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ORIGINAL ARTICLE

An Investigation of the Impact of Spatiotemporal Changes of Land Use and Land Cover and Land Surface Temperature Using RS Techniques for Selected Cities in Sri Lanka

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ABSTRACT

Changes in land use and land cover (LULC) have an impact on land surface temperature (LST) locally, regionally, and globally. This research focused on the spatiotemporal dynamics of LULC and LST between 2000 and 2021 at six selected meteorological stations, belonging to the different climatic zones of Sri Lanka. The LULC were classified from Landsat ETM+ and OLI/TIRS data using the maximum likelihood classification approach, while LST was retrieved using the thermal band of both Landsat images. Results reveal that the built-up areas have increased in all selected locations and bare land, vegetation cover, and agricultural land have all declined in the last 20 years. In Galle and Batticaloa areas, built-up areas have grown significantly by 11.9% and 11.14% respectively, by 2021. The thermal environment spatiotemporal alterations were consistent with the urbanization trend. Since many other land use types have been converted into urban areas, the average LST in Vavuniya, Anuradhapura, Batticaloa, and Galle has been rising steadily. This showed that increasing built-up area density has played a significant role in raising LST in the study areas. The vegetation cover, agricultural land, and water bodies showed the least LST change. By examining the correlation analysis between the Normalized Difference Vegetation Index (NDVI) and LST, a somewhat positive relationship was revealed only in the areas of Galle, Batticaloa, and Hambantota. Nevertheless, the findings of this study will serve as a helpful benchmark for future landscape and urban design initiatives aimed at reducing the detrimental effects of LST on urban sustainability.

1 Introduction

The population explosion and economic progress of developing countries have had a direct impact on the changing environment during the last few decades (Chen and Zhang, 2017). Changes in Land Use and Land Cover (LULC) will be an essential factor in meeting the ever-increasing food demand. Also, all other essential activities can be affected by changes in land use. While land use refers to how people utilize the land, land cover describes the physical characteristics of the area, such as a forest or open water (NOAA, 2023). The economic growth of any region or country depends on the LULC pattern (Li, 2014). Currently, rapid urbanization has led to significant changes in biodiversity, natural landscapes, and physical climate. Due to globalization, almost half of the world's population now resides in urban areas. In addition, the urban population tends to grow due to the socioeconomic needs of people in a period of rapid urbanization (Sarif et al., 2020). Some favorable and unfavorable results can be highlighted as a consequence. Hence, using relevant research studies, it has been possible to unearth information about several areas. A number of sensitive issues influencing human existence could be recognized in today's environment when compared to the past, in addition to studies fostering integration between the environment and economic progress. In today's world, which is growing with technology, methods such as satellite technology are being used to understand some of the phenomena that have occurred on the surface of the earth. A classification can be made based on global changes and their transformative characteristics.

It is a period in which various research is being conducted on how the changes in land use that have occurred in a certain area through such geospatial techniques have affected the changes in the surface temperature

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(Dissanayake et al., 2019a; Ranagalage et al., 2018). According to the NASA Earth Observatory in the USA, Land Surface Temperature (LST) is the amount of heat that the "surface" of the Earth feels like to the touch in a specific area, as well as what a satellite sees when it peers down through the atmosphere at the ground. An important aspect of watersheds, agricultural land, and other covered areas can be detected as LULC (Sinha et al., 2019). LULC is becoming significantly more complex due to human-induced environmental changes, such as the growth of agricultural land, declining forest cover, irregular land use, and urbanization that have been occurring for many years. It is important to carry out an investigative study related to this by corporate officials such as planners, decision-makers, and land resource managers. Such changes have led to various environmental problems globally and regionally (Son et al., 2017). As a result, there is a tendency for the surface temperature to rise in both bare land and built-up areas, which tends to form Urban Heat Islands (UHIs). To evaluate the link between vegetation and LST, the Normalized Difference Vegetation Index (NDVI) is typically utilized as an indicator of plant abundance. Scatter plots are utilized to demonstrate the association between NDVI and LST. Land use patterns are changing with population growth, and forest cover is also decreasing due to the establishment of human settlements. On the other hand, agricultural land is growing due to the need for food production. Climatic variables such as temperature, rainfall, and humidity in the environment make a significant contribution to food production (Masipa, 2017). In particular, identifying and understanding the behavior and changes in LULC and LST should be investigated from a specific perspective. Additionally, several researchers have noted that data collection with many time points, as opposed to a single picture of a Landsat image, allows for a more precise temporal comparison of LST (Ravanelli et al., 2018). In understanding the spatial distribution pattern of LST in detail, the environmental information required for it is provided through various literature. NDVI is a measure that directly affects LST analysis, and LULC changes and LST are crucial elements in land use management.

The dynamics of land use patterns are directly linked to changes in energy conversion. Simulation models are crucial for analyzing LULC changes. Studies based on such spatial methods will be very important for the decision-making and mapping of land use patterns in any region. Therefore, by investigating the dynamics of such LULC patterns and characteristics such as variations in LST, the social and economic background of the area can also be understood. Depending on the area, the land use pattern varies, and the LST also varies due to their influence (Chen and Zhang, 2017). Land use may be altered by a variety of activities, and this type of study has been used to examine a wide range of land use changes. Determining the exact composition of existing land uses is also essential when calculating changes in LST. In particular, the precise identification of land use in a complex urban system is a critical task. Therefore, efforts are being made to classify land use patterns through theoretical and practical approaches based on Geographic Information Systems (GIS) and Remote Sensing (RS) (Dissanayake et al., 2019b). Many researchers have been inspired to use these geospatial technologies effectively in understanding environmental and climate variability (Gupta et al., 2019; Patel et al., 2022; Swain et al., 2022). Also, such techniques can be used to study the dynamics of land use, temperature, and hydrological characteristics along with their effects (Palmate et al., 2022; Sahoo et al., 2021). In addition, there is also the possibility of obtaining land use and vegetation cover data at regular intervals using RS. It can be identified as a basic need in the study to correctly manage the data obtained through geospatial technology and use it for analysis.

For this research, six urban areas as Anuradhapura, Vavuniya, Batticaloa, Bandarawela, Hambantota, and Galle covering the entire Sri Lanka have been selected. This selection was mainly based on three climatic zones, namely dry zone, wet zone, and intermediate zone. Accordingly, the six study areas comprise of a dry area, an area belonging to the wet zone, a mountainous area, and a coastal area. The study has been conducted for 21 years, from 2000 to 2021, with the intent to investigate how time has affected the seasonal changes in LULC and LST in that area. In today's developing world, rapid urbanization with increasing urban population and land use dynamics are constantly taking place. Some significant changes can be detected within the study areas during the past 20 years. Construction of built-up zones, decrease-increase in agricultural land, development of open land, and dynamics within watersheds are notable features. Today, in a developing world, the use of geospatial techniques are increasingly used to carry out related studies. In the context of Sri Lanka and concerning several of these study areas, such studies have not been conducted on a significant scale, and this study will contribute to filling that gap. It is also a useful opportunity to present the novelty of the study. Monitoring the changes in land usage can be viewed as an alternative kind of good governance for the administration to execute sustainable development. In this empirical investigation, land-use patterns and spatiotemporal variations are identified using RS and GIS approaches. This is to respond to the question of how the LULC has evolved and how it has affected LST variance in particular study regions between 2000 and 2021. Hence, this study aimed to evaluate LULC changes in selected areas during the twentieth year and to explore the involvement of LULC on LST variation.

2 Materials and Methods

2.1 Study Area Description

The selection of the six study areas is based on the climate zone classification of Sri Lanka. Accordingly, six locations were selected on dry zone, wet zone, and intermediate zone.

Two areas were selected related to the wet zone and the intermediate zone, while the other four areas were selected focusing on the dry zone. In selecting the specific location of those regions, the area with a weather station has been selected. In determining the land size related to the study areas, a 7 km buffer has been used from the location of the weather station and the surrounding area has been used for the research (Fig. 1). The land use and pattern changes and LST changes in the past 21 years have been calculated. The selection of the six regions was based on factors such as urbanization, land use patterns, physical factors, and population. Depending on their temporal changes, several dynamic changes can be identified even within a certain area. There have been significant dynamics in LULC and LST in the selected study areas within the three climate zones during the last 20 years. A temperature distribution of 27 °C to 31 °C in the dry zone, a temperature range of 18 °C to 24 °C in the wet zone, and a temperature range of 22 °C to 28 °C can be identified in the intermediate zone. Areas with plains and mountainous topography have an additional direct effect on the occurrence of dynamic changes in land use and surface temperature.

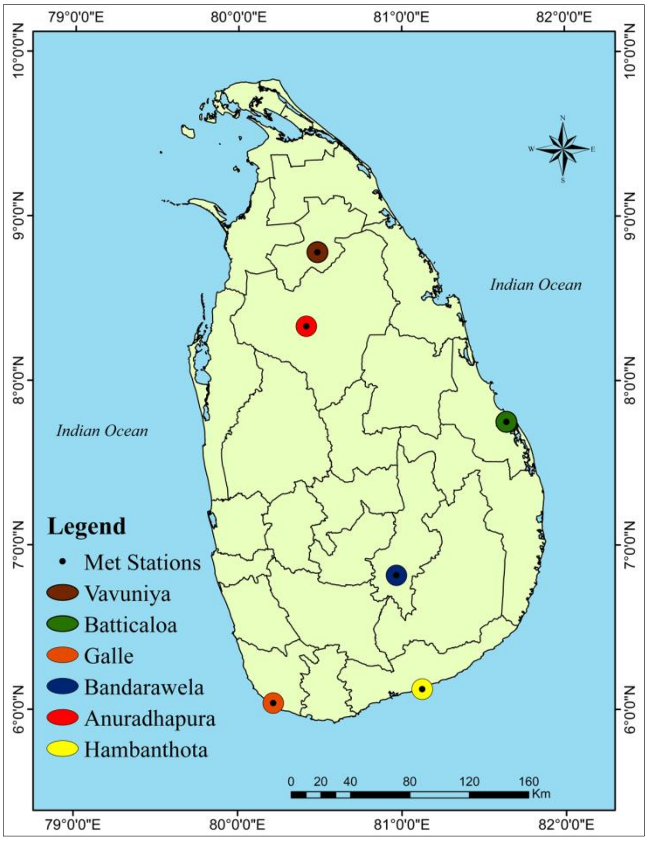

Fig. 1: Geographical setting of the study area.

