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Surface Urban Heat Islands Dynamics in Response to LULC and Vegetation across South Asia (2000–2019)

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Abstract: Urbanization is an increasing phenomenon around the world, causing many adverse effects in urban areas. Urban heat island is are of the most well-known phenomena. In the present study, surface urban heat islands (SUHI) were studied for seven megacities of the South Asian countries from 2000–2019. The urban thermal environment and relationship between land surface temperature (LST), land use landcover (LULC) and vegetation were examined. The connection was explored with remote-sensing indices such as urban thermal field variance (UTFVI), surface urban heat island intensity (SUHII) and normal difference vegetation index (NDVI). LULC maps are classified using a CART machine learning classifier, and an accuracy table was generated. The LULC change matrix shows that the vegetated areas of all the cities decreased with an increase in the urban areas during the 20 years. The average LST in the rural areas is increasing compared to the urban core, and the difference is in the range of 1–2 (°C). The SUHII linear trend is increasing in Delhi, Karachi, Kathmandu, and Thimphu, while decreasing in Colombo, Dhaka, and Kabul from 2000–2019. UTFVI has shown the poor ecological conditions in all urban buffers due to high LST and urban infrastructures. In addition, a strong negative correlation between LST and NDVI can be seen in a range of −0.1 to −0.6.

Keywords: surface urban heat island; land use land cover; land surface temperature; normalized difference vegetation index; urbanization

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1. Introduction

Since the Second World War, global urbanization has expanded considerably. The Population Reference Bureau has revealed that 50% of the world population (3.4 billion) is settled in urban areas [1]. In fact, by 2030, the population of cities is projected to hit 60 percent, which means that some two billion additional people will live in the towns by that year. Moreover, there is an estimated rise of around 100 towns with over one million between 2005 and 2015 [1]. The rapid urban development expansion, which increases impervious surface growth in urban areas, affects the local environment, climate variables, and other aspects, either directly or indirectly. Mass building is in progress to meet the growing demand for housing [2]. This unplanned and unsustainable urban construction has caused adverse side effects worldwide. One of the most observed impacts is the urban heat island phenomenon. Urban heat islands (UHIs) as a result of urbanization were first documented by Howard, [3] in 1818. An urban heat island is a closed isotherm that indicates a relatively warm area compared to the surroundings, most frequently associated with human urban environments. [4]. Specific interactions between humans and natural systems are responsible for UHI. Many factors exist, but the most important are human activities, dark environments, and the lack of vegetation. [5]. There are mainly two types of heat islands: (a) atmospheric UHI, which includes canopy layer heat island (CLHI), and boundary layer heat island (BLHI) (b) surface heat island (SHI). Here BLHI is entirely affected by small-scale weather changes which form a plume of heat and acquires additional heat from roofs, vents, chimneys, etc. In short small-scale anthropogenic activities the CLHI extends from the BLHI to the top of buildings and infrastructure which forms a canopy layer similar to the canopy of trees in forests [4]. It is affected by the atmospheric heat as well as the BLHI heat from anthropogenic activities. The height of the CLHI varies according to the urban infrastructure with the heights of buildings. The SHI or SUHI is strictly related to urban land surfaces. SUHI is affected and influenced by various factors including anthropogenic and natural ones. Others include orientation to the Sun, wind, sky, reflection and absorption of solar and infrared waves, surface moisture, evaporation, surface roughness, conduction and diffusion of heat, etc [4].The first two refer to a warming of the urban atmosphere; the last refers to the relative warmness of urban surfaces. The urban canopy layer (UCL) is the air layer nearest to the surface of the towns and stretches upwards to about the medium height of the houses. The city boundary layer, which may reduce to hundreds of meters, or less during the night, is above the urban canopy layer. It is the BLHI that is in the form of a dome of warmer air that extends downwind of the city.

Summer UHI causes significant decreases in the outdoor air quality (OAQ) and the energy consumption of an area increases. This energy increase may cause widespread power losses owing to the increased and excessive usage of air conditioning systems [2]. The latest example is the deaths of about 50,000 individuals in Europe caused by an extreme heatwave in August 2003. In addition to the impact of heat and higher energy consumption by UHI, it also intensifies the concentration of contaminants in urban areas [6]. UHI also influences local weather by causing fluctuating local wind patterns, clouds, and fog formation, moisture increases and precipitation decreases [4]. In terms of absorption, sweating, anthropogenic heat release, and blocking prevailing wind, the action of an artificial urban system varies dramatically from the simplistic essence of short-wave and long-wave energy.

That urbanization can significantly influence local weather and the environment is well known and documented [7]. This has caused an increased interest in LULC knowledge in recent years. This knowledge can explore the urban ecology, geography, morphology, and the developing idea of urban intensity, diversity, a pattern of land use, UHI phenomenon, and others [8,9]. The research carried out on LULC in urban areas in particular influences a wide range of urban planning and policy-making, network creation, transportation management, and economic growth [10]. In developing and developed countries, LULC was studied in two ways: urban increase and urban improvement, making sure that LULC is more critical in developed countries than developing countries as it is tough challenging in developing countries to establish green and enhanced environmental space because of a lack of space in general. [10]. Likewise, the green surfaces in the metropolitan cities of developing countries are also decreasing into built-up ones. That's why it is essential to study LULC in developing countries and its impacts in the form of UHI so that they can counter the effects before it gets too late for these. Much research has been conducted on the subject of the urban heat island effect in recent decades, and it is observed in many major cities across the world. These include Athens [10], Paris [11], Singapore and Kuala Lumpur [12], Tokyo [13], and Houston, Texas [14] and Washington, DC [15]. In addition, regional studies have also been done in Australia and Argentina [16], China [17], South Korea [18], in the United States [19].

Cities have varying physical surfaces, resulting in varying surface behavior patterns in terms of radiation, absorption, evaporation, and heat release for anthropogenic reasons. [20] The many elements that make up the urban physical surface differ greatly, as they include asphalt, gravel, stones, pebbles, flooring, and concrete, all of which increase sensitivity and decrease evapotranspiration. All of these factors have a significant impact on the city's climate. [21,22]. SUHI is one of the major influencing factors for extreme changes in the local space's atmosphere, affecting the lives of animals, including humans, as well as natural aspects (like macro- and microorganisms) [23]. Due to its negative impact on human health and environmental qualities like air quality, precipitation, temperature, carbon storage, and energy balance, SUHI has attracted the interest of politicians, health authorities, urban planners, urban investors, and other scientific communities [21], so it is very important to study UHI to counter its effects and to provide some solutions for the present heat island effects. There are many UHI studies published on largest cities around the world, but developing countries are still lacking behind in such studies and therefore not planning accordingly for their future metropolitan cities. The present study will focus on the surface level urban heat island (SUHI). The study will be based on remote sensing data, so the canopy layer and boundary layer UHI will not be observed as these require accurate ground level and fixed towers or stations temperature data. As the pace of urbanization and land use change is very fast in developing then the developed world, it is also need of the time to study these countries or regions to provide a comparative and detailed analysis on this problem. This paper will focus on SUHI in South Asian largest cities, and the temperature dynamics in countries according to cities. First of all, we need to know the present situation of UHI in our area of interest.

According to [24], Southern Asia's urbanization is chaotic, discreet, and increasing at a constant speed. The urbanization trends in South Asia have remained unchanged in terms of degree and speed relative to others, such as South-Eastern Asia and Latin America [25]. Interestingly, it is defined in terms of the number of people living in urban areas as the least urbanized part of this region. However, the scale and rate of growth of urban populations remain so high that a large proportion of the world's urban population will rise in this area. Across all regions with a leading position from Africa and Asia, the pace of urbanization is projected to increase in the period 2020–2050 [24]. The urbanization in Southern Asia rose from approximately 17% in 1950 to 24% in 1980 and finally to 35% by 2015. Therefore, spatial dynamics of a city's landscape is essential to incorporate mitigation strategies and, to understand the spatial dynamics of a city's landscape to deal with the adverse impact of UHI phenomena [20].

In the face of climate change, population development and resource management are significant challenges for developing countries' or rising economies in particular [26]. The area of South Asia that includes Afghanistan, Bangladesh, Bhutan, India, Nepal, Pakistan, and Sri Lanka, geographically known as the Asia Region, has 1.6 billion inhabitants, nearly a quarter of the world's total population. Current demographic estimates indicate that South Asia will have about 2.2 billion or more by 2050 [27]. On both sides, current and future South Asian regions are faced with urban development challenges. Present urban problems include deprivation, increased emissions of GHGs, levels of pollution, and increased demand for electricity. In South Asia, 45% of the world's underprivileged work for less than $2 per day [28], making it more vulnerable to climate impacts. Emissions of greenhouse gas (GHG) were doubled between 1990 and 2012 in India and Pakistan, with urban areas accounting for over 60% growth [29]. South Asia is home to 11 of the top 20 cities with the highest concentrations of pollutants (measured as $PM_{2.5}$) [30]. Between 1994 and 2002, the region's energy consumption increased by 64% [31]. The possibility of a spike in winter temperatures, as well as the frequency of extremely hot summer days and nights, are among the challenges ahead (IPCC, 2013) [32]. Excess mortality in cities was investigated by researchers [32], and the results showed that deaths increased from 4.1 % to 5.8 % for each 1 °C above a temperature threshold. In the face of threatening prospects of catastrophic climate change and uncontrolled environmental degradation, theoretically, scientists could identify far-reaching functional implications for energy and management, human well-being, comfort and efficiency, urban ecology, air pollution reduction, and therefore more sustainable urban development. [33].

