Application of Google Earth Engine to Evaluate the Signatures of Land-Use/Land-Cover Change on Land Surface Temperature Variation

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Abstract—**Rapid global economic expansion has resulted in a drastic increase of urbanization, which has, in turn, impacted the ecology of vast regions of the world. A series of problems have been introduced, such as changes in Land-Use/Land-Cover (LU/LC) and changes in the local climate. This work aims to exploit the capabilities of the innovative Google Earth Engine (GEE) platform to investigate the signatures of Land-Use/Land-Cover change on Land Surface Temperature (LST) variation using the freely available remote sensing data. Due to the rapid urban expansion and the higher Spatio-temporal difference in the climate, Dakshina Kannada district is taken for demonstration. The LU/LC of the district is extracted from high-resolution images of Landsat and Sentinel using random forest classification and LST from the thermal band of Landsat images using the mono window algorithm for the pre-monsoon period of the year 2001 and 2019. The district has seen a significant change in the land use and land-cover in almost two decades, 13.67% reduction in the forest area, 5.63% in agricultural land with 18.81% increase in the built-up areas and 0.6% in barren land has plunged the greenery into impervious cover. Also, the land surface temperature has seen a progressive drift in the past 19 years, with an increase of 2.25°C in mean temperature in the forest area, 1.16°C in the barren land, 1.90°C in agricultural land and 1.80°C in the built-up area. The higher variation in maximum land surface temperature is in built-up land in a range of 0.35°C/year (near the industrial area) indicates that LU/LC change signature is the predominant factor in LST variation, which is associated with the physical characteristics of the built-up area. The results of this research would be of great help to the government departments to mitigate the effects of the growing intensity of urbanization in the district, along with the consideration of other climatic variables.**

Index Terms—Google Earth Engine (GEE), Land Surface Temperature (LST), Land-Use/Land-Cover (LU/LC), Random Forest (RF).

I. INTRODUCTION

Growth in population led to an increase of urbanization in most cities and the coastal districts in Dakshina Kannada, Karnataka is no exception to it. The modification of the biophysical environment by the replacement of natural land covers with the impervious urban materials defines Urban Growth [1]. Urbanization is rapid growth and historical transformation of rural areas to urban land, which in turn reduces green space, increases impervious surfaces, and alters albedo and geometry compared to agricultural surfaces [2]. Nevertheless, the image of urbanization is not as glorious as it seems. Modern cities are developing in an unplanned manner [3]. It is caused by the transformation of natural land surfaces comprising of vegetation and pervious cover into built-up and impervious surfaces due to the growth in economy and population [4]. The population has increased from 4.2 lakhs in the 2001 Census to 6.6 lakhs in the 2017 Census report. A gradual increase of 63%. In the last few decades, land-use practices (agriculture, mining, logging, housing, recreation, etc.) have become so intensive and predominant, which resulted in uncontrolled development. Such impacts have reduced the local capacity of lands to support both ecosystem and human enterprise on a global scale [5]. To address such an issue of global scale, detailed information on existing land use pattern and sound knowledge about changes in land use through time is essential.

Remote sensors onboard satellites can acquire thermal-infrared data from which it is possible to retrieve the urban Land Surface Temperature (LST). LST is used to understand the biological, physical and chemical processes of earth systems; it is also a good indicator of the earth's surface energy. Land-Use/Land-Cover change has impacted LST [6]. Urbanization is not the only factor influencing increase or decrease of LST, but there are also a host of other factors [7].

Though there are studies at the regional scale on the effects of land cover change on temperature, they are inadequate for local planning. The objective of this study was to study the Impact of LU/LC change Signatures on Land Surface Temperature in one of the coastal districts of Karnataka using Google Earth Engine (GEE) platform.

However, it is not easy to handle and process the massive amount of Earth Observation (EO) data available because of the continuously increasing number of sensors, spatial and temporal resolutions. This will be even more evident shortly with the development of the micro-satellite constellations. Even today, much of the archived EO imagery is underutilized despite modern computing and analysis infrastructures. This is mainly due to processing limitations when faced with a considerable amount of data on standard computers and of the high technical expertise needed to use traditional supercomputers or large scale commodity cloud computing resources [8]. In the present era of Geo Big Data, new computing instruments to support remote sensing investigations are therefore necessary to fully exploit and make available the information content of the acquired data.

