other hand less temperature areas get diminished. It could represent as the following graph.

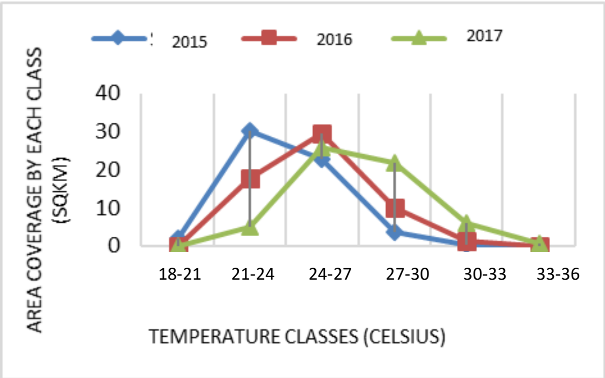

Figure 6. Graph of temperature class and the resultant area in 2015, 2016 and 2017.

As shown on the graph the maximum area correspondent temperature get increased with the time. In 2015 the highest of area correspond to temperature range of 21-24 and in 2016 it move toward up to 24-27 range and finally it approaches to 27-30 in 2017. Hence it shows identical temperature change with the time. Even though the maximum and minimum temperature has no identical variation with the time, the corresponding area of the highest temperature dramatically increased with the time. So it is difficult to identify with a graph of maximum and minimum temperature. Hence it require detailed investigation of the area to identify the pattern of changes with the time.

Vegetation indices analysis

Vegetation indices helps to understand and map the variables and parameters of required area. In this study NDVI and NDBI applied to obtain the relationship among variables, such as Building layer, vegetation layer and temperature. NDVI facilitate best platform for the identify vegetation layer. It has the ability of discriminate vegetation layer from other and also could be able to identify the greenness, healthiness of the area at a given time. Fundamentally it is the most used vegetation indices of the world because of ease of use and its flexibility of study. In this study we identify five NDVI regions which correspond to water, bare land, vegetation, forest and non-vegetative areas. All the values extracted from previous research and then cross check with current values of the resulted map and Google Earth.

NDBI effect to analyse the building layer efficiently than previous methods. Most of preceding methods based on the object recognition based mathematical functions and computer language codes. But NDBI provide best platform for analyse and identify building layer of the particular area without more processing steps and time wasting. According to the resulted NDBI values, it's also divided in to five section while considering the Landuse and land cove pattern. All the value extracted from previous research and then cross check with current values of the resulted map and Google Earth as the NDVI.

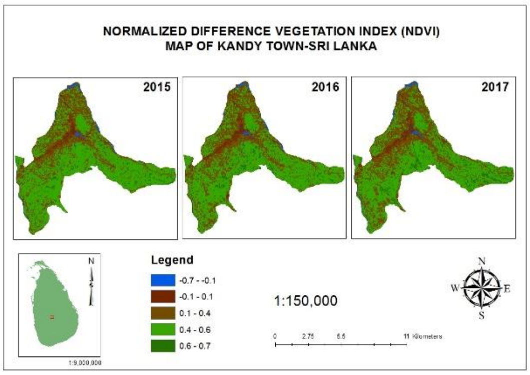

Figure 7. NDVI map of Kandy city limit in 2015, 2016 and 2017

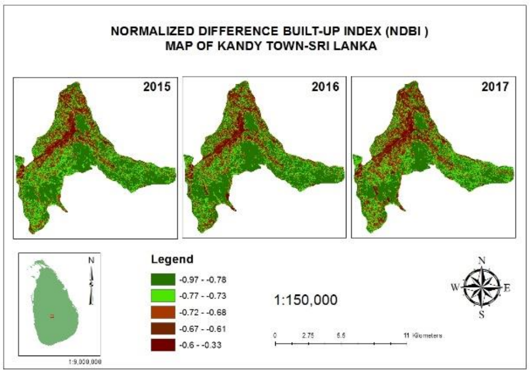

Figure 8. NDBI map of Kandy city limit in 2015, 2016 and 2017

The computed NDVI and NDBI maps of Kandy city limit in 2015, 2016 and 2017 are shown in figure 4 and figure 5 respectively.