The effect of a urban heat island (UHI) can be defined by measurements of temperatures in towns and suburbs, which are generally higher than in rural or suburban areas [34]. It can also be observed as an urban climate effect-based process. Artificial surfaces, such as buildings and roadways made of dry and transitory materials, are being implemented., and human activities change cities' energy balance and the air layers above are UHIs [35,36]. Furthermore, the greatest immediate effect of UHI on human health is the higher temperature, which can be particularly problematic during heat waves [26]. The current study will address the presence of urban heat islands (UHI) and their dynamics, which may be the most significant trend of local climate change in metropolitans in South Asia. The canopy-layer UHI has a wide range of effects on energy use, water irrigation, thermal circulation, air quality, and urban ecology, as well as affecting urban thermal comfort [26]. Regional climatic patterns, local circulation, precipitation, rainfall, and plant growth seasons may all be affected by the UHI boundary layer [26]. Various analytical and modeling methods were adopted to study UHI, depending on the form and size of the heat island to be investigated. Surface temperature spatial-temporal changes are best recorded by aircraft and satellite thermal scanners, the ambient atmospheric air temperature is measured using fixed weather stations and car traverse investigations [26,37]. As urban heat islands are a global phenomenon, their analysis in the last few decades has increased exponentially, reflected in the surprisingly fast growth of the available literature [37].

As mentioned above, the UHI phenomena are being studied with much interest in many parts of the world, but if we examine the published literary works, there are very few studies focusing on the big cities in developing countries as compared to developed countries. Furthermore, the available studies in South Asia are also focused on individual cities like Delhi, Mumbai, Colombo, Lahore, etc. We need to do an individual and comparative study on the largest cities of this region as a whole for comparative analysis of UHI. Based on land cover/land use (LCLU), LST, and normalized difference vegetation index (NDVI), this study will look at the geographical and temporal fluctuations in SUHI, which will be quantified and correlated with vegetation activity in South Asia's largest cities from 2000 to 2019. This will provide more knowledge about the UHI problem in each of the cities and also in comparison to other cities of the same region for better planning and development strategies of urban areas. This will also show the change in UHI between these twenty years. This study will fulfill the following objectives: (a) To observe the spatial and temporal (2000–2019) SUHI trends and temperature differences in South Asian cities. (b) To look at the effects of long-term changes in LULC in SA megacities on UHI. (c) To examine urban thermal changes, compute and investigate the several heat indices (SUHII, UTFVI) and LST. To evaluate the impacts of these factors along with LULC on LST. (d) The role of city size and other factors (elevation, geography) in the UHI effect and finally, suggest sustainable solutions to prevent this problem.

Study Area

South Asia, sometimes known as Southern Asia, is the Asian continent's southern section, which includes the sub-Himalayan countries as well as, according to some sources, neighboring countries to the west and east. Topographically, the Indian Plate, which rises above sea level as northern India south of the Himalayas and the Hindu Kush dominates this region. The Indian Ocean borders South Asia in the south, and land borders Western Asia, Central Asia, East Asia, and Southeast Asia (clockwise from the west). South Asia comprises Afghanistan, Bangladesh, Bhutan, the Maldives, Nepal, India, Pakistan, and Sri Lanka [38]. South Asia covers around 5.2 million km^2 (2.0 million sq mi), accounting for 11.71 % of the Asian continent and 3.5 % of the global land surface area [38] ranging from 114°09′–122°43′ E, 34°22′–38°23′ N. South Asia has a population of about 1.891 billion people, or roughly one-fourth of the world's population, making it the world's most populous and densely populated geographical region [39]. Overall, it is home to around 39.49% of Asia's population and over 24% of the world's population, and it is home to a diverse range of people [39]. The cities selected for the present study are Colombo, Delhi, Dhaka, Kabul, Kathmandu, Karachi, and Thimphu. As mentioned in the UN-Habitat Report [40] and World Bank [41] the definitions of cities differ around world. Most of the countries apply two or more definitions to define urban areas which are an administrative definition, which includes population size, density, economic functions, etc., and another the uses only population size and density [40]. The criteria used for this study are based on the city and population size. Every city has more than 100,000 inhabitants at least and the city areas and population sizes that were more than those of the other cities of the same country were selected.

Figure 1 shows the study area map of the cities from South Asian countries that will be studied. South Asia's borders differ depending on how the region is defined. The Indian Plate forms the majority of this region, which is separated from the rest of Asia by mountain ranges [42]. Much of the region is made up of a peninsula in south-central Asia that resembles a diamond and is bounded on the north by the Himalayas, the west by the Hindu Kush, and the east by the Arakanese [42] and which extends southward into the Indian Ocean with the Arabian Sea to the southwest and the Bay of Bengal to the southeast.

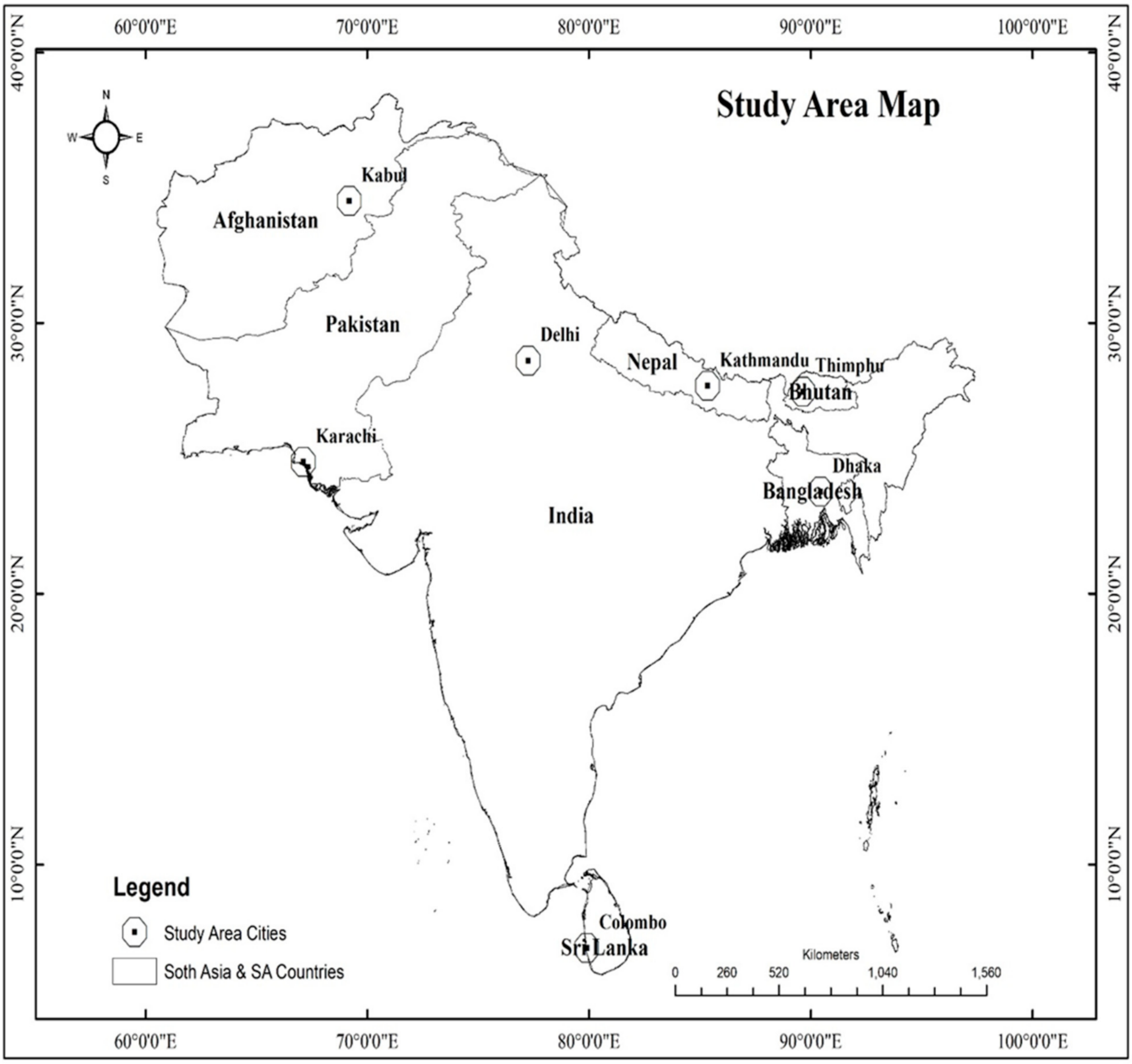

Figure 1. Study area map.

South Asia is home to some of the world's most densely inhabited cities. Four of the world's largest megacities are Dhaka, Delhi, Mumbai, and Karachi. The present cities are also chosen based on population and city size from all the countries of SA. These cities are the largest based on their size and population from other cities of each country, so we have seven cities, one each from the countries mentioned above as the Maldives is very small in size and population in comparison to other countries, so it will be excluded from the present study area. Table 1 above shows some details about the study area cities.

Table 1. Study Area Cities Details (Source: World Atlas [43]).