A. Google Earth Engine (GEE) vs other Big Earth Observation (EO) Data Platforms

Earth Engine comprises of a multi-petabyte analysis ready data catalogue co-located with a high-performance, intrinsically parallel computation service. It is accessed and controlled through an Internet-accessible Application Programming Interface (API) and an associated web-based Interactive Development Environment (IDE) that enables rapid prototyping and visualization of results. The data catalogue contains an extensive repository of geospatial datasets, including observations from a variety of satellite and aerial imaging systems. It consists of optical and non-optical wavelengths, environmental variables, weather and climate forecasts and hindcasts, land cover, and topographic and socio-economic datasets. All of this pre-processed data is ready-to-use in an information-preserving form that allows efficient access and removes many barriers associated with data management. Users can access and analyze data from the public catalogue as well as their private data using a library of operators provided by the Earth Engine API. When running complex transformations, the user should be able to manipulate functions and modify them to adapt them to tackle specific problems. Hence it becomes necessary for users to have backend access in processing platforms. In most open-source data analysis tools such as SciDB [3], users have access to the source code, which enables them to understand commands in detail. However, the backend computing that takes place in GEE does not allow this. Users can share scripts openly within their directories, which makes analysis reproducible in a certain restricted sense.

In this way, many of the limitations related to the data downloading, storage and processing, which usually occur when such a large amount of Geo Big Data is analyzed, are effortlessly solved by using GEE.

II. DESCRIPTION OF STUDY REGION

Dakshina Kannada is one of the three coastal districts of Karnataka state with a geographical area of 4859 sq.km. The district is bound by 12.57° and 13.50° North Latitudes and 74.0°and 75.50° East Longitudes. Situated between the lower region of the western ghats in the east and the Arabian Sea in the west, it is flanked by Udupi District towards the north, Chikkmagaluru district towards the northeast, Hassan District to the east, Kodagu District to the southeast, and Kasaragod District in Kerala to the south. The choice of this district was due to effective change in landcover. An all-weather port is located in Mangalore and is the only major port of Karnataka. The development programs do not commensurate with the physical growth of the city, and hence the city is facing challenging economic, social and technological problems. This city is the headquarters of a very literate district. The literacy rate among the population here is typically high (about 85-95%) and attracts many intellectual industries as well as other large industries. However, the resultant impacts on the environment are, to a great extent, damaging and unsustainable. The location map of the study area is shown in Fig.1.

III. METHODOLOGY

In this section, an overview of the datasets and software used is described. Description of essential functions used within GEE to load data into the GEE API, access uploaded imagery and perform raster overlays is further explained.

It is followed by the description of the signatures of LU/LC change on Land Surface Temperature (LST) variation analysis using Landsat and Sentinel data.

A. Data Description and Software's Used

Dakshina Kannada has a highly urbanized landscape which makes it worthwhile to explore its urban sprawl.

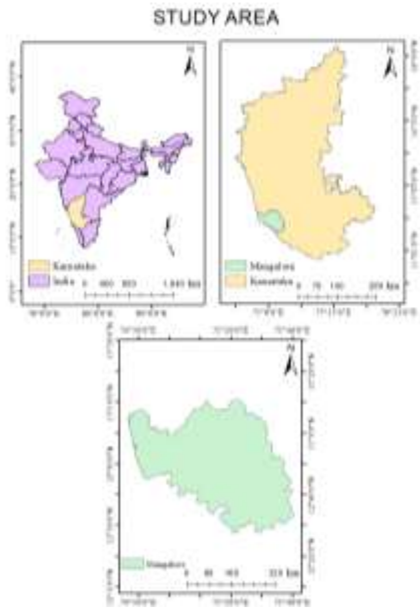

Fig. 1: Location Details of Study Area

This analysis can be deepened by obtaining land- use/land-cover classes using Sentinel-2 MSI: Multi-Spectral Instrument, Level-2A with 20m spatial resolution, and Landsat 8 Operational Land Imager (OLI)/ Thermal Infrared Sensor (TIRS) C1 Level 2 with 30m spatial resolution. The Land Surface Temperature was derived using Landsat 8 Operational Land Imager (OLI)/ Thermal Infrared Sensor (TIRS) C1 Level 2 and Landsat7 Enhanced Thematic Mapper Plus (ETM+) C1 Level 2 with 30m spatial resolution. For this study, Google Earth Engine- A planetary-scale platform for Earth science data analysis is used along with other software like ArcGIS and SpaceStat for further investigation of results obtained from GEE.