2.2 Satellite Image Acquisition and Pre-processing

With the recent development of computer technology, techniques such as GIS and RS are evolving. Accordingly, remotely sensed data can be obtained through freely accessible open sources such as the United States Geological Survey (USGS) Earth Explorer (www.usgs.gov). These sources are very useful for land use mapping and LST estimation. The Landsat images acquired for the study are in raster format with a resolution of 30 m × 30 m. Landsat images from 2000 to 2021 with an interval of 21 years have been used for the study. For some of the selected study areas, satellite images related to the year 2000 were not in a suitable condition to be used for analysis, so the images released in the year 2001 have been used. Landsat 8 (OLI/TIRS) and Landsat 7 (ETM+) satellite RS imagery data were used. In this study, all bands were employed, especially the thermal bands, which are frequently used to diagnose LST. The surface temperature may be calculated using Landsat data, which are also often used for assessments of changes in LULC (Dissanayake et al., 2019a; Majeed et al., 2021; Rehman et al., 2022; Shamsudeen et al., 2022). The USGS-provided Landsat level 2 data that have been radiometrically calibrated and atmospherically adjusted, have been analyzed in this study using various functions. LST for each image was retrieved to calculate and manage data using attribute tables in ArcGIS. All files were transformed to vector formats before being imported into the GIS. Fig. 2 depicts the flow chart that illustrates the overall methodology used in this study. The details of the downloaded satellite images are listed in Table 1.

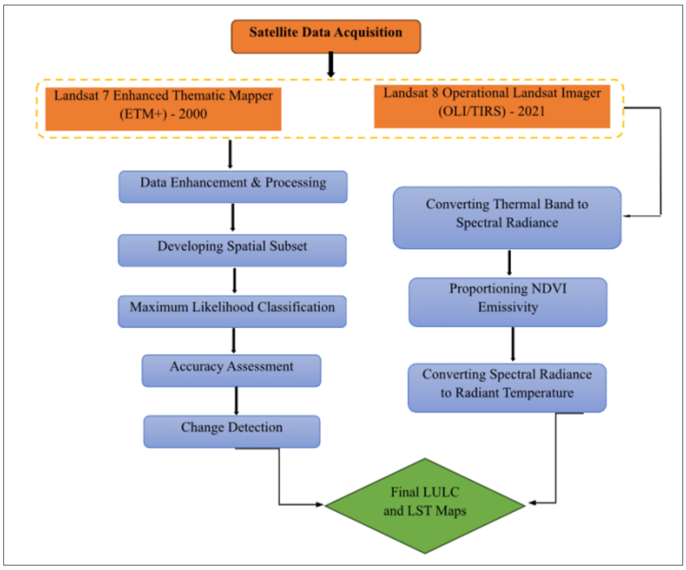

Fig. 2: Methodological Flow chart of the research study.

2.3 Image Classification and Accuracy Assessment

With the use of ArcGIS 10.8 software, satellite images between 2000 and 2021 were acquired, utilizing every band in each image. The process of automatically classifying all of the pixels in a picture into different land cover classifications is known as image classification (Lillesand et al., 2008). The production of thematic maps of land cover is the main goal of image classification. One of the most significant and reliable classifiers for supervised classification is the Maximum Likelihood Algorithm, which

Table 1: Details of Landsat Satellite Images.

Study Area	Acquisition date (2000-2021)	Sensors/ID	Path/Row	Spatial Resolution (m)
Anuradhapura	06.09.2001	Landsat 7 Enhanced Thematic Mapper (ETM+)	141/54	30m
	29.03.2021	Landsat 8 Operational Landsat Imager (OLI/TIRS)	141/54	30m
Vauniya	17.07.2000	Landsat 7 Enhanced Thematic Mapper (ETM+)	141/54	30m
	29.03.2021	Landsat 8 Operational Landsat Imager (OLI/TIRS)	141/54	30m
Batticaloa	26.05.2001	Landsat 7 Enhanced Thematic Mapper (ETM+)	140/55	30m
	27.09.2021	Landsat 8 Operational Landsat Imager (OLI/TIRS)	140/55	30m
Bandarawela	23.01.2000	Landsat 7 Enhanced Thematic Mapper (ETM+)	141/55	30m
	26.12.2021	Landsat 8 Operational Landsat Imager (OLI/TIRS)	141/55	30m
Hambantota	28.09.2000	Landsat 7 Enhanced Thematic Mapper (ETM+)	140/56	30m
	26.12.2021	Landsat 8 Operational Landsat Imager (OLI/TIRS)	140/56	30m
Galle	14.03.2001	Landsat 7 Enhanced Thematic Mapper (ETM+)	141/56	30m
	26.12.2021	Landsat 8 Operational Landsat Imager (OLI/TIRS)	141/56	30m

employs all spectral bands with the exception of the sixth spectrum. Training samples were developed while analyzing all the images concerning their spectral and spatial profiles. Especially, a selected color composition (RGB = 432) was used to digitize polygons around each training site for equal land coverage. A unique identification was then issued to every known form of land cover (Ahmed and Ahmed, 2012). The reference data and auxiliary material gathered from numerous sources served as the foundation for the training sites created for this study. The final land cover maps for various years were created by reclassifying the generalized images. The goal of accuracy evaluation is to measure how well pixels are sampled and categorized into appropriate land cover categories. Furthermore, Landsat high-resolution images, Google Earth and Google Maps have been prioritized in the pixel selection process to evaluate the accuracy of the study areas. The confusion matrix technique was widely used to assess the accuracy of LULC categorization. The confusion matrix method was used to produce Kappa coefficient values in assessing LULC classification accuracy (Yu et al., 2014). The producer and user accuracy is computed using the confusion matrix. Henceforth, the classified results of the producer accuracy, user's accuracy, overall accuracy, and Kappa coefficient are calculated using the following equations (1), (2), (3), and (4) (Gao, 1998):

$$\text{Producer Accuracy} = \frac{\text{Number of accurately classified pixels in the each category o f LULC}}{\text{Total number of reference pixels in that category (The column total)}} \times 100 \quad (1)$$

$$\text{User's Accuracy} = \frac{\text{Number o f accurately classified pixels in the each category of LULC}}{\text{Total number of reference pixels in that category (The Row total)}} \times 100 \quad (2)$$

$$\text{Overall accuracy} = \frac{\text{Total number of accurately classified pixels (Diagonal)}}{\text{Total number of reference pixels}} \times 100 \quad (3)$$

$$\text{Kappa coefficient} = \frac{(\text{Observed Accuracy} - \text{Chances of Assessment})}{(1 - \text{Chances of Aggrement})} \quad (4)$$

2.4 Estimation of Land Surface Temperature (LST)

With the use of Landsat 7 ETM and Landsat 8 OLI/TIRS Thermal band, the LST was determined (bands 6 and 10). For LST, the thermal bands that had been geometrically and radiometrically adjusted served as the basis for the Landsat satellite images. Two processes are required to convert digital numbers (DN) on thermal bands to Kelvin temperatures. First, equation (5) was used to convert the thermal infrared band DN values from Landsat images into spectral radiance (Jung et al., 2021; Sekertekin et al., 2016).

$$L_\lambda = \left\{\frac{L_{max} - L_{min}}{Q_{CAL_{min}} - Q_{CAL_{max}}}\right\} \times (DN - 1 + L_{min}) \quad (5)$$

Where,

L_{max} = the spectral radiance that is scaled to $Q_{CAL_{max}}$ in W/(m^2 *sr *μm)

L_{min} = the spectral radiance that is scaled to $Q_{CAL_{min}}$ in W/(m^2 *sr *μm)

$Q_{CAL_{max}}$ = the maximum quantized calibrated pixel value (corresponding to L_{max}) in DN = 255

$Q_{CAL_{min}}$ = the minimum quantized calibrated pixel value (corresponding to L_{min}) in DN = 1

The formula given in equation (6) must be used to convert Spectral Radiance to Temperature in Kelvin (Rodriguez-Galiano et al., 2012):

$$TB = \frac{K_2}{\left(\ln \frac{K_1}{L_\lambda}\right) + 1} - 273.5 \quad (6)$$

Where,

K_2 is the calibration constant (K)

K_1 is the calibration constant (W/m² *sr* µm) an L_λ is the spectral radiance.

Using the following formula given in equation (7), Kelvin is finally converted to Celsius:

$$TB = TB - 273 \tag{7}$$

Where,

R = Radiance values (W/m² *sr* µm)

TB = Surface Temperature (°C)

2.5 Computation of Normalized Difference Vegetation Index (NDVI)

The NDVI a trustworthy index for determining the vegetation conditions of remotely sensed data, and is one of the most often used urban climate indicators in environmental research (Pal and Ziaul, 2017). The NDVI is a metric for relative greenness that may be used as a broad indication of vegetation cover (Raynolds et al., 2008). The decrease in visible and near-infrared light data was compared by summing the two data sets to determine the NDVI values. As the difference between the red and near-infrared (NIR) bands, NDVI values are defined as having a range of -1 to +1. Equation (8) was utilized to obtain the NDVI of the studied region:

$$NDVI = \frac{(\text{NIR}-\text{RED})}{(\text{NIR}+\text{RED})} \tag{8}$$

NIR – Band 4 for Landsat 7 and Band 5 for Landsat 8 are used as the reflectance value in near-infrared spectral bands.

RED – Band 3 for Landsat 7 and Band 4 for Landsat 8 are used as the reflectance value in the red spectral band.