No.	Countries of SA	Megacities/ Largest	Area (km^2)	Population (year)	Elevation (m)	Geography/ Landform
1.	Afghanistan	Kabul	275	4,434,550 (2020)	1790	Mountain Valley
2.	Bangladesh	Dhaka	306.4	14,543,124 (2011)	9	Plain Area
3.	Bhutan	Thimphu	26.1	146,500 (2019)	2300	Mountain Valley
4.	India	Delhi	1484	16,787,941 (2011)	215	Plain Area
5.	Nepal	Kathmandu	51	1,003,285 (2011)	1336	Mountain Valley
6.	Pakistan	Karachi	3780	16,054,988 (2017)	21	Coastal Plain
7.	Sri-Lanka	Colombo	37.31	2,324,349 (2012)	4	Coastal Plain

2. Materials and Methods

2.1. Datasets

This study will be based on remote sensing data because other datasets like atmospheric temperature and weather station data are not accessible to everyone as this study will be focused on South Asian countries so it would be difficult to get these data from all the countries for reference or atmospheric UHI studies, so this study will only be focused on SUHI. Most of the studies on UHI have used Landsat and MODIS data. For the present study, MODIS data is used due to its high temporal resolution for yearly average studies, and Landsat data which provide medium spatial resolution is used for the classification of LULC of the study area cities. For the period 2000–2019, MODIS LST and NDVI products were collected from the National Aeronautics and Space Administration's website (NASA), United States Geological Survey (USGS), and Google Earth Engine (GEE). These products are collected for seven major cities of each country. As the main focus for the SUHI study will be the major cities of SA and temperature differences have a direct relationship with elevation and geographic location, so for the elevation data digital elevation - shuttle radar topography mission (SRTM) data is used for drawing up DEM maps of all cities. The LST product (MOD11A2) has a spatial resolution of 1 km and includes temperature readings from daytime (about 10:30 Ante Meridiem) and nighttime (about 22:30 Post Meridiem). With a spatial resolution of 1 km, the NDVI products (MOD13A3) are utilized to reflect vegetation activity. The resolution for SRTM void-filled data is one arc-second (approximately 30 m) for the United States and three arc-seconds for global coverage.

2.2. Methodology

In the backdrop of growing urbanization in various places, cities' size and spatial extent change with time. This study involves different steps and analyses for different outputs. Firstly, with the help of MODIS, average LST and NDVI values were retrieved for the specific date and area from 2000–2019. Then LUCL maps for 2000, 2009, and 2019 are extracted from Landsat to identify urban core and other LC classes for SUHI study in cities. Furthermore, the study area cities are categorized into separate areas to better conduct the spatial-temporal analysis of SUHI and its association with vegetation. Like urban, vegetation, water, and barren. To get average LST and NDVI values, MODIS products are collected with the help of the Google Earth Engine (GEE) algorithm. That raw data is then processed (clipped/merged according to the study area and converted into desired formats (NDVI values and LST in °C with the help of GIS. The GEE is a cloud computing tool for the storage and processing of large-scale data sets for study and decision making [44]. Most of the data sets were archived by Google and connected to the cloud computing engine for open source use by scripts. Figure 2 below shows the flow chart of the methods and data pre-processing for the present study.

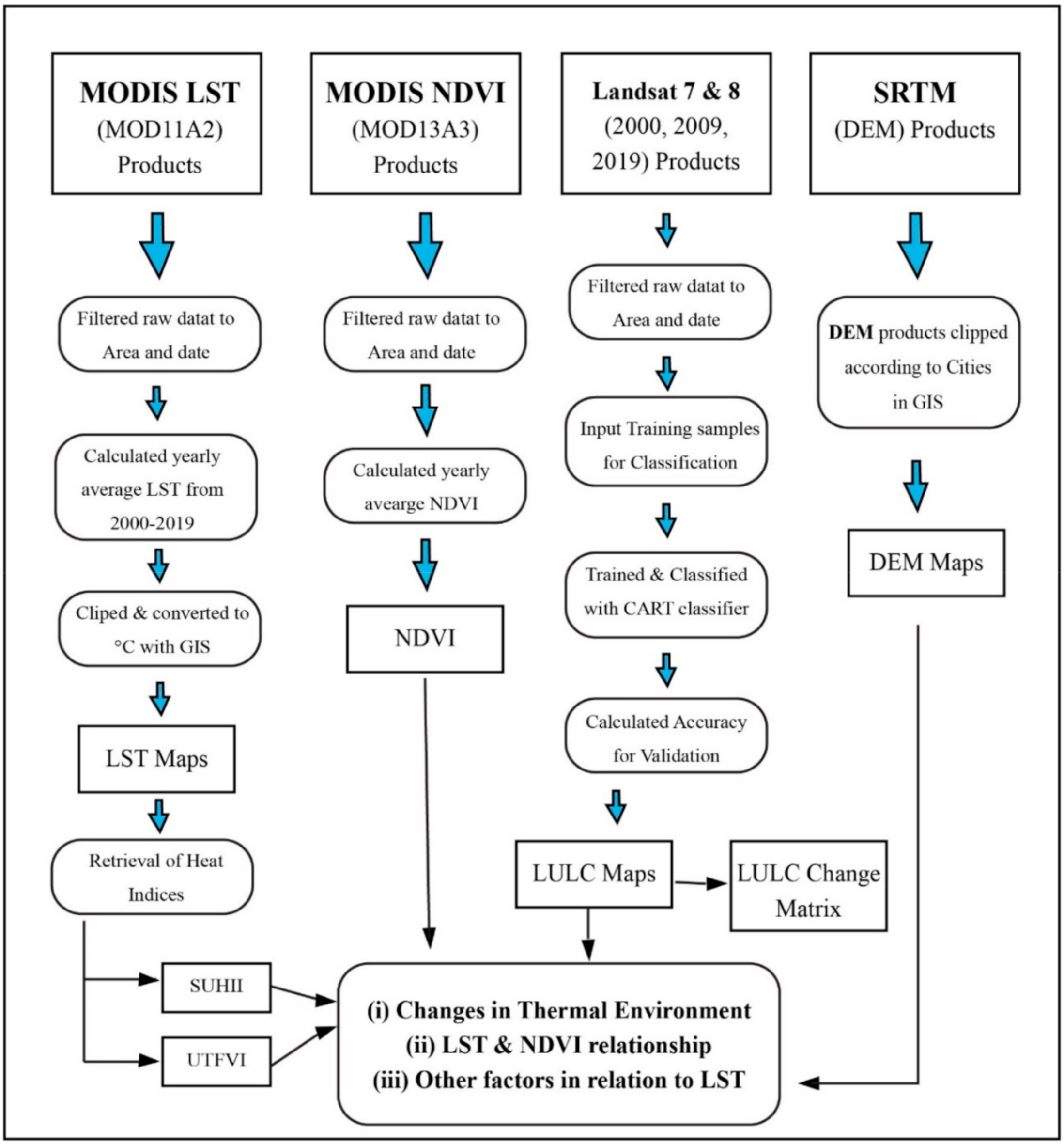

Figure 2. Flowchart of the methodology.

The user-friendly and conveniently available front-end of GEE offers a comfortable framework for the Interactive implementation of data and algorithms [44]. For the present study Earth Engine (EE) Code Editor is used, which is a web-based (Earth Engine JavaScript API) product for different processing and calculations. Firstly, scripts were designed to retrieve specific LST and NDVI for study areas for different years and with <10% cloud cover. Then the DEM maps by Shuttle Radar Topography Mission (SRTM) Global 30 m data are collected from open topography [45] and processed with GIS.

2.3. LULC Maps Preparation

The same platform is used with Landsat data and land cover classification algorithms for the complete process of LC classification from importing data, creating sample classes, classification and validation. The machine learning−classification and regression trees (CART) classification method was used in the present study. This name CART was coined by Leo Breiman to refer to decision tree algorithms that are used to solve classification or regression predictive modeling problems. This method is an important type of predictive modeling in machine learning [46]. This method is one of the common methods and the modern variations in it like random forest are the most powerful techniques [46]. By breaking the training sample set into subsets based on an attribute value test and then executing this process on each resultant subset, a tree can be created in a binary recursive partitioning technique with a CART classifier [47]. This method can be described easily as a binary tree [47]. The required area for different periods was extracted from the high-resolution Landsat images. Then the training samples were generated according to the four LC classes and trained with the CART classifier. This results in LULC maps which are then used to generate the LULC change matrix. During the classification of LC of study area cities, the overall accuracies of the classification are also considered. As poor classified images are not suitable for such studies, the CART classifier provided good overall accuracies for all images. A noticeable difference can also be seen in the results of Landsat 7 and Landsat 8 images for 2000, 2009, and 2019, respectively. The overall accuracy range is between 77% to 91%, and the overall accuracies for different years and cities are also shown in results below.

2.4. Retrieval of Urban Heat Indices

RS-based heat indices (SUHII, UTFVI) were used to analyze changes in the urban thermal environment of the seven research area cities.

2.4.1. Surface Urban Heat Island Intensity (SUHII)

SUHII is the surface temperature difference between urban buffer and rural buffer. For this investigation, urban and rural buffers were marked, having urban in the center and rural as surrounding. The following table shows the details of the urban and rural buffers. Then the SUHII was calculated with the help of the following equation from [48]:

$$\mathrm{SUHII} = \mathrm{T_u} - \mathrm{T_r} \tag{1}$$

In this equation, T_u is the temperature of an urban buffer (°C), and T_r is the temperature of a rural buffer (°C). By extracting pixel values from 2000 to 2019, the annual average values of the LST for each buffer were extracted.

2.4.2. Urban Thermal Field Variance Index (UTFVI)

The UTFVI index is used to measure the effect of urban heat intensity quantitatively on urban surfaces. UTFVI was used to measure UHI in this study and measured using the equation below [49]:

$$\mathrm{UTFVI} = \mathrm{T_s} - \mathrm{T_{mean}}/\mathrm{T_s} \tag{2}$$

where UTFVI is the urban thermal field variance index, T_s is the LST of a certain point(pixel) in the area, and T_{mean} is the mean LST temperature of the whole study area. UTFVI is further separated into six levels in accordance with six different ecological evaluation indexes to better depict changes [50]. Table 2 lists the particular thresholds for each of the six UTFVI levels, and results depicts the current study's UTFVI index in SA cities. A higher urban UTFVI value points out the greater urban heat intensity and the worse condition of the ecological ecosystem as red color in Table 2 below and green color shows the good condition and low UHII.

Table 2. Urban Thermal Field Variance Threshold. The colors show the excellent condition in green and worst condition in red.