B. Data Processing in Google Earth Engine (GEE)

GEE is a platform which can be used to process global-scale satellite imagery dating back up to 40 years [9]. It comprises of two main components that work together with each other, namely, the Google Earth Engine Explorer (EE) (for viewing datasets) and the Google Earth Engine Play-ground (EEP). The Google EEP application, a JavaScript API, is used to upload and analyze large satellite imagery and to conduct complex geostatistical and geospatial operations in the provided representation. We use Google EEP to load the "Sentinel-2 MSI: Multi-Spectral Instrument, Level-2A" and "Landsat 8 Operational Land Imager (OLI)/ Thermal Infrared Sensor (TIRS) C1, Level 2" along with their respective colour palettes.

C. Land-Use/Land -Cover Classification

The main aim was to isolate the data for five major land classes. Urban/Built-up class which includes residential, transportation, industrial and commercial complexes and mixed urban and built-up land. Forest land cover class consists of deciduous and mixed forest. Agriculture land cover class contains cropland, pastures, vineyards and other agriculture lands. Waterbody consists of rivers, streams, canals, lakes and reservoirs. Barren land cover class includes bare exposed rocks, quarries, dry salt flats, beaches, gravel pits, mixed barren land and transitional areas. Import Sentinel-2 MSI: Multi-Spectral Instrument, Level-2A and Landsat data using search datasets option. Data is filtered for the complete collections to obtain, years 2001 and 2019. Fig. 2 depicts the exact methodological flow of the input and output variables, reducers and functions used within the GEE API.

Once the data is filtered according to dates, metadata has to be rectified to obtain images with cloud cover less than 10%. Further, the collection is sorted using the mean () and clip () functions. First, reference samples are selected for each class. In this process, at least 80 training points were used with around one-third of the samples being used for training the classifier and two thirds for validating the classification results. Forest class was not further classified into sub-areas since the main objective was to identify the urban areas. The high-resolution images from Google Earth Engine were used, corresponding to each year of the Sentinel and Landsat images of Dakshina Kannada.

Random Forest (RF) is the most popular machine learning method, which is comparatively applied to the supervised classification of urban landcover. RF is a decision tree-based classifier, which consists of a set of decision trees, with each tree trained based on a randomly selected subset of the total training samples [10]. The final classification result of RF is a voting-based decision based on the classifications of all the decision trees. The successful application of RF depends on the optimal settings of two key parameters, the number of decision trees and the number of features that are randomly selected to split each node in the decision trees. According to the previous study, a more significant amount decision trees will produce a better result. However, the performance of RF will become stable with no significant improvement after a certain number of decision trees [11]. To achieve the optimal performance of RF, the number of decision trees is set to 100. Finally, the images are classified into five classes: Built-up, Forest, Agriculture, Water Body and Barren Land. A new variable is created in GEE to merge all the training points added to categorize all the five different land-use/land -cover classes.

Further, a palette for the International Geosphere-Biosphere Programme (IGBP) classification is defined to identify different classes. An accuracy assessment is then obtained by generating an error matrix, which provides information about the reliability of the classification results, including overall accuracy, user's accuracy, producer's accuracy, and the kappa coefficient for each classified image. This image is then exported in GeoTIFF format for further analysis.

D. Land Surface Temperature Estimation

The Landsat-8 and Landsat-7 data is imported into Google Earth Engine API and further steps are followed by adding a new function that contains the equations mentioned below. The first step of the proposed work is to convert the satellite-based Digital Number (DN) at-sensor spectral radiance (λ) using equation (1)

$$L\lambda = M_L * Q_{cal} + A_L \quad (1)$$

Where ML= Band specific multiplicative rescaling factor from the metadata, Qcal= Quantized and calibrated standard product DN value of a pixel, and AL= Band-specific additive rescaling factor from the metadata.