2.6 Trend Analysis

The "Liner Trend Analysis" and "Mann-Kendall Trend Analysis", which are frequently used quantitative analysis methods in Global Climate change research, have been used for the analysis in this study (Ampitiyawatta and Guo, 2009; Chattopadhyay and Edwards, 2016; Jayawardene et al., 2005; Salami et al., 2014; Schaefer and Domroes, 2009). Temporal changes in the annual and seasonal rainfall and temperature were analyzed by Mann-Kendall Analysis to detect the trends and to confirm the significance of the trends in climatic time series. According to the Mann-Kendall Analysis, Z value ≥ 1.96 was considered as a statistically significant level under the 95% level of confidence. First, equation (9) is used to calculate the variance of S, accounting for the possibility of ties;

$$VAR(S) = \frac{1}{18}\left[\, n(n-1)(2n+5) - \sum_{p=1}^{q} t_p \left(t_p - 1\right)\left(2t_p + 5\right)\right] \tag{9}$$

Where q is the number of tied groups and t_p is the number of data values in the p^th group

The test statistic Z is calculated using the values of S and VAR(S) in the manner shown in equation (10):

$$Z = \begin{cases} \frac{S-1}{\sqrt{VAR\ (S)}}\ if\ S > 0 \\ 0 \qquad\qquad if\ S > 0 \\ \frac{S+1}{\sqrt{VAR\ (S)}}\ if\ S > 0 \end{cases} \tag{10}$$

3 Results and Discussion

3.1 Spatiotemporal Pattern of LULC Dynamics between 2001 and 2021

3.1.1 Batticaloa

Located along the coast of the Eastern Province, Batticaloa is an area with dry environmental characteristics. A bare land landscape is prevalent throughout the area and several agricultural land use patterns are prevalent. This study has attempted to identify changes in land use patterns over 20 years from 2001 to 2021 (Table 2).

Table 2: Changes in LULC obtained from Landsat ETM+/OLI images in Batticaloa from 2001 to 2021.

Land use/cover classes	2001 Area of LULC km²	%	2021 Area of LULC km²	%	Changes (%) in LULC for 2001–2021
Water Bodies	67.16	43.67	66.79	43.4	-0.27
Paddy	15.82	10.28	12.70	8.25	-2.03
Built-up Areas	5.18	3.36	22.43	14.5	11.14
Bare Land	65.62	42.6	51.87	33.7	-8.9
Total	**153.78**	**100**	**153.78**	**100**	**0**

The built-up area can be identified as a significant factor in land use in 2001. It is found only over an area of 5.18 km² and is 3.36% of the total area. During this period, due to the 30-year civil war that broke out in the area, these sprawling settlements and a large population were not seen. As a result, there has been very little construction of built-up areas. It has also led to the creation of these bare lands in large numbers and by 2001, it was possible to identify this land use over a large area of 65.62 km². Paddy lands are also spread over an area of 15.82 km². Water bodies cover 43.67 km² of the entire study area, including the coastal area. By 2021, bare land areas decreased by 8.9%. With the growing population and urban development, the built-up areas are increasing. Built-up areas have spread over an area of 22.43 km², while the paddy land area has decreased by 12.70 km². The remaining areas have been acquired for built-up zones. There are no significant changes in the water system though several significant temporal changes in land use can be identified in the Batticaloa urban area over 20 years (Fig. 3 and 4).

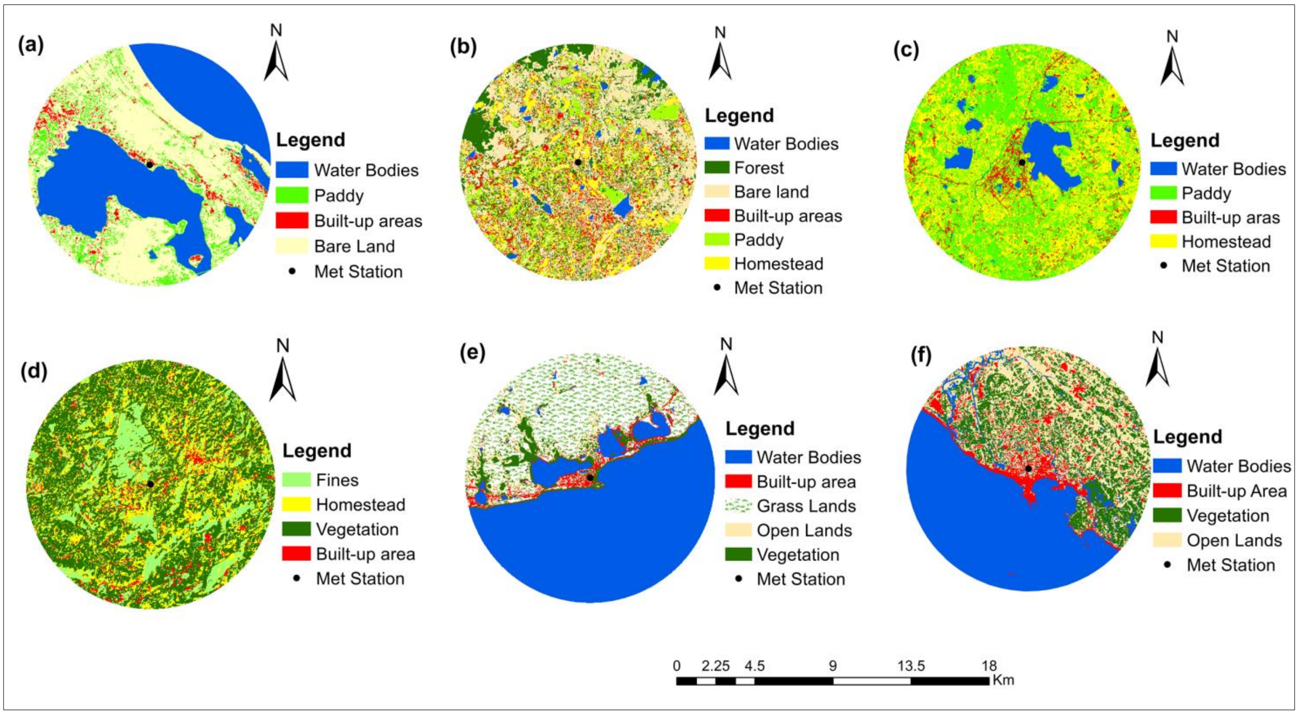

Fig. 3: LULC change maps of the selected study areas in 2000 for (a) – Batticaloa, (b) – Vavuniya, (c) – Anuradhapura, (d) – Bandarawela, (e) – Hambantota, and (f) – Galle.

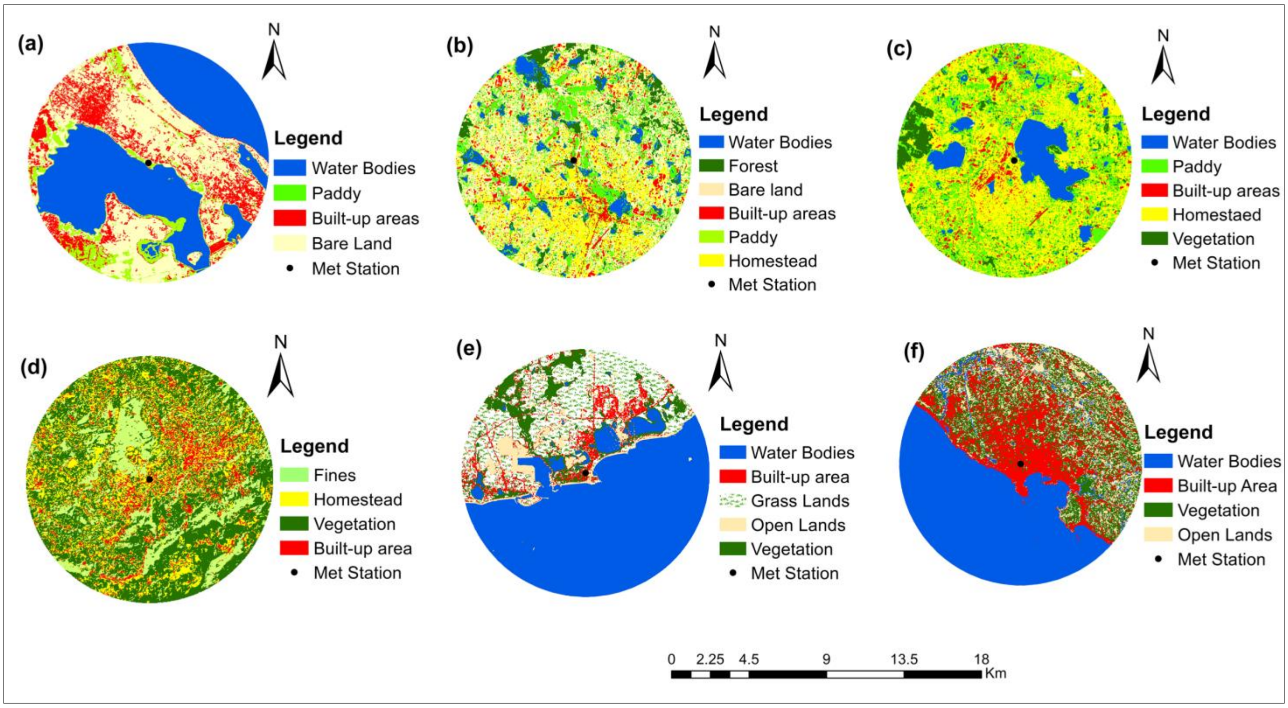

Fig. 4: LULC change maps for the selected study areas in 2021, for (a) – Batticaloa, (b) – Vavuniya, (c) – Anuradhapura, (d) – Bandarawela, (e) – Hambantota, and (f) – Galle.

3.1.2 Vavuniya

Adapting to the dry weather characteristics of the Northern Province, several seasonal changes can be covered in this area with different land use patterns within 21 years. Six LULC patterns have been selected for the study and there have been temporal changes in different land use patterns during this period. As of 2000, bare land covered an area of 70.14 km^2, and paddy land, forest, and homestead areas was found to be 25.72, 32.49, and 12.50 km^2 respectively (Table 3). The built-up area consisted of a small area of 6.5% of the total area, and it can be recognized that during this period, the population decreased as the civil war was at its peak in this area. Also, as a severe dry weather pattern can be identified, the water body areas cover less than 2.80 km^2 of the total land. By the year 2021, several temporal dynamics have been revealed in these land use/cover patterns. The built-up area has increased by 1.7% of the land area and the homestead by 14.09%. In this context, constructions related to urban areas are expanding with increasing population and urban development. With the creation of various tank projects, the water bodies have increased by 3.58%, and in 2000, nearly half of the entire area was covered by bare land. By the year 2021, the bare lands have decreased by 36.2 km^2, i.e. 9.4%. The amount of agricultural land has also increased by 3.47% compared to 2000, while the amount of forest has decreased by 13.5% by 2021 due to various human and environmental impacts (See Fig. 3 and 4).