Urban Thermal Field Variance Index Threshold	Urban Heat Island Phenomenon	Ecological Conditions Evaluation
<0	None	Excellent
0.000–0.005	Weak	Good
0.005–0.010	Middle	Normal
0.010–0.015	Strong	Bad
0.015–0.020	Stronger	Worse
>0.020	Strongest	Worst

2.5. Statistical Analysis

The Pearson correlation analysis was used to investigate the association between LST and NDVI in statistical analysis. The Pearson correlation coefficient or 'Pearson's r is defined as the association and relationship between two variables and the strength of their relationship. In other words, it shows how the change in one variable causes a change in the other variable. There are two kinds of variables in this analysis one dependent, and the other is independent. For the present study, the LST is the dependent variable, and NDVI is independent, which will show how the changes in vegetation can change the LST. The correlation calculations were performed in Excel and SPSS as well for validations of the results. The Pearson coefficient correlation has a high statistical significance. It is also helpful in terms of interpretation of the results as it seeks to draw the relationship in the form of the line that is calculated with the help Pearson coefficient calculator with the equation. This linear relationship can be positive or negative. Following is the equation used in this analysis:

$$R^2 = \frac{\mathrm{N}\sum \mathrm{xy} - (\sum \mathrm{x})(\sum \mathrm{y})}{\sqrt{\left[\mathrm{N}\sum \mathrm{x}^2 - (\sum x)^2\right]\left[N\sum \mathrm{y}^2 - (\sum y)^2\right]}} \tag{3}$$

where: N = the number of pairs of values, Σxy = the sum of the products of paired values, Σx = the sum of x values, Σy = the sum of y values, Σx^2 = the sum of squared x values, Σy^2 = the sum of squared y values. The correlation coefficient formula finds out the relation between the variables and gives the value of r square. It returns the values between -1 and 1, which shows the strength and direction of the relationship. The negative 1 indicates a high negative correlation, which suggests that when one variable rises, the other falls. While the positive 1 indicates a high positive correlation, meaning that if one variable rises, the other will rise as well. In the present analysis, LST and NDVI values were used as two different variables. The relationship is calculated for 20 years.

3. Results

3.1. Spatial-Temporal Variations in LST (2000–2019)

The mean annual spatial variation of LST in SA cities from 2000–2019 was extracted. The changes in the annual average LST for 2000, 2009, 2019 and the spatial variation in LST are shown in Figure 3 below. The results show the SUHII increased in the surrounding urban area moving outwards from the central urban area as a result of rapid urbanization. The LST maps show the spatial variation and the UHI effect prominent in urban areas in the form of red spots showing high temperatures. The results show the difference in average temperature in the urban and rural areas is in the range from 1–2 (°C), while reaches up to 3 °C or more only once in 20 years' time period. The overall average temperature can be seen decreasing from 2000 to 2019 in the range of 1 °C in Delhi, Kabul, Karachi, Kathmandu while it stayed constant in Dhaka, Thimphu, and increased in Colombo.

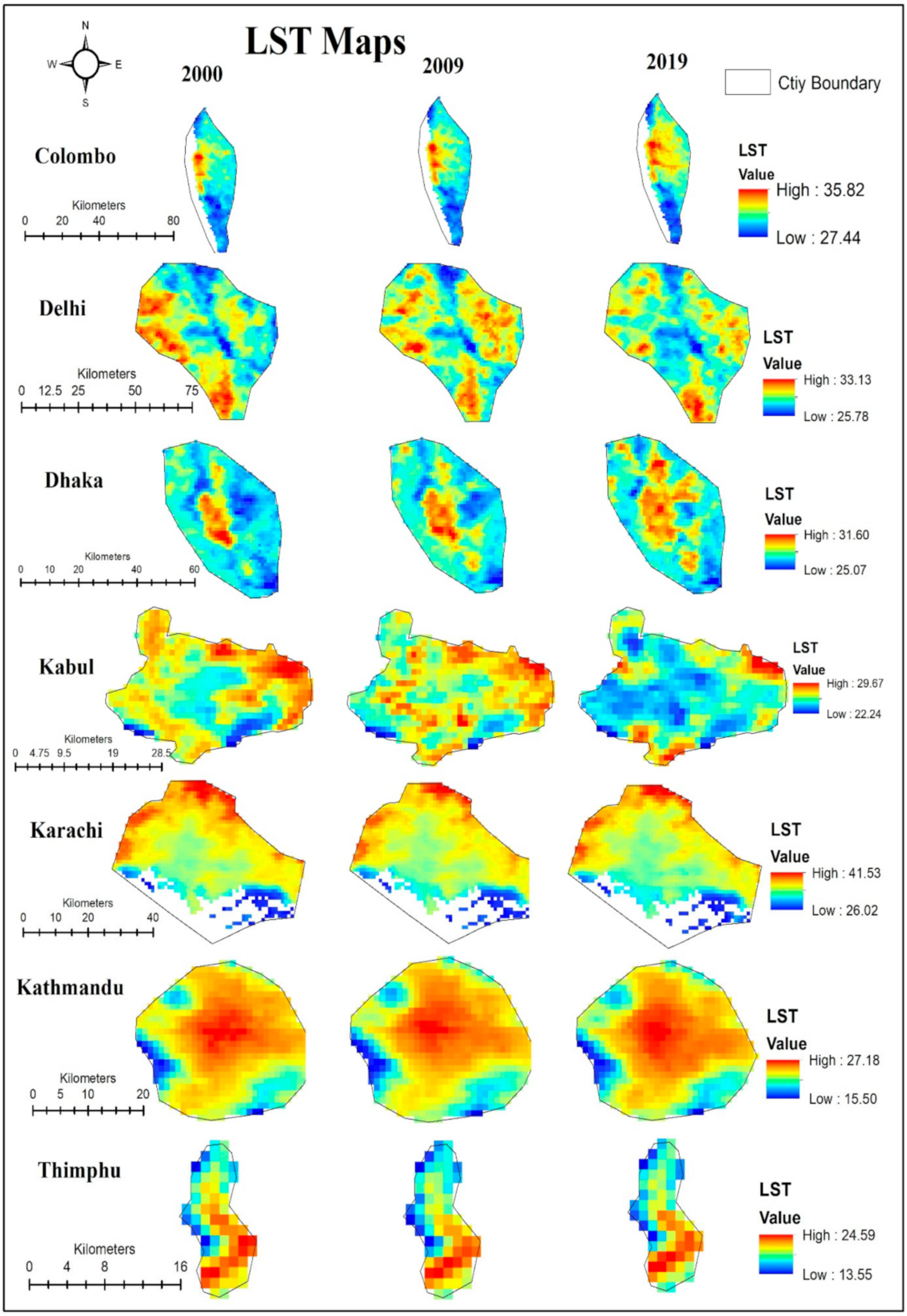

Figure 3. LST Maps of SA Cities from 2000–2019.

The possibility of a spike in winter temperatures, as well as the frequency of extremely hot summer days and nights, are among the challenges ahead The shift in the LST from 2000 to 2019 is observed to increase in the main urban core areas in all cities while the cities having rivers, mountainous peaks or other low-temperature bodies shows some light spots in the urban areas like in Delhi and Kabul mainly, but the spread was observed to increase in the rural parts as the urban sprawl spreads in the cities. The LULC maps and LULC change show the shifts of urban areas to rural parts and, in turn, the change in the transferred areas in km for all the seven cities from 2000 to 2019. The average LST changes at the rate of +2.21 °C, −1.83 °C, +0.78 °C, −2.67 °C, −1.68 °C, −1.4 °C, +0.07 °C in Colombo, Delhi, Dhaka, Kabul, Karachi, Kathmandu, and Thimphu, respectively, with a positive sign showing increasing and negative as decreasing trend from 2000 to 2019. Urban sprawl (urbanization) in these cities can be seen as the prominent reason for these changes, this occurred as a result of the transformation of vegetation into urban areas, which altered the geographical variation in temperature in all cities.

3.2. Spatial-Temporal LULC Changes in SA Cities from 2000–2019

LULC maps were generated for all the cities with a ten-year difference for 2000, 2009, and 2019. These maps were classified into four classes: urban, water, vegetation, and barren in all cities. The accuracy was also calculated for the classified images to validate the LULC results shown in Table 3 below. The LULC can be seen changing rapidly inside the study area marked buffers. The buffers were generated according to the size of each different city with different radii. The vegetation cover can be seen dominant in most of the cities during the time of 2000 with comparatively few portions of other classes in rural buffer and dominant urban cover in urban buffers.

Table 3. Overall accuracies of LULC Classification results of cities 2000–2019.

No.	Classified SA Cities	Overall Accuracy 2000	Overall Accuracy 2009	Overall Accuracy 2019
1	Colombo	80 %	83 %	90 %
2	Delhi	79%	82 %	91 %
3	Dhaka	78 %	83 %	88 %
4	Kabul	77 %	82 %	86 %
5	Karachi	79 %	86 %	88 %
6	Kathmandu	81 %	85 %	91 %
7	Thimphu	78 %	81 %	87 %

These vegetated parts of the cities can be seen transforming dramatically to urban and barren land cover in 2009 and 2019 in increasing order. The urban buffer can be seen as overly filled with the urban cover, and the rural buffers can also be from having vegetation cover to urban cover between these 20 years. These transformations are the results of new infrastructures, roads, and paved areas built up upon the land which was previously vegetation to fulfill the needs of city inhabitants. These extensions and modifications are observed and calculated in the form of km^2 to easily interpret the variations in all study area cities. During these twenty years, the vegetation cover is reduced to 2.44 km^2, 177 km^2, 35 km^2, 84 km^2, 19 km^2, 5 km^2, 2 km^2 in total while the urban area was increased to 7 km^2, 485 km^2, 98 km^2, 117 km^2, 232 km^2, 29 km^2, 2 km^2 in all cities: Colombo, Delhi, Dhaka, Kabul, Karachi, Kathmandu, Thimphu respectively as shown in Table 4.