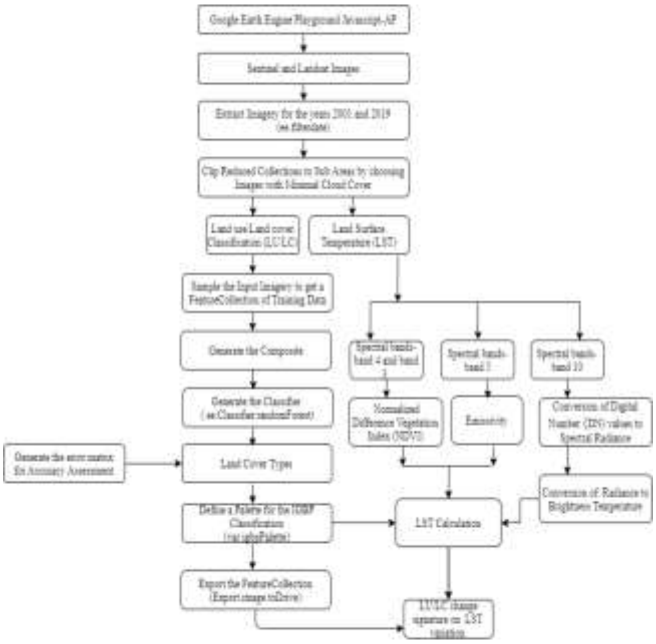

Fig. 2: Methodology

- The thermal infrared bands are converted to brightness temperature (BT) using metadata and equation (2)

$$BT = (K2 / (\ln (K1 / L) + 1)) - 273.15 \quad (2)$$

Where K1 and K2 are the thermal infrared (TIRS) bands of band 10 and band 11, the value of band 10 and band 11 can be obtained from metadata file linked with the satellite image. To get the results in Celsius, absolute zero is added, which is approximately equal to – 273.15°C.

- Normalized Difference Vegetation Index (NDVI) is necessary to categorize land cover types of the study area. The NDVI ranges from -1 to +1. NDVI is computed on a per-pixel basis as the normalized difference between the red band and near-infrared band of images using equation (3)

$$NDVI = (NIR - RED)/ (NIR + RED) \quad (3)$$

Where NIR is the near-infrared band value of pixel and RED is the red band of the same pixel. The NDVI is essential to calculate proportional vegetation (Pv) and emissivity (ε).

- From the obtained value of NDVI calculate proportional vegetation (Pv) using equation (4). This proportional vegetation gives the estimation of the area under each land cover type.

$$Pv = Square ((NDVI – NDVImin) / (NDVImax – NDVImin)) \quad (4)$$

- Land Surface Emissivity (LSE) is required to obtain LST, equation (5)

$$\varepsilon = 0.004 * Pv + 0.986 \quad (5)$$

Where ε = Land Surface Emissivity, P_V = proportion of vegetation

- Finally, LST is calculated using brightness temperature (BT) of two bands 10, band 11 and LSE that is derived from Pv and NDVI. LST can be derived using equation (6)

$$LST = (BT / (1 + (0.00115 * BT / 1.4388) * Ln(\varepsilon))) \quad (6)$$

The obtained output of LST is then exported in GeoTIFF format for further analysis using Export.image.toDrive function.

E. Land-Use/Land-Cover classes and Land Surface Temperature

The distinctive LST patterns are associated with the thermal characteristics of the land cover types [1]. It is necessary to further study the temperature changes by LU/LC for studying the effect of urbanization on the local thermal environment. A detailed analysis of LST with LU/LC is shown in Fig.3 and Fig.5. The significant implication of these results has been discussed to provide a better understanding of spatial-temporal changes in the microclimate of Dakshina Kannada district. These analyses were carried out using SpaceStat software which offers many useful capabilities for plotting and visualizing data and has an extensive library of built-in functions for data analysis.

IV. RESULTS AND DISCUSSIONSUS

A. Accuracy Assessment

The added training points of each class are accurately classified, resulting in an overall accuracy of 99.0% and 99.05%, and the Kappa coefficient of 0.987 and 0.988 in 2001 and 2019, respectively. Forest, agriculture, and barren land have similarly high user and producer accuracy values. These land-use classes never fall below an accuracy of 88%. Waterbody and built-up area show a low user accuracy compared to other classes. It indicates that about 3% of the pixels that are classified as water body and built-up are a member of another class

B. LU/LC Change Analysis

In the year 2001, more than 39% of the Dakshina Kannada district was covered by the greenery of the forest. The agriculture land and forest land seemed like a dominant land-use type with 36.35% and 39.33% of the total area, respectively. The built-up area and barren land contributed to only 11.6% and 10.6% of the area, highlighting that most of the taluks of Dakshina Kannada district were in the transition zone from semi-rural area to urban area but today are within the city.