Table 3: Changes in LULC obtained from Landsat ETM+/OLI images in Vavuniya from 2000 to 2021.

Land use/cover classes	2000 Area of LULC km^2	%	2021 Area of LULC km^2	%	Changes (%) in LULC for 2001–2021
Water Bodies	2.80	1.82	8.38	5.4	3.58
Paddy	25.72	16.7	31.02	20.17	3.47
Homestead	12.50	8.1	34.13	22.19	14.09
Built-up Areas	10.13	6.5	12.73	8.2	1.7
Forest	32.49	21.1	11.83	7.6	-13.5
Bare Land	70.14	45.6	55.71	36.2	-9.4
Total	**153.78**	**100**	**153.78**	**100**	**0**

3.1.3 Anuradhapura

At present, Anuradhapura urban area can be identified as a rapidly growing urban area and the study has revealed remarkable changes in several land uses over the past 20 years. The temporal dynamics of four types of land use related to this area have been investigated within a period of 20 years (Table 4). As the area has an agricultural land use pattern, most of the land areas are comprised of paddy fields. In the year 2001, 69.89 km^2 of land has been allocated for paddy cultivation, and homestead lands have been spread over an area of 62 km^2. 5.4% of the total area has been used for built-up areas and 11.53 km^2 of land has been reserved for water bodies. Irrigated agriculture based on the tank system is being implemented in this region. Therefore, many water bodies consist of large tank systems. By the year 2021, the built-up area has increased by 3.5 %, while the amount of paddy land has gradually decreased. That is, this decrease has been revealed to be 51.89 km^2, and homesteads can be observed as 46.1% of the total area in the year 2021 with the growth of the urban population. No significant level of changes can be identified concerning the water bodies and it is also seen that the tank system has been built up and the new tank system has been created in the urban area under urban planning projects (See Fig. 3 and 4).

Table 4: Changes in LULC obtained from Landsat ETM+/OLI images in Anuradhapura from 2001 to 2021.

Land use/cover classes	2001 Area of LULC km^2	%	2021 Area of LULC km^2	%	Changes (%) in LULC for 2001–2021
Water Bodies	11.53	7.4	17.29	11.2	3.8
Paddy	69.89	45.4	51.89	33.7	-11.7
Built-up Areas	8.38	5.4	13.7	8.9	3.5
Homestead	62	40.3	70.92	46.1	5.8
Total	**153.8**	**100**	**153.8**	**100**	**0**

3.1.4 Bandarawela

Bandarawela, which belongs to the central highlands of the wet zone of Sri Lanka, has several distinctive LULC patterns. Agricultural land use patterns and vegetation characteristics mainly from the wet zone can be identified. In the period of 21 years from 2000 to 2021 in the selected study area (Table 5), it is observed that the vegetation cover is 74.59 km^2 of the total area in the year 2000. 43.45 km^2 of the homestead were observed as several settlements are found in the vicinity of the urban area. As prominent vegetation and widely recognized in those areas, pine tree land covers spread over an area of 27.12 km^2 in 2000. The built-up area is reported to be 8.66 km^2 and by 2021 it has grown to 15.46 km^2 i.e., an increase of 4.4%. Due to the mountainous topographical features, large population densities cannot be identified compared to other areas. Pine and vegetation cover are gradually decreasing with the clearing of the land. By 2021, it can be detected as 18.7% and 46.2% respectively. Currently, due to the various urban projects that are being implemented in the area, the amount of pine cover is decreasing rapidly. On the other hand, it will also affect the development of built-up areas (See Fig. 3 and 4).

Table 5: Changes in LULC obtained from Landsat ETM+/OLI images in Bandarawela from 2000 to 2021.

Land use/cover classes	2000 Area of LULC km²	%	2021 Area of LULC km²	%	Changes (%) in LULC for 2001–2021
Fines	27.12	17.6	28.84	18.7	1.1
Built-up Areas	8.66	5.6	15.46	10	4.4
Homestead	43.45	28.2	38.46	25	-3.2
Vegetation	74.59	48.4	71.07	46.2	-2.2
Total	**153.8**	**100**	**153.8**	**100**	**0**

3.1.5 Hambanthota

In the Hambantota district, which belongs to the dry zone of the Southern Province, the land areas with less human habitat can be identified. Comparatively more bare and open land are constantly seen and the population is low compared to other areas. Five LULC types were selected for the study and as of 2000, grasslands spread over an area of 43.63 km² from the total land area (Table 6).

Table 6: Changes in LULC obtained from Landsat ETM+/OLI images in Hambanthota from 2000 to 2021.

Land use/cover classes	2000 Area of LULC km²	%	2021 Area of LULC km²	%	Changes (%) in LULC for 2001–2021
Water Bodies	87.92	57.1	85.96	55.8	-1.3
Open Lands	8.72	5.6	8.73	5.6	0
Vegetation	8.45	5.49	12.58	8.1	2.61
Built-up Areas	5.06	3.2	9.17	5.9	2.7
Grassland	43.63	28.3	37.34	24.2	-4.1
Total	**153.78**	**100**	**153.78**	**100**	**0**

In these areas with a harsh landscape, unique vegetation is found. Built-up areas comprise a very low land area of about 5.06 km² out of the total area, and the vegetation cover is about 8.45 km². No significant level of water bodies can be identified within the land area and about 87.92 km² of the total area is coastal. The study area also consists of 8.72 km² of open land with chena land, while abandoned lands are more distinctive within the environment. In the year 2021, compared to 2000, some changes have been detected in land use. The built-up area is 9.17 km² of the total land and the vegetation cover has grown by 2.61% compared to 2000. That is, it is 12.58 km² from the total land and its growth can be identified towards the northern border of the area. There has been no change in open land and grassland areas have decreased by 4.1%. With the increase of built-up areas and the construction of small settlements in the area surrounding the Salt Flats, the built-up areas are growing in size. With the ongoing urban development, open land and grassland areas are decreasing due to land reclamation for other areas (See Fig. 3 and 4).

3.1.6 Galle

While being the main center of the Southern Province, Galle can be recognized as an area belonging to the wet zone in the classification of climate zones in Sri Lanka. Bordering the southern coast, the coastal topography is characterized by many features. In the study, four land use patterns were selected as water bodies, built-up, vegetation, and open lands (See Table 7, and Fig. 3 and 4).

Table 7: Changes in LULC obtained from Landsat ETM+/OLI images in Galle from 2001 to 2021.

Land use/cover classes	2001 Area of LULC km²	%	2021 Area of LULC km²	%	Changes (%) in LULC for 2001–2021
Water Bodies	70.47	45.8	69.03	44.8	-1.3
Built-up Areas	13.01	8.4	31.31	20.3	11.9
Vegetation	30.45	19.7	31.58	20.5	0.8
Open Lands	39.89	25.9	21.92	14.2	-11.2
Total	**153.8**	**100**	**153.8**	**100**	**0**

In 2001, 70.47 km² of waterbodies were identified along with the ocean area. Areas with open land are found as 39.89 km² in 2001, and under open land, cleared zones, other crops, and so on, are included. Several built-up areas are found in the areas surrounding Galle Fort and it was observed to be 13.01 km² of the total area. This built-up area can be identified towards the western border of the area. A few vegetation are also found along the northern and eastern portion, and it has spread over a large area of about 30.45 km² in the year 2001. According to the classification map, it is revealed how the built-up areas are spread over the entire study area, and makes up 31.31 km² of the total area. The amount of open land has gradually decreased, and by 2021, it is shown as 21.92 km², with some open land reserved for built-up areas. In the 20 years, the vegetation cover showed a slight increase of 0.8% compared to 2001.

3.2 Accuracy Assessment

Table 8 shows the overall accuracy assessment results and Kappa (K) coefficient, i.e. for the six selected locations. Baseline data were gathered using 30 preparation samples for each type of land use and reference location. These were then overlaid using Google Earth on high-resolution satellite images. Afterwards, the correctness of the classification was quantified with the K coefficient. The K statistic measures accuracy while accounting for all factors, however, it does not consider how random fluctuation may affect accuracy. The K statistics are used to evaluate the overall accuracy of the LULC classes since they offer a statistically reliable assessment of the quality of categorization. The modeling of LULC change is deemed to be good when the K value is more than 0.5 (Table 8). Also, the proportion of samples that were successfully identified may be found via an error matrix, which can be used to gauge the overall accuracy of the classification. It is calculated by dividing the total number of reference pixels by the total number of correctly categorized pixels.

Table 8: Accuracy assessment of the LULC types.

Study Area	Overall Accuracy (%)		Kappa Coefficient (%)	
	2001	2021	2001	2021
Baticaloa	70.4	73.3	69.53	71.04
Vavuniya	69.9	70.3	68.7	69.61
Anuradhapura	74.6	73.2	73.72	71.48
Bandarawela	68.5	70.2	67.3	70.47
Hamabanthota	73.3	90	72.1	86.6
Galle	76.6	76.6	74.53	73.81

3.3 The Pattern of Land Surface Temperature Spatiotemporal Distribution (LST) Between 2001 to 2021

In the study of LST, significant growth can be detected in each study area within 20 years. Depending on the LULC, the LST rises and falls in certain areas. Concepts such as UHIs are on the rise, especially as urban areas grow. The construction of built-up areas and urban development projects such as road development, have had both positive and negative outcomes. In the year 2001, high LSTs were detected in the Batticaloa area in association with bare land regions. Since the ground is open in that area, solar heat is absorbed directly. Due to that, the surface temperature is gradually increasing. A maximum temperature of 38°C and a minimum temperature of 23°C have been recorded in that area. When compared with the land use map in 2021, it can be recognized that the temperature has increased by 40°C in the area with the increase of some built-up areas in the regions that were bare land. A minimum temperature of 25°C can be detected in paddy fields and water bodies. Compared to that, when focusing on Vavuniya, it can be recognized that the LST is high in the bare lands. The maximum temperature was recorded as 33.5°C, while the minimum was observed as 19.21 °C. In 2021, with the increase of built-up areas in the city of Vavuniya, there is an increase in the LST of the land, and with the expansion of settlements, the bare land zones are gradually decreasing. However, towards the western border of the area, there is some expansion of temperature and it is confirmed as 34.09°C.