After 2000, LULC maps (Figure 4) ensured that urban expansion was visible in all cities, particularly in both urban and rural buffers. The cities' size grew as a result of the urbanization factor, and the urban buffer infrastructures grew as well. These steady shifts are the result of urbanization. The urban areas expand with the reduction in the vegetation areas with fewer parks and green spaces, and the vegetation cover is converted to urban areas and barren land as well. The conversion is in the form of new housing societies emerging outwards from the city core area, the road networks, and industrial complexes. The central core urban part can be seen spreading in all urban buffers of study area cities. It shows the vegetated area has been lost, and in return, the urban and barren land has been acquired from 2000 to 2019.

Table 4. LULC Change Matrix for SA Cities 2000, 2009 and 2019.

Cities	LC Type	2000	2009	2019	Transferred Area
Colombo	Urban	6.32	8.1	13.75	7.43
	Water	13.48	13.64	12.99	−0.49
	Vegetation	11.78	12.69	9.34	−2.44
	Barren	4.68	6.27	5.36	0.68
Delhi	Urban	145.63	273.74	631.01	485.38
	Water	28.01	30.66	26.31	−1.7
	Vegetation	921.4	1056.59	744.23	−177.17
	Barren	93.26	101.95	123.51	30.25
Dhaka	Urban	90.03	127.27	188.16	98.13
	Water	66.83	80.98	54.53	−12.3
	Vegetation	181.33	161.66	145.99	−35.34
	Barren	18.54	11.79	10.84	−7.7
Kabul	Urban	112.23	195.68	229.81	117.58
	Water	1.73	1.99	0.14	−1.59
	Vegetation	282.4	357.9	197.52	−84.88
	Barren	16.55	18.34	18.9	2.35
Karachi	Urban	164.27	256.46	397.17	232.9
	Water	96.47	163.97	159.01	62.54
	Vegetation	102.33	91.76	82.91	−19.42
	Barren	114.73	143.6	164.91	50.18
Kathmandu	Urban	5.6	17.82	35.21	29.61
	Water	0.49	0.29	0.47	−0.02
	Vegetation	41.75	62.16	36.35	−5.4
	Barren	53.81	29.18	14.89	−38.92
Thimphu	Urban	4.94	5.57	7.46	2.52
	Water	0.34	0.39	0.81	0.47
	Vegetation	19.21	21.68	16.63	−2.58
	Barren	3.79	2.97	4.5	0.71

The continuously growing population and migration of people from surrounding areas to towns have caused the green land along with barren and water bodies to change in urban areas. We can see how during this period; the urban buffers are showing have full urban cover in an internal buffer. It is evident that LULC changes were very persistent in the study sites. Furthermore, it is clear that from 2000 to 2019, fast LULC changes were seen in the study sites within the buffers, as well as how urbanization was increasing spatially with time. The details of urban and rural buffers labeled for this study are mentioned in Table 5 below.

3.3. Surface Urban Heat Island Intensity (SUHII) Changes in Twenty Years

This part of the study covers the main objective of the present study in which the spatial and temporal (2000–2019) SUHI trends and temperature differences in seven major South Asian cities from each country were analyzed. As mentioned above, the SUHII was calculated by measuring the difference between urban and rural buffers' LST. The annual variations of the SUHII of all the seven cities can be seen in Figure 5**.** The SUHII trend can be seen increasing in Delhi, Karachi, Kathmandu, and Thimphu, while decreasing in Colombo, Dhaka, and Kabul. If we have a close look, we can see how the SUHII was rapidly increasing in Karachi from 1.33 °C in 2000, 1.42 °C in 2009 to 2.97 °C in 2019, which shows the rapid increase in the SUHII in the last ten years' span. Like Karachi, every city's SUHII trend can be seen fluctuating through these twenty years. Most of the cities have a constant increase in the trend while the cities like Colombo, Dhaka, and Kabul have a decreasing trend which is due to the average annual temperature observed in the SUHII plot due to a drop in LST in some years.

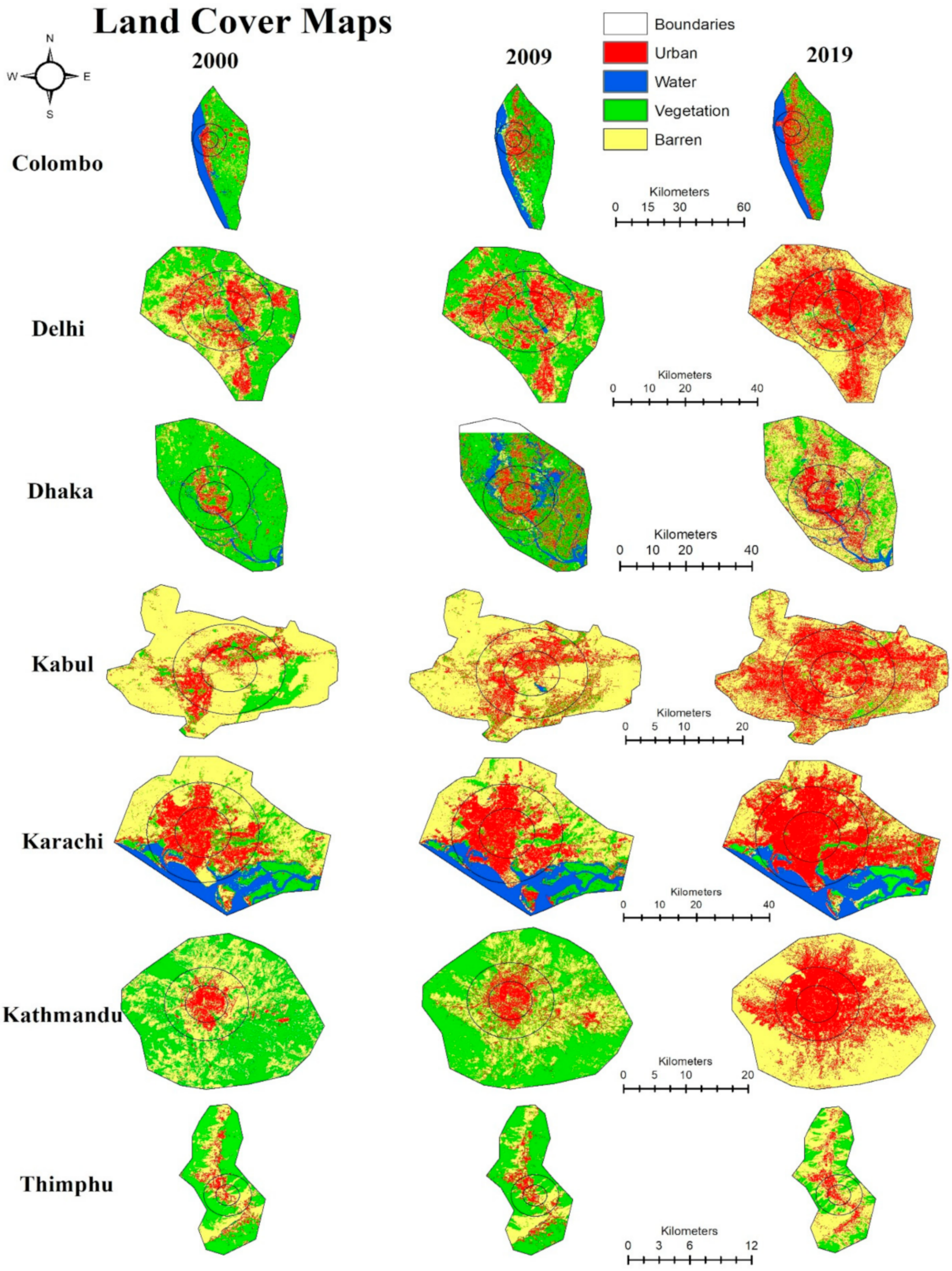

Figure 4. Land Cover Maps of SA Cities 2000, 2009 and 2019.

Table 5. SA Cities radii for Urban & Rural Buffers.

Cities	Radius of Urban Buffer (km)	Radius of Rural Buffer (km)	Koppen-Gelger Zone Classification
Colombo	4	8	"Af" (Tropical Rainforest Climate)
Delhi	8	16	"Cfa" (Humid Subtropical Climate)
Dhaka	5	10	"Aw" (Tropical Savanna Climate)
Kabul	4	8	"Dfb" (Warm Summer Continental Climate)
Karachi	7	14	"Bwh" (Tropical and Subtropical Desert Climate)
Kathmandu	3	6	"Cfa" (Humid Subtropical Climate)
Thimphu	1	2	"ET" (Tundra Climate)