Table I: Land-Use/Land-Cover Area (sq.km)

Classes	**2001**	**2019**	**Increase (%)**	**Decrease (%)**
Agriculture Land	1656.54	1399.84	-	5.63
Water Body	96.19	88.47	-	0.17
Forest	1792.35	1169.58	-	13.67
Built-up Area	529.03	1386.44	18.81	-
Barren Land	483.20	513.22	0.66	-

Table I provides data on the spatial extent of the landcover in square kilometers of the study area for the year 2001and 2019. The rapid growth in the built-up area and development of the city has changed most of the green coverage to impervious coverage in the year 2019. The built-up surface area has seen a tremendous increase of 18.81% in the past 19 years by dominating all other land use classes. The growth in the built-up area and reduction in the agricultural land is primarily due to the intensive urban growth and the industrial revolution [12]. The area of agriculture land reduced from 1656.54 sq.km (36.35%) to 1399.84 sq.km (30.71%) in the year 2019. This is mainly due to the conversion of cropland to commercial use along the major highway. Although there are many Government programmes to conserve forest land and environments such as Karnataka Act No. 09 of 2018 and The Karnataka Forest Act, 1963 even then there is a significant reduction in a forest area of 13.67% over the years. Mixed forest cover area in Sulya taluk reduced by 5% and a 4% reduction in forest land is seen in Belthangady taluk in 2019. This highlights the need for monitoring the encroachment of forest area within the district.

The area of barren land over the district has increased from 483.20 sq.km (10.6%) to 513.22 sq.km (11.26%) in the year 2019. The water body has slightly decreased from 96.19 sq.km (2001) to 88.47 sq.km (2019). Overall there is a slight decrease in areal extent of agriculture land and negligible reduction in the area of the waterbody, i.e., 0.17%. Also, a significant increase in the built-up area.

C. Relationship Between Signatures of Land-Use/Land-Cover (LU/LC) change on Land Surface Temperature (LST) variation

Fig.3 shows the estimated LST values over different LU/LC classes for the year 2001 and 2019 in Pre-Monsoon period. The maximum surface temperature in the barren land varied from 20.78°C to 34.10°C with a mean value of 27.71°C. The temperature in water body changed from 20.07°C to 30.63°C having a mean value of 25.53°C.

Low LST characteristics of water may be attributed to its high thermal inertia owing to which it warms up slowly during day time. The temperature over the forest land has shown a mean of 24.34°C with a variation of 20.0°C to 33.98°C and 20.0°C to 33.51°C with a mean of 26.26°C in built-up land.

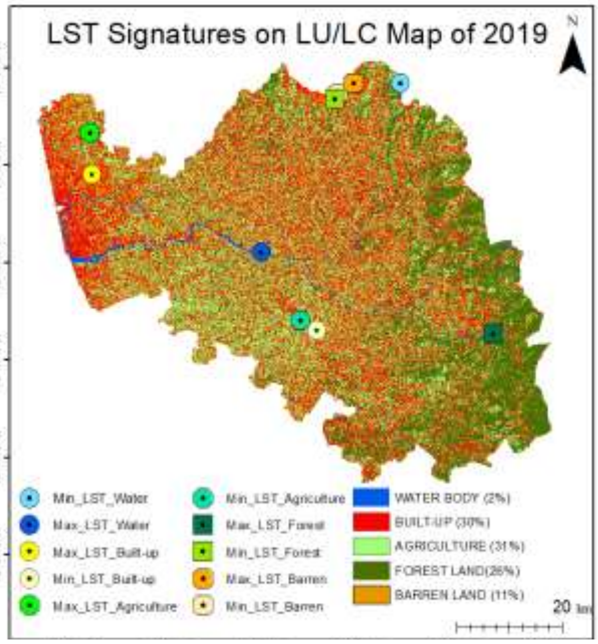

Fig. 4: Signatures of Minimum and Maximum LST

The temperature has seen a progressive drift in the past 19 years, which is evident from the temperature variation in these classes in the year 2019. The forest land has seen an upsurge of 2.25°C in mean temperature, 1.16°C in the barren land, 1.80°C in built-up and 1.90°C in agricultural land.

The location details of the maximum and minimum LST over different LU/LC class in the year 2019 is given in Fig. 4. The variation in the years 2001, 2006, 2011 and 2016 is analyzed for those locations, which is shown in Fig. 5. The maximum LST of the built-up area has increased significantly at a rate of 0.35°C/year in almost two decades.

Even though the minimum temperature has increased gradually over the region, the temperature in the year 2019 has shown reduction than the previous years. In 2019 the minimum LST decreased in almost all LU/LC types.

V. CONCLUSIONS

Dakshina Kannada is a fast-developing city that has promoted its potential in attracting the industries. Urban extension primarily changes the land-use/land-cover (LU/LC) of the region, which may influence the local climatic patterns.