There is also a high increase in LST in the Anuradhapura urban area and airport area. It was 34.06°C in the year 2001, and by 2021, it has increased to 36°C with the rapidity of urban growth. There is a low and moderate temperature pattern in the tank area and paddy lands, and the minimum temperature can be identified as 19.44°C in 2021. "Nuwara Wewa (Tank)" is located within the urban area and as the water undergoes the evaporation process, it also leads to control of the growth of LST. Focusing on Bandarawela which belongs to the wet zone, there have been some temperature changes, with a maximum temperature of 31°C in 2000, observed in several zones, and has increased to 32°C in 2021. It is also a unique feature that the LST is detected at a level of 30°C in a wet zone. Furthermore, LULC have been influential in identifying seasonal changes in LST in the Hambantota urban area. Especially since there are many open areas in this region, the LST has increased compared to other areas. As per the calculations made in 2000, a maximum temperature of 36°C was detected due to severe dry weather. Due to the implementation of urban development projects in this area, road development occurred to the greatest possible extent in the recent past. Through heat-absorbing materials like tar, the temperature of the land surface increases and as a result, the maximum temperature has been recorded as 36.3°C in the year 2021. Accordingly, it can be determined that there is a possibility of UHIs in this connection. Finally, in the urban area of Galle, a noticeable increase in LST can be seen with the increase in the built-up areas. Built-up areas have increased by 11.9% by 2021, resulting in surface temperatures of 36.3°C since 2001 and 37.6°C by 2021. Hence, it can be determined that there is a significant relationship between LULC and the increase in LST in the selected study areas (See Fig. 5 and 6).

3.4 The Spatiotemporal Distribution Pattern of Normalized Difference Vegetation Index (NDVI) Between 2001 to 2021

The land use changes identified from satellite images were verified, and the study area's green regions were identified using NDVI analysis. The spatial distribution of NDVI values within the chosen Sri Lankan cities is depicted in Fig. 7 and 8. Table 9 presents the corresponding quantified statistical data. In the year 2001, agricultural lands were detected as vegetation cover around the city of Batticaloa, and bare

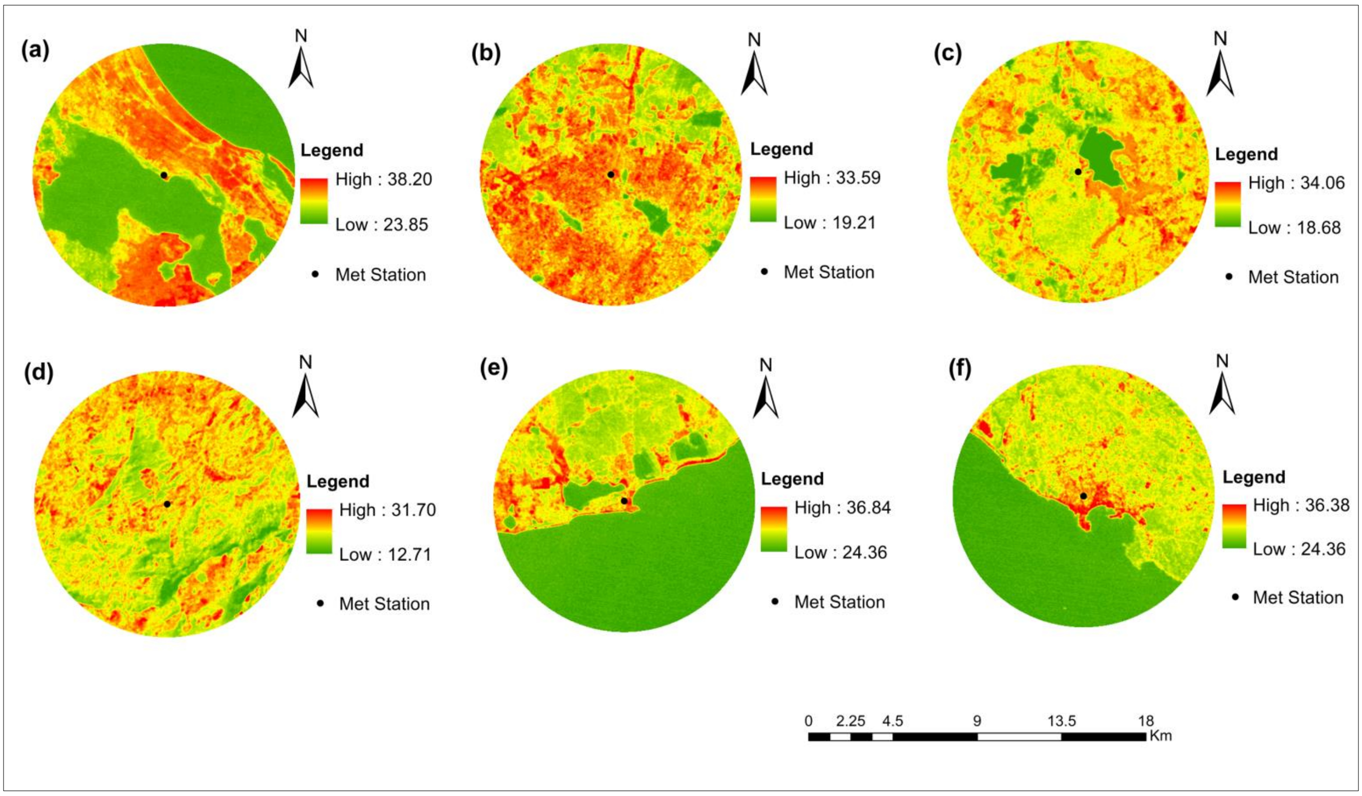

Fig. 5: Land Surface Temperature (LST) in 2000. (a) – Batticaloa, (b) – Vavuniya, (c) – Anuradhapura, (d) – Bandarawela, (e) – Hambantota, and (f) – Galle.

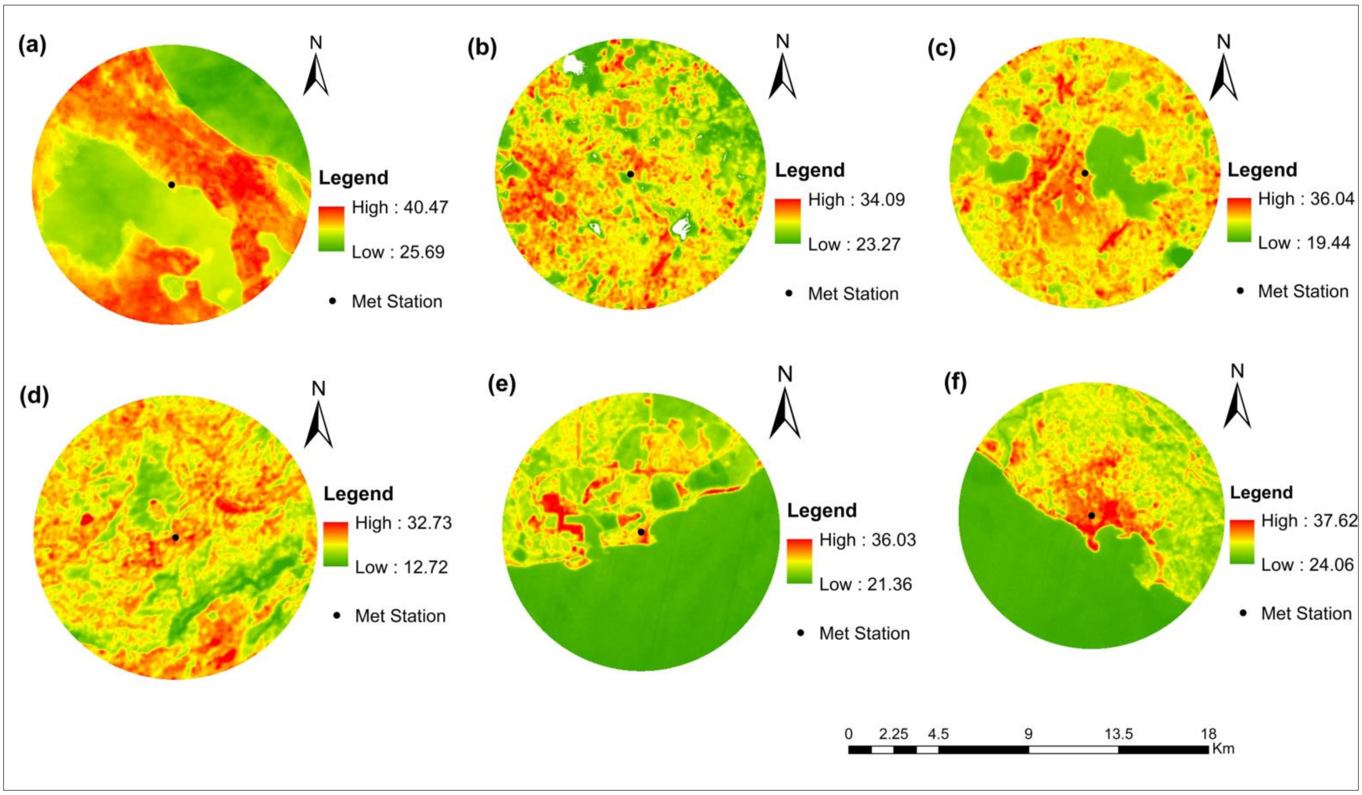

Fig. 6: Land Surface Temperature (LST) in 2021. (a) – Batticaloa, (b) – Vavuniya, (c) – Anuradhapura, (d) – Bandarawela, (e) – Hambantota, and (f) – Galle.