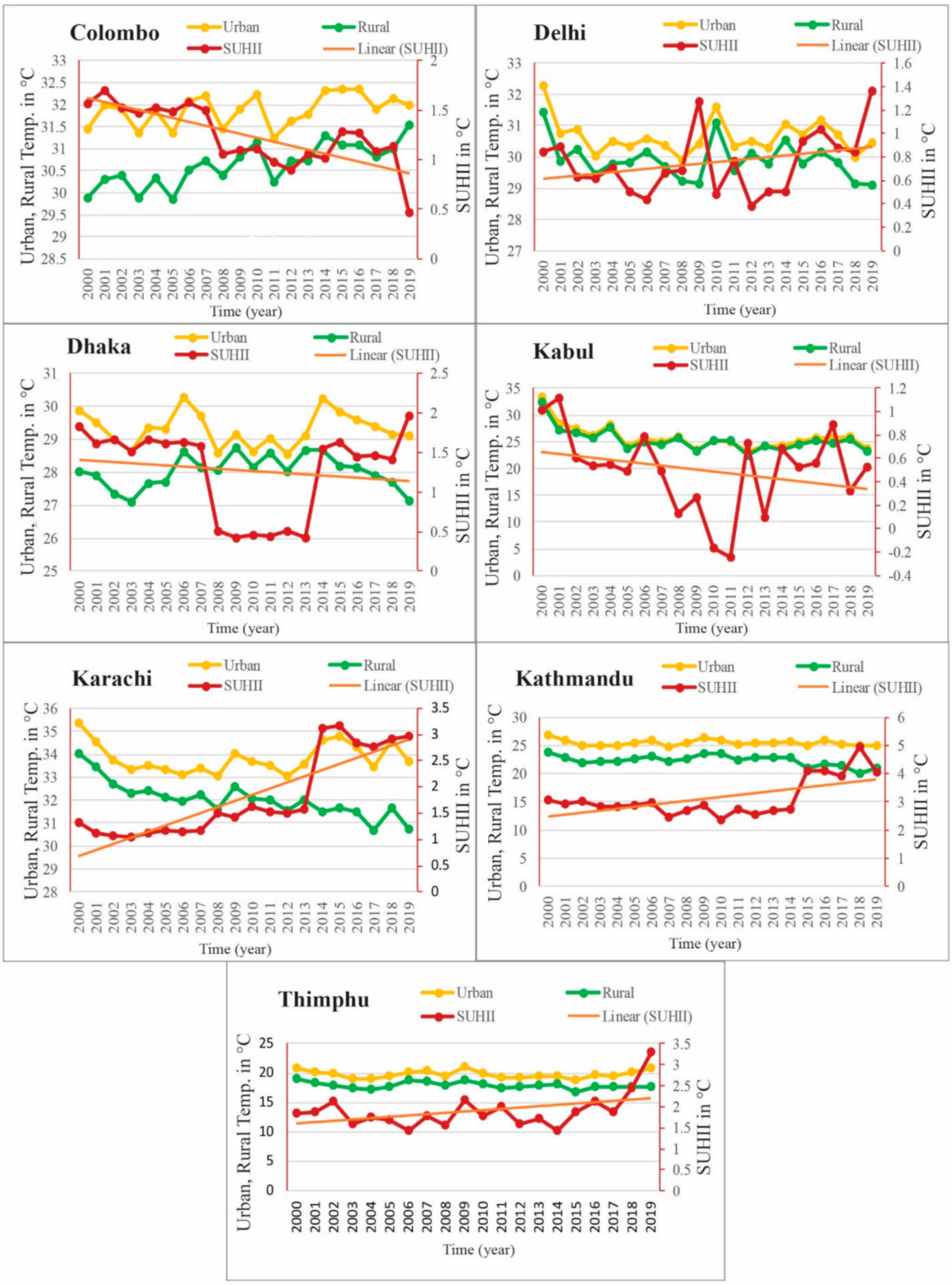

Figure 5. SUHII Trends for SA Cities for 20 years.

The increasing trend can be explained where the temperature difference is prominent between urban and rural buffers, which shows the SUHII line rising upwards. At the same time, some cities were showing a decreasing trend because the rural buffer temperatures are increasing more rapidly than the urban buffer, which is causing the temperature difference in buffers to decrease as a whole. The other reason is the natural drop in the temperature values, as shown in the SUHII graphs Figure 5**.** Urbanization is the main reason for the increase in temperature, which results in SUHII, while the increase in vegetation cover by planning and planting green spaces in modern urban environments causes a decrease in temperature and SUHII. It can be seen through the LST maps in Figure 3 that the UHI effect is going to transfer from urban areas to rural due to urban sprawl. In addition, in cities like Delhi and Kabul, the UHI in the form of red spots can be seen disturbed due to the presence of the river and high mountain area in the middle of the urban areas. These landforms have obvious low temperatures than the surrounding urban environment, which causes a drop in SUHII or blue spots in LST maps. In conclusion, SUHII is evident in all the cities, and the heat spots are prominent in urban areas, while the increase or decrease in this trend is due to various factors as explained.

3.4. Changes in Urban Thermal Field Variance Index (UTFVI)

To measure the effects of UHI in urban areas, UTFVI was calculated for all cities. It also investigates the ecological conditions in urban areas. The spatial variations in the urban thermal field variance are shown in Figure 6. To better evaluate the changes In UTFVI, it can be divided further into six levels according to six different ecological evaluation indices [50]. These threshold values are shown in Table 2 and the ecological variation in the index is shown in UTFVI maps.

Two extreme levels of this index have appeared in all the study area cities. The UTFVI maps also provide the environmental quality of these cities to provide a better understanding and information for urban studies and planners. The UTFVI can also be seen as similar to the LST distribution as it is the effect of urbanization and UHI. The UTFVI can be seen spreading from the inner urban core to the surrounding like the SUHI. The highest value of UTFVI can be seen in Karachi 0.2359, which is evident as we have also observed the rapid SUHII is also increasing in the same city, while the lowest values can be seen in Dhaka −0.1018. This shows that very poor, environmental conditions are present in the urban area of Karachi city as a result of urbanization.

All the cities are showing different ecological conditions in urban and rural areas with red or bad conditions in urban and green or good ecological conditions in rural or vegetated areas. The minimum values are showing very good conditions around vegetation cover (rural) and water bodies. This index also proved that the UHI is strongest in the urban areas with high values. This is also the result of rapid and continuous urbanization and more infrastructures.

3.5. Role of Other Factors in UHI

The UHI is investigated for all the cities and can be seen evidently, but more factors can affect (enhance or reduce) the presence and visualization of this phenomenon. Some of those factors are the water bodies, high elevated areas with relatively low temperature, and the location or geography of the cities as well. The LST maps (Figure 3) of the cities show the spatial temperature variations in all the cities. The cities having blue spots or low temperatures are the result of the abovementioned factors in UHI. For example, in Delhi, low-temperature spots can be seen all along the river in the urban area; in Kabul, the high elevated area is showing relatively low temperature and less urban development in the central core. Karachi's urban core is not as hot as the surrounding barren land due to the desert and drylands along the northern part of the city and having low temperature in the southern part due to the coastal area. Here we can observe the role of geography and landforms in the disturbance of UHI in different cities. To easily visualize and understand elevation maps for all the cities were also generated (Figure 7) to compare with the LST maps. The dark blue's low elevation is shown as rivers, ocean, and valley, which can be seen having low temperature in LST maps. The cities having a pure urban core with no major water bodies or low-temperature features are showing the UHI phenomenon clearly as red spots on the urban core and orange to blue around the surrounding rural area. Moreover, heatwaves in the humid and dry and snowfall, snow cover in mountainous cities also tend to enhance or reduce this phenomenon. However, the size of the cities does not have a strong influence on UHI as all the cities are showing UHI regardless of their size or population. The increase in city size only enhances the intensity of UHI. We can see the clear differences in all the SA city's locations, sizes, and population sizes of the present study area Table 1, and in relation, UHI and its changes can also be seen in different cities.

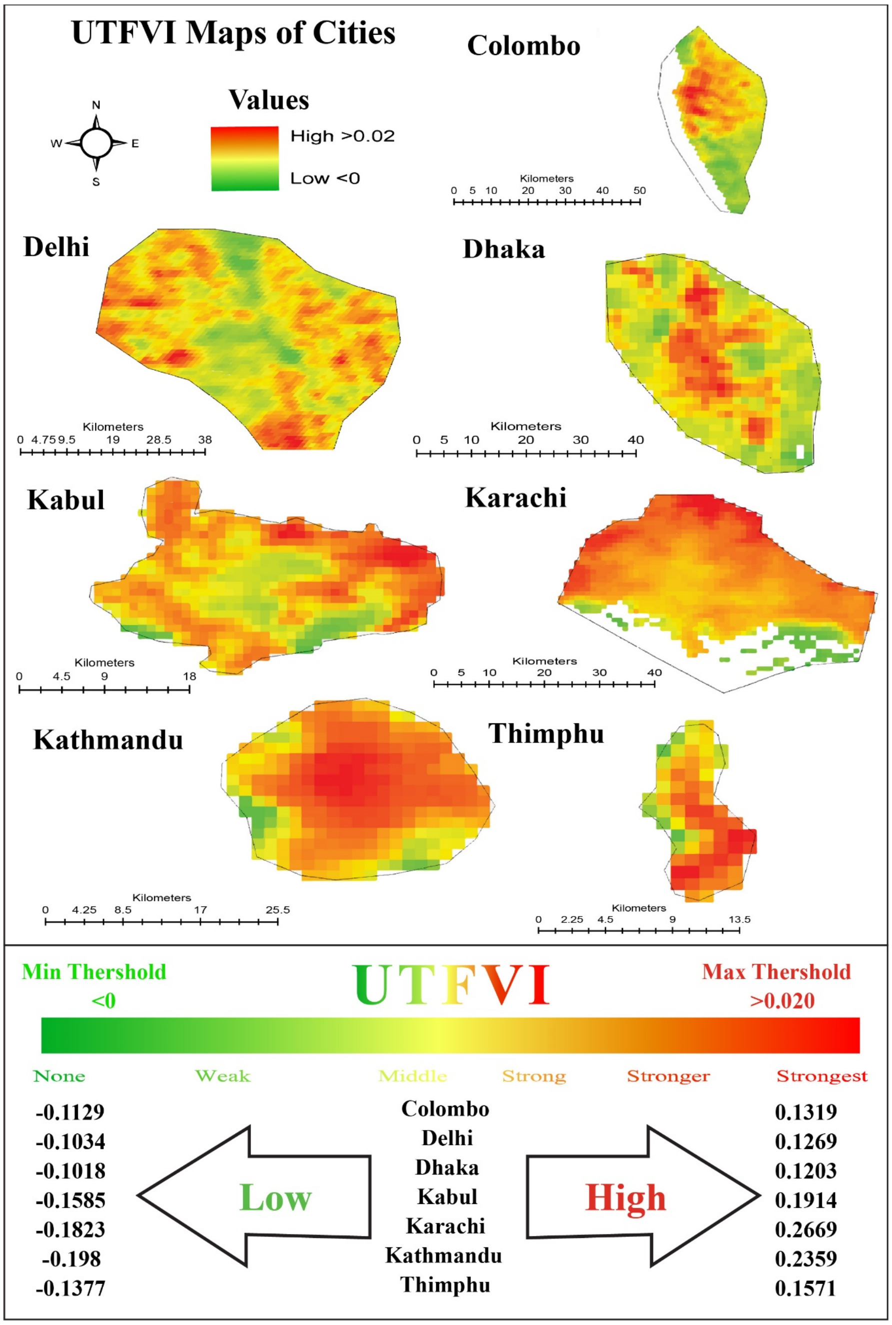

Figure 6. UTFVI Spatial trend of SA Cities.