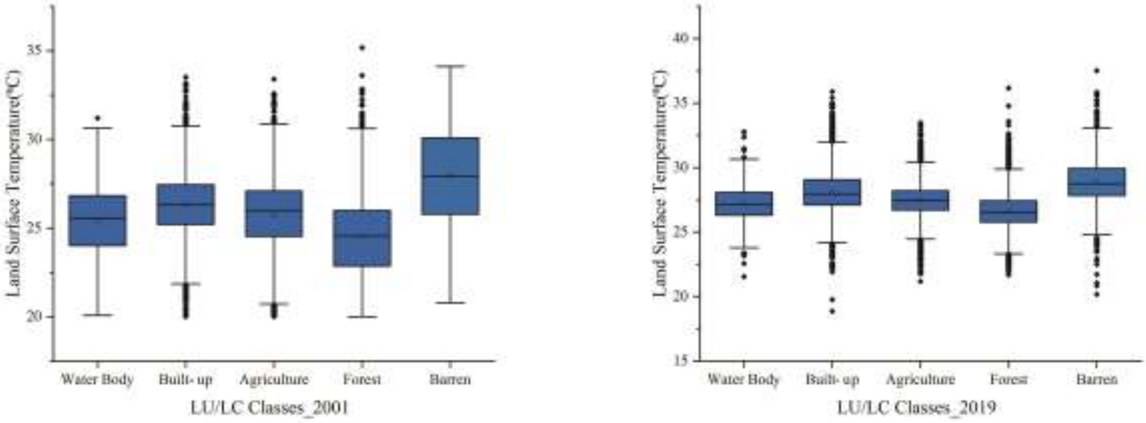

Fig. 3: LST variation for different LU/LC classes

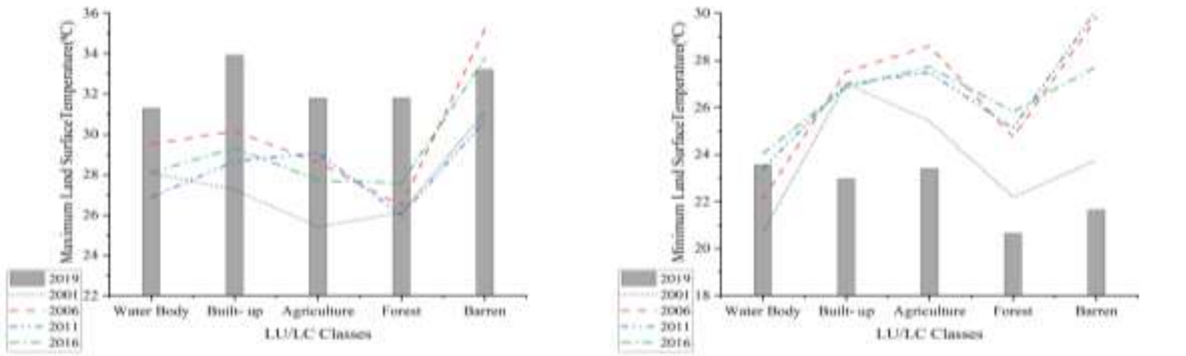

Fig. 5: Signatures of Land Cover Change on LST

The change in the LU/LC patterns in the district is explored using Landsat and Sentinel satellite data with a powerful cloud platform Google Earth Engine (GEE)[1], which is used to analyze the wide variety of data[2]. The district has seen a significant change in the land use and land cover in two decades, which plunged the greenery to impervious cover. 13.67% reduction in the forest area, 5.63% in the agricultural land, 18.81% increase in the built-up areas and 0.6% in the barren land within almost two decades. A significant signature of LU/LC change on LST variation is, maximum LST increased, and minimum LST decreased over all the years consistently in all the LU/LC classes. Thereby the difference between the maximum and minimum LST is increasing. It is apparent that signatures of LU/LC change are the predominant factor in LST variation, which is found to be closely associated with the physical characteristics of the built-up area. The land surface temperature has seen a progressive drift in the past 19 years, with an increase of 2.25°C in mean temperature in forest area, 1.16°C in the barren land, 1.80°C in the built-up and 1.90°C in the agricultural field in the same two decades. The higher variation in maximum land surface temperature is observed in the built-up land with a range of 0.35°C/year. Though there is a signature of change in LU/LC on the LST variation, there might be an influence of other climatic and topographical parameters on the variation of LST. Incorporation of important hydroclimatic parameters (humidity, rainfall, evapotranspiration) may reveal the combined signature on LST. Also, the use of excellent resolution data product may expose the signature of land -use/land-cover change on the land surface temperature variation even at the micro-level.

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