As shown in the maps we could identify the vegetation layer get decreased and building layer get increased with the time because of the development activities and urbanization on Kandy city limit.
But it's difficult to identify the changes just with the map. Hence it require better representation of the phenomenon and its relationship with other factors with the time. Then analyse the association in between the temperature, building layer and vegetation layer in Kandy. Therefore use the correlation matrix to identify the statues of the relationship.

Correlation analysis
The correlation coefficient is a statistical measure that calculates the strength of the relationship between the relative movements of two variables. The values range between -1.0 and 1.0. Pearson correlation used as the algorithm of the study which measures strength and direction of the linear relationship between two variables. The Pearson correlation coefficient, r, can take a range of values from +1 to -1. A value of 0 indicates that there is no association between the two variables. A value greater than 0 indicates a positive association; that is, as the value of one variable increases, so does the value of the other variable. A value less than 0 indicates a negative association; that is, as the value of one variable increases, the value of the other variable decreases. +1 indicates a perfect positive linear relationship: as one variable increases in its values, the other variable also increases in its values via an exact linear rule.-1 indicates a perfect negative linear relationship: as one variable increases in its values, the other variable decreases in its values via an exact linear rule.

Table 1: Correlation Coefficient values and the strength of relationship

Value of r	Strength of relationship
+0.7 or higher	Very Strong
-0.4 to -0.69 or +0.4 to +0.69	Strong
- 0.30 to -0.39 or +0.30 to +0.39	Moderate
-0.20to -0.29 or +0.20 to +0.29	Weak
-0.01 to -0.19 or +0.01 to +0.19	None or very weak
0	No relationship

Then we used 1 to 5 scaled numbering for each layer to transfer all the layers for same scale. Its helps to build the relationship of the different category of Landuse/Land cover and the temperature. The Scaled values represent in following tables.

Table 2. NDVI scaled value range according to the Landuse type

NDVI Range	Scaled value
-1.0- -0.1	1
0.6 – 0.7	2
0.4 – 0.6	3
0.2- 0.4	4
-.1 – 0.2	5

Table 3. NDBI scaled value range according to the Landuse type

NDBI Range	Scaled value
-0.97- -0.78	1
-0.77- -0.73	2
-0.72 - -0.68	3
-0.67 - -0.61	4
-0.60 - -033	5

Table 4. LST scaled value range according to the Landuse type

LST Range	Scaled value
18-21	1
21-24	2
24-27	3
27-30	4
30-33	5

Then, calculate the correlation matrix of the all layers. The following table specify the relationship of the parameters used in the study.

Table 5. Correlation matrix of NDVI, NDBI and LST**.**

Layer	Temperature	NDVI	NDBI
Temperature	1	0.56384	0.64687
NDVI	0.56384	1	0.8165
NDBI	0.64687	0.8165	1

According to the correlation matrix, it shows it has strong positive correlation among NDVI, NDBI and Temperature. And also it shows it has very strong positive correlation among NDVI and NDBI values. Which means that the urbanized building areas consumes the highest correlation with the high temperature and on the other hand the vegetation or forest areas takes the highest correlation with the less temperature areas.

IV. DISCUSSION AND CONCLUSION

In this study, the land surface temperatures in Kandy city limit analysed using the Landsat ETM+ data. Through the retrieved temperature data, it is found that the distribution of urban heat islands in Kandy is mainly located in City limit. And also it revealed that, even though there is not identical changes in minimum and maximum temperature in recent years, the corresponding area and the temperature range get amplified. The same result proof by the vegetation indices of NDVI and NDBI.

In addition, from the correlation analysis of the retrieved LST with NDVI and NBVI, it was found that the green land can weaken urban heat island effect, but the built-up land can accelerate the effect. Thus, we have learnt that in the future city planning and development that more attention should be paid to urban greening.

Furthermore, the correlation matrix shows there is strong positive correlation among the NDVI, NDBI and Temperature in the study area, which means that high temperature area in relationship with building layer and less temperature areas in relationship with vegetation layer.

The results of this study could be applied successfully in future city expansion and development projects as well as a outline for applying instructions and guidelines by the specialists for a ecological urban expansion through an ecologically friendly approach. Appropriate dissemination of vegetation cover and Building cover create the most effective urban centres rather than these urban UHIs.

However, Kandy is environmentally sensitive fragile area with high biodiversity and we all have responsibility to protect Kandy for the future.

V. ACKNOWLEDGEMENT

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