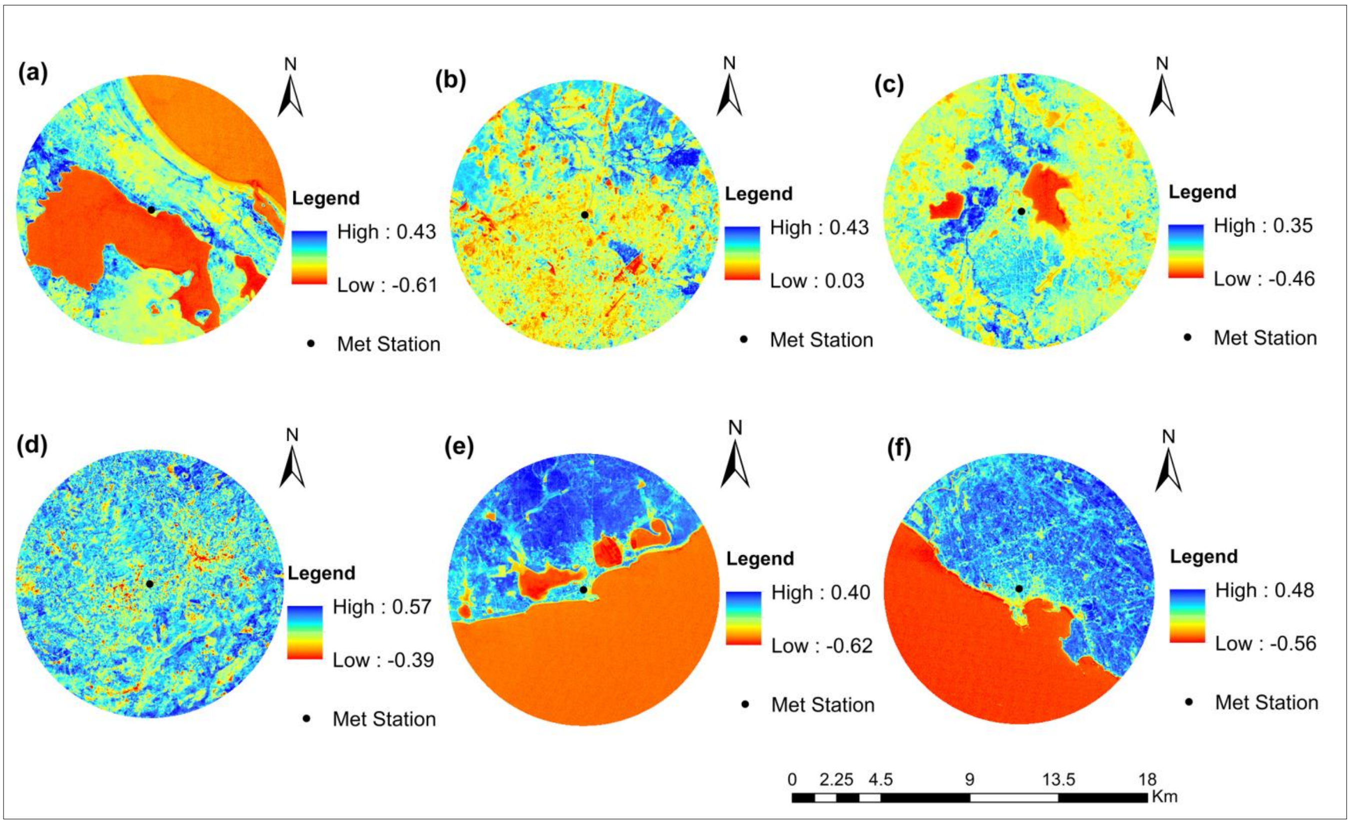

Fig. 7: NDVI Distribution of selected cities in 2000. (a) – Batticaloa, (b) – Vavuniya, (c) – Anuradhapura, (d) – Bandarawela, (e) – Hambantota, and (f) – Galle.

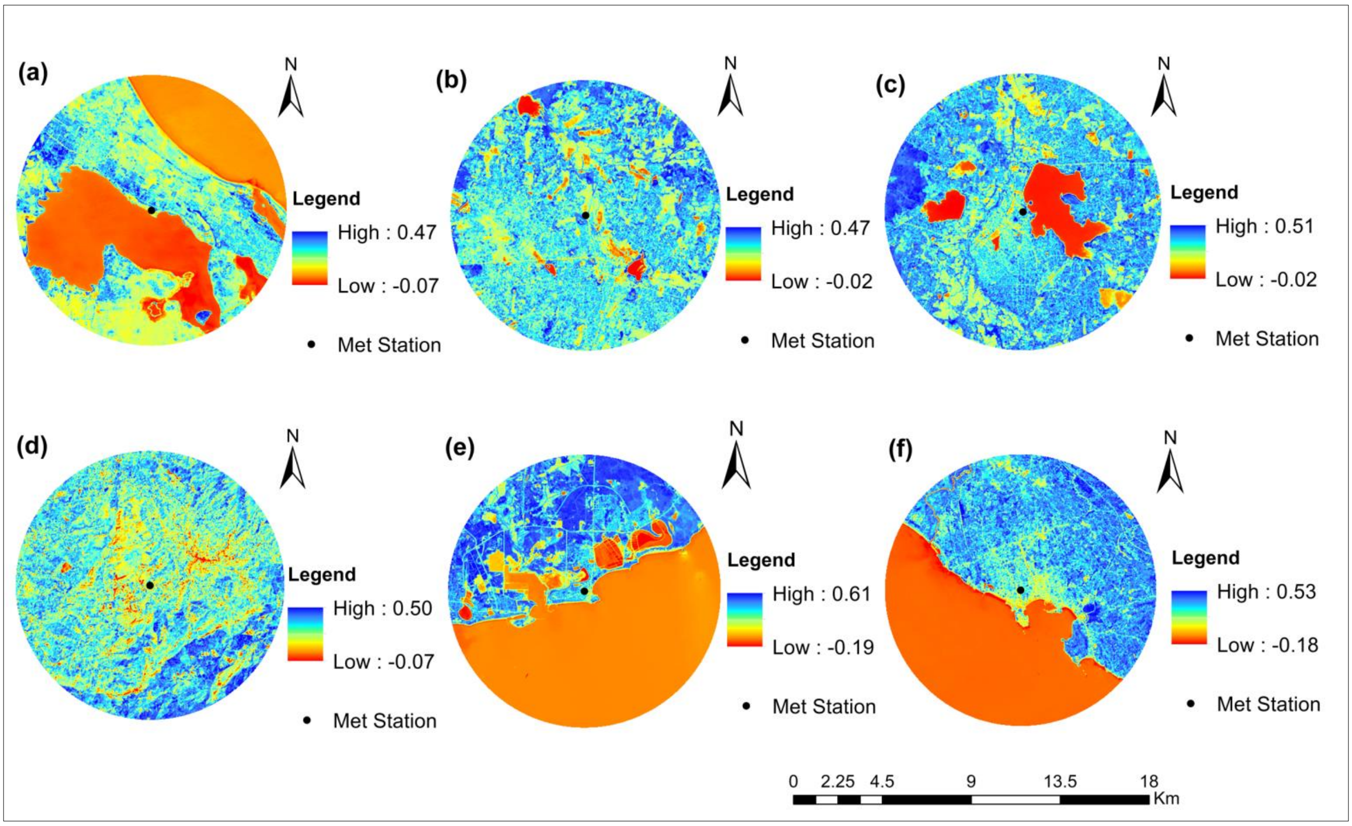

Fig. 8: NDVI Distribution of selected cities in 2021. (a) – Batticaloa, (b) – Vavuniya, (c) – Anuradhapura, (d) – Bandarawela, (e) – Hambantota, and (f) – Galle.

land and water bodies can be identified on the other hand. There is no large vegetation cover and only a small amount of land is covered with paddy fields, and the NDVI has been calculated with a value range of 0.43 - -0.61. By 2021, the NDVI value has increased to 0.47 and the spread of built-up areas has also increased. Though the NDVI value had increased, there was no increase in vegetation cover in this area. It can be determined by the distribution of these values that there is some vegetation cover in the agricultural land. An NDVI value of 0.43 has been observed in Vavuniya city in 2000 and it can be identified through the forest cover that has spread to the border of the area. Values like 0.03 are seen in bare land areas. There is no spread of large dense forest cover in the entire territory and the NDVI has increased to 0.47 by 2021. Some form of vegetation cover can be observed in bushy terrains. During the detection of vegetation cover density in the urban area of Anuradhapura, an NDVI distribution of 0.35 - -0.46 was evident in the year 2001. The city has a large system of tanks and on the other hand, paddy fields and abandoned lands can be observed. By 2021, the NDVI value has increased to 0.51 and as evident from the 2021 land use map, some land in the western portion has become a forest area. Homestead and undeveloped surface areas have some vegetation cover, and they have contributed to the NDVI variation. Along with the rapid increase in built-up areas, the vegetation cover has decreased in the center of the area.

Table 9: Descriptive statistics in NDVI variations in the selected study area.