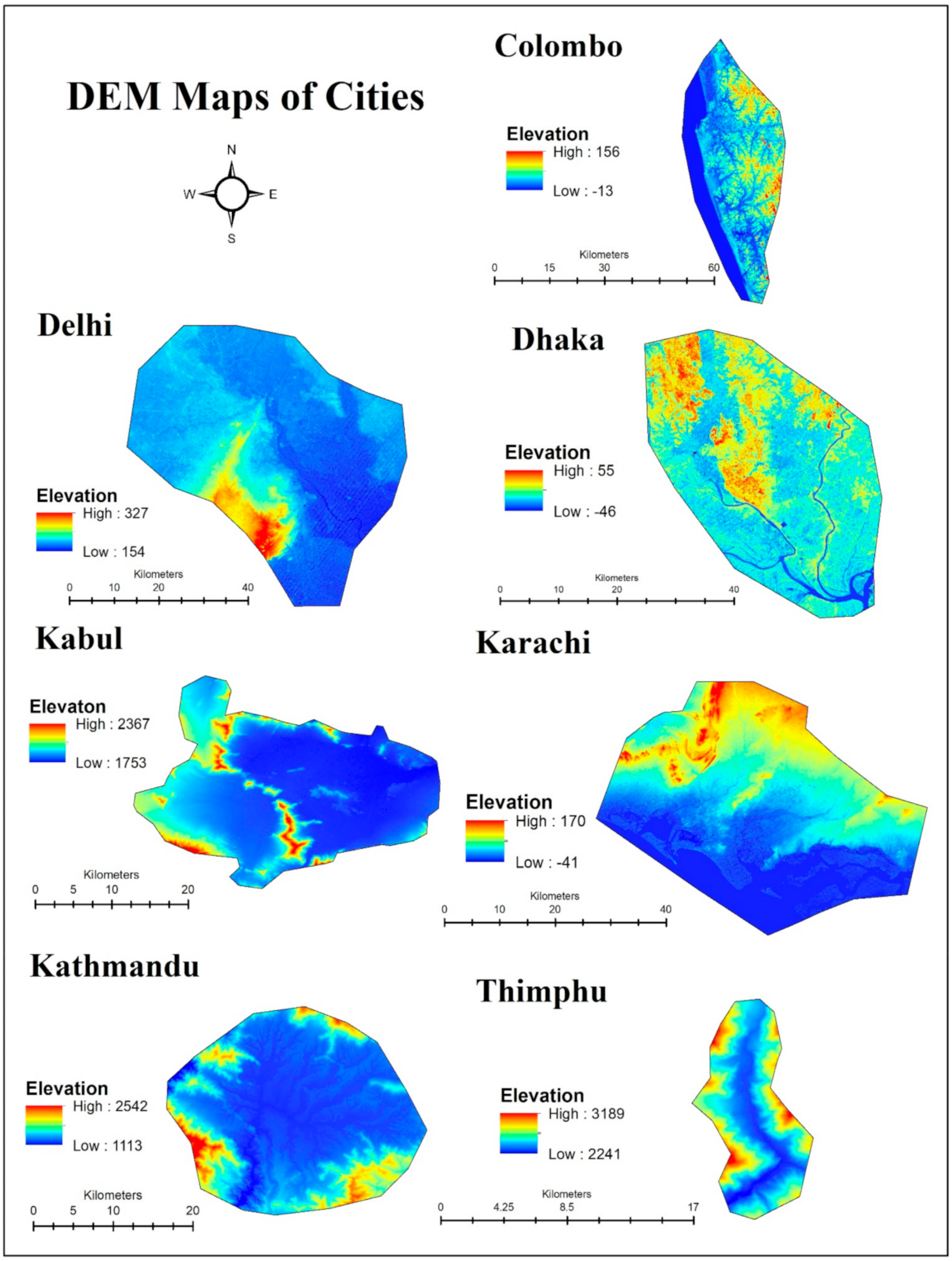

Figure 7. DEM Maps of SA Cities (STRM).

3.6. Statistical Analysis (Relationship between LST and NDVI

To calculate the relationship between vegetation and temperature here, we have done the correlation analysis for all the cities with twenty years of data. The analysis shows that the vegetated areas have a strong negative correlation with the LST in all the cities. However, the strength of the relationship differs in different cities. The low vegetation cover is the result of the increase in LST, as shown through the correlation value and trend. The correlation trend line can be seen going down, which is due to a negative correlation. The strongest value can be seen in Kabul, with a value of −0.15. The correlation results return the values in the range from −1 to 1, so here the values closest to −1 are showing a strong negative relationship between these variables. Between 2000 and 2019, LST levels were strongly and negatively associated with NDVI. The Pearson correlation coefficient

(R^2) values as shown in Figure 8 were −0.51, −0.35, −0.30, −0.15, −0.23, −0.67, −0.57 in Colombo, Delhi, Dhaka. Kabul, Karachi, Kathmandu, and Thimphu, respectively.

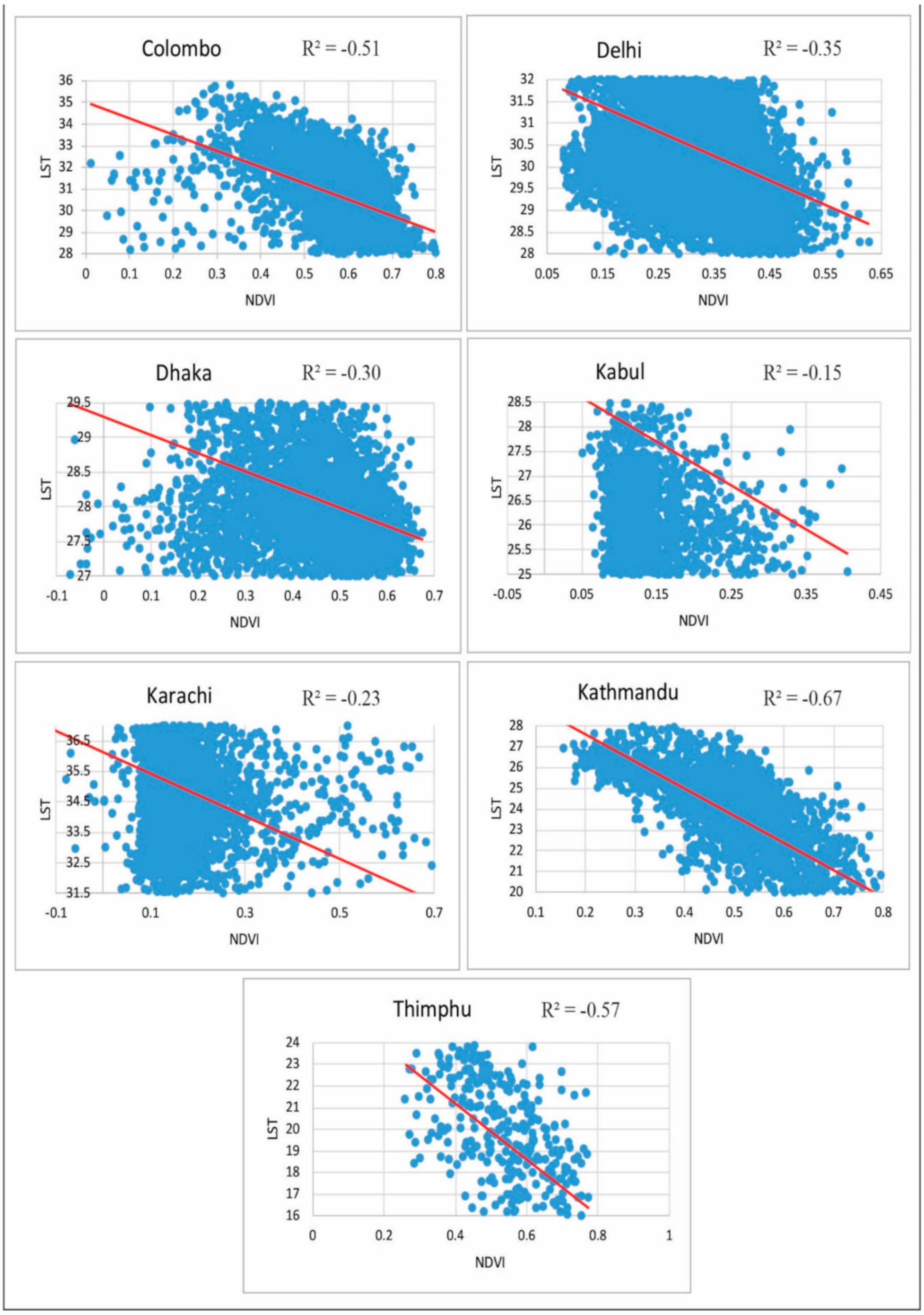

Figure 8. Pearson Correlation Scatter Plots of SA Cities.

4. Discussion

The present study highlighted the SUHI variations and trends along with the urban thermal changes with LULC and NDVI. The machine learning classification method is used for LULC classification which provided good results accuracy. Evident changes in LULC can be seen in all the cities, which are the result of urbanization. These changes have led to an effect on the urban thermal environment and results in UHI. The urban land cover increased in all the cities with the decrease in vegetation cover. Secondly, the transitions in LULC led to variations in SUHII and LST trends which shows their cause and effect relationship. The urban areas expanded, causing the transformation of rural buffers to be converted into the urban area as well as the development of new infrastructures. The temperature difference was also investigated, which was seen higher in the urban core as compared to the surrounding areas. Moreover, the change in the rural temperature was increasing as with the urban areas. For example, Through the relationship between LULC and LST, we observed the urban areas have high LST values [51]. The mean temperature was seen increasing in some cities while decreasing in others, regardless of the spatial size of the cities. [52] Also explained and clarified is the fact that a key role in the increase of South Korean urban temperature was urban expansion. In 2007, urban growth was proven to be the cause of increasing mean temperature in Beijing [53]. In 2015 [54] assessed the urban expansion and its effect on UTE of Shenyang city with the help of Landsat images. The temperature differences between urban and rural buffers aid in determining the intensity of the surface urban heat island. The phenomenon was very evident and strong in urban buffers [51]. In the urban core, the dense infrastructure and urbanization caused the heat to trap and increased SUHII [55]. However, this phenomenon can be reduced with the help of sustainable development and vegetation cover. The UHI effect has caused poor ecological conditions in the urban areas, which was also observed during this study. The conditions were very poor, with the highest value in Karachi, and all the cities have high UTFVI values ranges from 0.12 to 0.26. The values were greater in the urban buffer than the rural buffer. The thermal gradient was also moving towards rural buffers along with UHI. Previous researchers have also studied this and made similar findings with the UTFVI [49,56]. Many studies have investigated the temporal relationship between NDVI and LST [57,58]. These indices, along with LULC change, also help in indicating the thermal changes of the areas. Thus NDVI also helps in studying the variability in the thermal environment. Poor ecological conditions were seen well in the vegetated cover area of the present study area sites, which concludes that vegetation plays an important role m the sustainable ecological conditions [59]. The Pearson correlation between NDVI and LST also shows their strong correlation values. Which was calculated using the 'pixel's values from each city NDVI and LST image, and around 2500–3000 values were extracted for each city, while for Thimphu city, the values were only 1500 due to the small area of the city. These relationships concluded that the decrease in the NDVI values could be seen with the increase in LST values for all the study area cities of the present study. This negative association between these two variables can be seen in other studies as well [20,60]. A recent study in Pakistan cities [61] also investigated the thermal climate changes in response to LULC and vegetation their results also indicates the strong negative correlation of NDVI with LST and urbanization as the cause of increase in UHI. Similarly, a related study in Africa cities showing strong negative relation of vegetation with LST also supports the present study results [51].

The scatter plots show the statistical results of the relationship between vegetation and temperature. The role of other factors was also discussed in the present study, which somehow influences the SUHI trend and can enhance or reduce the phenomenon. The urbanization phenomenon was also observed to cause poor living conditions in urban areas due to increased temperature. This reminds us to move towards sustainable developments, which can help to reduce the phenomenon of UHI and SUHII. Rapid urbanization reduces the urban capacity for humans as well as microorganisms [23]. The previously green spaces of the cities are now rapidly converted into new housing societies, road networks, and industries. These transformations are alarming and need some mitigating strategies to cope with the present problems. There is the term green infrastructure by [62], which, if applied correctly, can help in fighting the UHI effect. This green infrastructure development was made part of the urban policy of the city of Stuttgart in such a way that it will help the thermal environment, improve air quality and biodiversity [62]. In reference to sustainable development, we can see Stuttgart is one of the greenest metropolitan cities in Germany through working towards the sustainable development of the city that is based on the principle of the cool city [63]. Moreover, Mell has highlighted the green infrastructure and how to implement this in policymaking and sustainable development in his book [64]. Some global examples are also mentioned around the world including; USA water management in Chicago, UK green infrastructure strategy in London's Olympic Park, European green infrastructure development in Paris and Milan, Indian green infrastructure planning in New Delhi, China evaluating green infrastructure in Shanghai and Suzhou [64]. Urban parks are also a way to reduce the UHI and overall temperature in the surrounding areas. Urban parks can be built as main park (vegetation) areas in the core urban areas along with some water bodies to reduce the heat of the cities and generate low heat spots to reduce UHI for a sustainable future [62]. There are many other features suggested by [62] like vegetation in the form of big trees, green roofs, water bodies installations, green corridors, open spaces, street orientation, and environmental management that can help in coping with UHI and provide a very eco-friendly environment to live. Other studies also emphasize mitigating strategies for UHI to provide a better place and have mentioned various solutions to this emerging problem [65]. These steps should also be taken by the developing cities of South Asia to reduce the present problems caused by UHI. The government should make policies and urgent measures to reduce the temperature (heat) and increase the green spaces and water bodies by urban tree plantation and making water and green parks. The present study has proved that the study of LULC and vegetation changes help in understanding and investigating the urban thermal variations. The study provides the LULC role in the increase in average temperature in all cities and then the relationship between the vegetation and LST, so governments should also encourage researchers to do more research studies and provide more knowledge about the present problem. There are other factors like population, the cities landscapes, and socioeconomic that should also be considered in UHI studies, so there is still a need to do future research for more quantitatively studying UTE and UHI by using these factors. There are also some limitations to the present study as well. It should be noted that it is not possible to have steady images from the urban surface. This is partly due to the capabilities of the instruments utilized and in part to atmospheric interactions. For example, satellites that orbit the Earth spend a limited amount of time over one place, and there is always the risk of overcast skies when satellite photographs capture UHI over land.

The surface UHI differs from the atmospheric UHI in that the ambient air temperature is affected by turbulence and velocity activities. This means that the observed surface temperature inside roadway canyons can vary greatly from the ambient air temperature. To effectively utilize the observed data, it is important to first predict the actual UHI (atmospheric UHI) from the measured data. Even if we try to develop a sensor-view model in which we will need both surface and air temperature (atmospheric) data, that will be very difficult to collect for each city from each country. The stations that provide data will also be limited in every area with poor accuracy. Another drawback of this strategy is that the three-dimensional structures of the urban realm prevent seeing a considerable amount of the urban surface. This means that the study domain's vertical field is not captured in this methodology. As a result, the UHI distribution must be recovered once more using thermal data collected using sensors from a birds-eye perspective.

Limitations and Future Research Directions

In this study, authors have used MOD11A2 and MOD13A3 products (2000 to 2019) for LST and NDVI, respectively. Better temporal and spatial resolution datasets should be used in the future to avoid uncertainties caused by cloud cover or low spatial resolution. There is no online database present to retrieve official stations LST dataset for validation of extracted LST so future studies should also gather ground or station level temperature data to validate the dataset. Moreover, further research should be done with new methodologies to provide new techniques for future studies. Despite the use of vegetation and LULC change (urbanization) for the UHI studies future studies must consider other factors like regional climate change and its effect on UHI and urbanization influence on climate change.

We have explored UHI effect in relation to LULC and vegetation change and also analyzed the SUHII and UTFVI to provide enough understanding of daytime SUHI. Future studies should also consider the night-time difference in UHI temperatures to provide comparisons with daytime UHI differences. This study encourages more research studies to focus on South Asia region and to provide more deep insights on UHI and related problems on regional and small levels to understand and mitigate this problem.

5. Conclusions

A spatial-temporal analysis of SUHII in relation to LULC and vegetation was done from 2000 to 2019 for South Asian cities (Colombo, Delhi, Dhaka, Kabul, Karachi, Kathmandu, Thimphu) with the help of MODIS and Landsat data. A machine learning classifier was used in the study which provided good accuracy in the classification of LULC. It was concluded that urbanization is causing the rapid transformation of vegetation cover to urban cover in all the cities. The LST trends were also visualized and can be seen fluctuating in different cities, which results in the variation in increase or decrease of SUHII trends in all the cities. The trend of SUHI can be seen moving outwards from the urban core towards the rural along with the urban sprawl. Irrespective of the cities' location and size, UHI can be observed in all the cities. Moreover, the UTFVI calculated with the help of LST and LULC helped in understanding the ecological conditions in the SA cities. The results concluded the poor ecological conditions exist in all the urban areas of the cities with Karachi having the highest value. The relationship between vegetation and temperature was calculated with the help of Pearson correlation which showed that there is a strong positive correlation between LST and NDVI in all the cities. The increase in LST can be seen in the form of a decrease in NDVI. This study indicates the important association of LST with NDVI and LULC, which can be studied to research the UHI effect. There is a need now for the government, researchers, and policymakers to study and develop sustainable solutions to mitigate this problem. Some sustainable solutions are also mentioned in the study, which can be used as a measure to reduce this phenomenon. This study provides a clear observation and understanding of the long-term LULC and vegetation changes that caused the variation in LST and SUHII with the help of RS-based data.

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Abbreviations

SUHI	Surface Urban Heat Island
GHG	Green House Gas
UHI	Urban Heat Island
IPCC	Intergovernmental Panel on Climate Change
LULC	Land Use Land Cover
LST	Land Surface Temperature
MODIS	Moderate Resolution Imaging Spectroradiometer
UTFVI	Urban Thermal Field Variance Index
NASA	National Aeronautics and Space Administration
SUHII	Surface Urban Heat Island Intensity
USGS	United States Geological Survey
NDVI	Normal Difference Vegetation Index
GEE	Google Earth Engine
CART	Classification And Regression Trees
SRTM	Shuttle Radar Topography Mission
CLHI	Canopy Layer Heat Island
DEM	Digital Elevation Model
BLHI	Boundary Layer Heat Island
UTE	Urban Thermal Environment
SHI	Surface Heat Island
UN	United Nations
UCL	Urban Canopy Layer
°C	Degree Celsius
OAQ	Outdoor Air Quality
°K	Degree Kelvin
RS	Remote Sensing
SPSS	Statistical Package for Social Sciences

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