Study Area	Year	Minimum	Maximum	Mean	Standard Deviation
Batticaloa	2001	-0.61	0.43	-0.23	0.21
	2021	-0.07	0.47	0.10	0.11
Vavuniya	2000	0.03	0.43	0.23	0.05
	2021	-0.02	0.47	0.25	0.07
Anuradhapura	2001	-0.46	0.35	-0.07	0.11
	2021	-0.02	0.51	0.26	0.10
Bandarawela	2000	-0.39	0.57	0.26	0.10
	2021	-0.07	0.50	0.32	0.06
Hambantota	2000	-0.62	0.40	-0.16	0.29
	2021	-0.19	0.61	0.13	0.17
Galle	2001	-0.56	0.48	-0.06	0.31
	2021	-0.18	0.53	0.18	0.17

In the Bandarawela area, there are some unique differences in the identification of vegetation density. As the area belongs to the wet zone, dry weather conditions cannot be observed to a large extent. A high vegetation cover of 0.57 can be observed and vegetation like pine has also been included in it. By 2021, as the NDVI value has decreased to 0.50, it has been observed that there is a slight decrease in vegetation cover. It also shows an increase in the spread of built-up areas towards the center of the area. Hambantota, which is an area belonging to the severe dry zone, had an NDVI of 0.40 in 2000, and within the land use, it is possible to observe grass with many thorn bushes. The sea area and lagoon system can be identified as an aquatic ecosystem, although widespread dense forests are not visible. This has grown to 0.61 by 2021 and when looking at land use, it can be observed how a vegetation cover has been created towards the north and northwest border. There has been a decrease in forest areas recently due to the rapidly expanding built-up regions (such as the road network and administrative buildings in Hambantota). When observing the distribution of NDVI in the Galle area, a value ranging between 0.48 - -0.56 was identified for the year 2001. The range of values has been expanded in association with lightly wooded areas and open lands. The urban zone is located towards the area's central portion, and as of 2021, the built-up area has expanded quickly. An NDVI value of up to 0.53 was observed by 2021. In some regions, the vegetation cover zones that existed in 2001 have slightly decreased by 2021, but as the vegetation in other zones have increased, it is evident that associated areas have a constant vegetation density.

3.5 Relationship between NDVI and LST

The scatterplots of NDVI and LST are illustrated in Fig. 9. When an average estimate between NDVI values and LST values was constructed based on data from the literature during the research period, a correlation between both parameters in both negative and positive form was found (Kaplan et al., 2018; Lo et al., 1997). It became clear while observing the NDVI results that there has been an increase in the value of the other 5 areas, except the Bandarawala area. This is because it has been confirmed that the grasslands, bushes, croplands, and undeveloped natural surface land that surround such places have some sort of vegetative cover. Built-up areas, bare lands, and water bodies have a lower range of NDVI values. Compared to the year 2000, there was an increase in the built-up areas by 2021, so an increase in the associated surface temperature can be observed. Accordingly, although it is revealed that there is a positive relationship between NDVI and LST in the study areas of Galle, Batticaloa, and Hambantota, the (r^2) coefficient does not show much growth. In Galle and Batticaloa, the rapid development of built-up areas in 2021 has resulted in increased surface temperatures due to reduced vegetation cover. But beyond the Hambantota and Galle urban areas, a slight increase in vegetation cover has been detected through land use. Anuradhapura city by 2021 shows a moderate relationship between NDVI and LST as the built-up area increases and there is an increase in vegetation cover towards the western part of the city. There is a negative relationship between NDVI and LST in relation to Vavuniya. As there is a small vegetation cover such as grasslands and bushes around the area, it is possible to detect some kind of vegetation density in it.

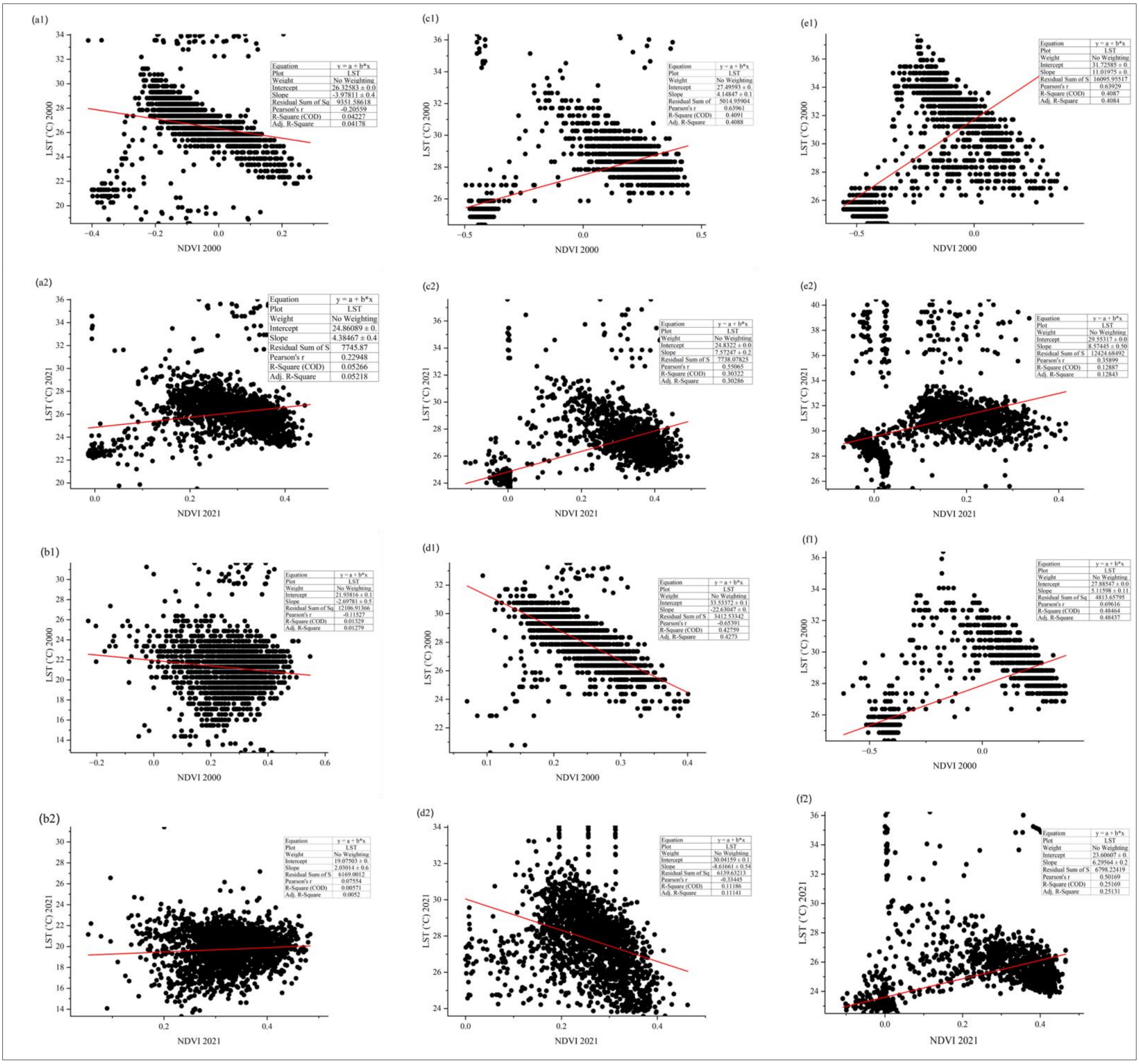

Fig. 9: Correlation analysis between NDVI and LST for; (a1) Anuradhapura for 2000, (a2) Anuradhapura for 2021, (b1) Bandarawela for 2000, (b2) Bandarawela for 2021, (c1) Galle for 2000, (c2) Galle for 2021, (d1) Vavuniya for 2000, (d2) Vavuniya for 2021, (e1) Batticaloa for 2000, (e2) Batticaloa for 2021, (f1) Hambantota for 2000, and (f2) Hambantota for 2021..

The results do not confirm that there is a significant level of relationship between these two criteria in the Bandarawala area, and it has been revealed that the (r^2) value for the two years is 0.0024 and 0.0057 respectively, which is a low value. Through vegetation cover, we can directly present that there is some relationship between vegetation and LST because it acts as a main index for the fluctuation of thermal radiation in any area. Also, one of the main factors lowering the quantity of heat radiation is vegetation (Chakraborty et al., 2014).

3.6 Trend Analysis for Temperature Data

The Linear Trend Analysis was used to measure the magnitude of the trend. In this study, yearly data for two time periods were subjected to the Linear Regression Model: 1901-2020, and 1961-2020. The regression coefficients were calculated and as a measure of significance, the 'Trend-to-Noise-Ratio (T/N)' was calculated.

Table 10: Calculation of Annual Mean Temperature (1901 - 2020).

Station name	Annual Mean Temperature Trend (1901-2020)			
	Linear Trend Statistics		Mann Kendall Statistics	
	Linear Trend	T/N ratio	Sen's Slope Estimate Q	Z value
Anuradhapura	0.0106	**2.32**	0.0119	**7.97*** **
Galle	0.0075	1.95	0.0089	**7.56*** **
Hambantota	0.0032	0.77	0.0033	**2.51***
Bandarawela	0.0083	1.76	0.0088	**7.54*** **
Batticaloa	0.0076	**2.11**	0.0078	**7.00*** **
Vavuniya	ND	--	ND	--

Table 11: Calculation of Annual Mean Temperature (1961 - 2020).

Station name	Annual Mean Temperature Trend (1961-2020)			
	Linear Trend Statistics		Mann Kendall Statistics	
	Linear Trend	T/N ratio	Sen's Slope Estimate Q	Z value
Anuradhapura	0.0199	**2.69**	0.0200	**6.47*** **
Galle	0.0188	**2.77**	0.0187	**6.79*** **
Hambantota	0.0219	**2.93**	0.0222	**7.57*** **
Bandarawela	0.0194	1.74	0.0203	**6.22*** **
Batticaloa	0.0168	**2.63**	0.0161	**6.57*** **
Vavuniya	0.0193	**2.35**	0.0187	**5.58*** **

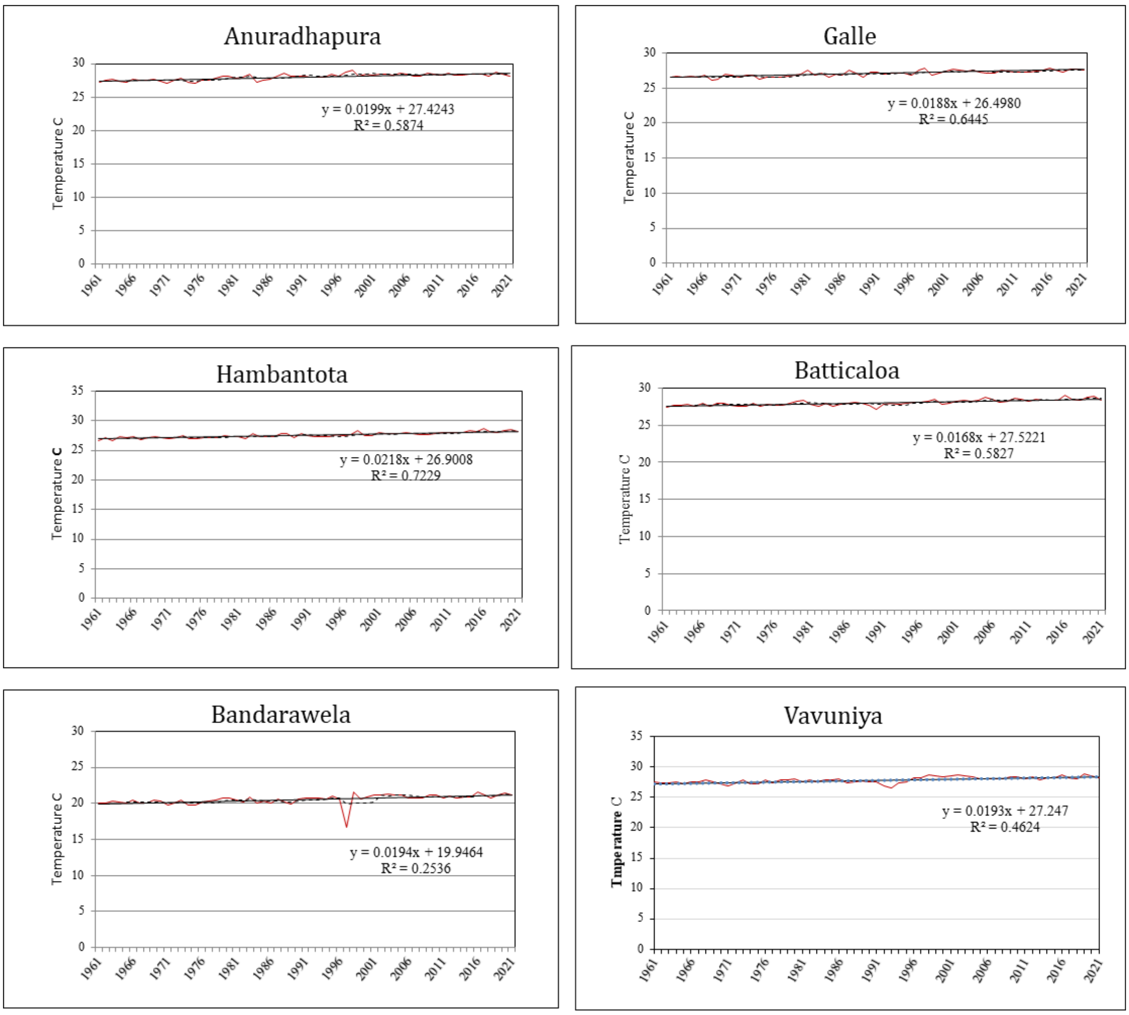

Fig. 10: Trend analysis for each station; top to bottom and left to right; Anuradhapura, Hambantota, Bandarawela, Galle, Batticalao, and Vavuniya.

The trend value was divided by the noise, which is represented by the data's standard deviation, to determine the significance. T/N values greater than 1.96 are considered statistically significant (95%) (Schaefer and Domroes, 2009; Sneyers, 1991).

The surface temperature of the earth was calculated for the years 2001 and 2021 using satellite images for the 6 selected locations. Further, it was analyzed through Trend Analysis methods such as Mann Kendall by getting the correct temperature data related to two periods to verify the true falsehood of this. According to the calculations made for the years 1901-2020, four study areas with a significant level of 99% were detected. During that period, a Mann-Kendall value of 2.51 was calculated in the Hambantota area and it was confirmed as a 90% significant level. During this period, there is a gradual increase in temperature according to the accurate data calculations of the annual mean temperature related to these places and it has also been confirmed through the analysis using satellite data. Also, according to the Mann-Kendall analysis conducted between 1961 - 2020, a 99% significant level value was confirmed in all 6 study areas. A gradual increase in surface temperature from 2001 to 2021 was observed in the analysis using satellite images. In regression analysis, true falsehood can also be confirmed by calculating a positive value in each r value (See Table 10 &and 11 and Fig. 6).

3.7 Effect of LULC to Create Urban Heat Islands (UHI)

Nowadays, given the swiftly growing population and the development of infrastructure, there is a decrease in open land and an expansion of built-up areas. This is a phenomenon experienced in any country in the world today. The creation of hot urban zones that retain heat rather than environmentally friendly urban environments has become problematic. Most of the people are in the process of migrating from the rural areas to the city aiming for an urban lifestyle. They must decide whether they come to the city mainly to find a solution to their socio-economic context. It should be understood through this phenomenon that there is a possibility for the creation of an UHI mainly in this way. The temperature is the highest in the city center. Beyond the urban core, the temperature gradually decreases. The boundary zone of thermal islands is semi-urban or rural areas. Due to temporal and spatial factors, the activity of heat islands varies according to the season. A major factor contributing to the high temperatures observed in 2021 compared to 2000 has been the swift expansion of urban areas. After bare land, vegetation, open lands, agricultural land, and water bodies, it was discovered that the built-up region has experienced the greatest rise in LST over the previous 21 years. According to the study, there is a correlation between urban growth and high LST values in various regions of the center, which may be linked to the development of commercial, residential, and industrial spaces. In the analysis, the surrounding area has been selected from the weather station established in about six urban locations, and based on that, the Trends Analysis conducted by obtaining temperature data from 1901 - 2020 / 1961 - 2020 has also confirmed that there is variation in temperature in these areas. It is also important to pay attention to the results that have been revealed through previous but similar investigations.

This suggests that the reduction of vegetation has been significantly influenced by urban expansion and changes in land use, which has raised surface UHI through increased LST (Dissanayake et al., 2019a; Karakuş, 2019; Simwanda et al., 2019). Ranagalage et al. (2018) through their research related to the Kurunegala urban area, have discovered the way that changes in the urban landscape affect LST in cities and how much they contribute to the UHI effect's occurrence. Since the civil war ended in 2009, there has been a noticeable surge in urban expansion and quick infrastructure development, which has resulted in a ten-year trend of rising annual mean LST. In the Indian context, from 1991 to 2018, there was a noticeable shift in Mumbai's LULC pattern, which had an impact on the spatiotemporal dynamics of the UHI phenomena there. Between 1991 and 2018, the city's built-up areas increased as a consequence of population growth and economic development, significantly decreasing the amount of green and open spaces at the expense of the built-up area (Dwivedi et al., 2019; Sahana et al., 2019). Further, ongoing changes in informal land use patterns will also provide opportunities for the creation of heat islands. Due to the changes that occur with irregular construction, changes in many physical components can be identified. It is recommended that future studies establish a connection between the temporal and geographical dynamics of extreme weather events, UHI, and LULC change. Also, to increase urban climate resilience, nature-based solutions can be recommended using the LST, UHI, and green cover maps that have been created (Balasubramanian et al., 2022).

3.8 Limitation and Future Research Direction

The constraints and future scope of the work have been determined in this section. This primary limitation of this research was that although the lengthier periods were chosen based on the study locations, the necessary data were not accessible. The Landsat satellite data were not pertinent to the needed time ranges. Additionally, the data for the chosen research region is only available during particular, limited hours. Particularly in urban areas, the 30 m spatial resolution level of the Landsat data does not yield exact details about tiny things like settlements. Although the study's results are quite acceptable, considering that the satellite images were acquired at different times, caution must be used when using and interpreting them for other studies. Using more reliable datasets, future research should aim to validate the results presented in this study. In considering this, more research should try to broaden the scope of the study by including rural and urbanized settings in certain regions to more accurately imitate the UHI impact. According to research, metropolitan areas that prioritize green city development or lose a lot of vegetated lands are more susceptible to the impacts of UHI, which can cause disruptions to ecosystem services.

4 Conclusion

This paper used and depended upon Landsat RS data to monitor changes in LULC and their effects on LST at 6 selected weather stations (cities) in Sri Lanka. The desired outcomes of the current research were successfully attained by the applicable strategies used in this investigation. The research made an effort to pinpoint changes in land use classifications and how they affected LST. Considering that the study is solely dependent on freely available Landsat data from the USGS, which was captured on a certain date by the satellite, in the future, the use of seasonal images will allow for a more precise and thorough investigation of LST variation. The rise in LST values is a result of the interaction between urbanization and the effects it has on climatic conditions. The study demonstrated that different kinds of land had varying LST values; for instance, bare land and urban areas had higher radiant temperatures. The findings showed that during the past 20 years, the yearly LST increased in Batticaloa and Galle. The findings suggested that there is a greater likelihood of continuing urban growth. It could also be impacted by the current vegetated area. On the other hand, new land transformation policies and methods are thus urgently needed to offset the detrimental impact on LST for the long-term sustainability of urban growth. However, these areas have seen an increase in LULC-caused warming due to their abundance of green space. Carefully considered spatial distribution maps of the NDVI and LST were produced using the link between the two variables that were explored. However, the urban built-up land had the greatest average temperature during the research period, while the higher NDVI values were discovered to be the vegetative areas. The study concludes that further research is now necessary to understand how surface temperature variations due to land use and cover affect local and regional climate. Because urban land use expansion has a significant impact on LSTs, future research should focus on the best ways to reduce the degradation of the thermal environment caused by this process and apply this solution to urban planning policies. These are important issues in the development of modern cities. Although the process of creating UHI in the world is based in developed countries, the trend that can be identified at present is that it is also gradually growing in less developed countries. The impact of industrial and agricultural changes taking place in developing countries can be identified as causal factors. The concrete and tar on the surface of the city surrounding the city are directly affected by the excessive heating and the very limited moisture on the surface of the land. The results of this study show that the selected cities' LULC alterations have had a significant impact on the city's rise in LST, which has led to the development of surface UHI. The development of grasses, trees, and other tiny plants can help to regulate this by drastically lowering the city's surface temperature by evaporative cooling and shading the surrounding area.

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Author Contributions

Conceptualization, methodology, analysis, writing - original draft preparation, W.M.D.C, P.H.A and writing - review and editing, W.M.D.C, P.H.A. All authors have read and agreed to the published version of the manuscript.

Conflict of Interest

The authors declare no conflict of interest.

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