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Assessment of LULC and their impact on land surface temperature, using geospatial techniques in Kolar River catchment area, Madhya Pradesh, India

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Abstract
In this study different patterns of land cover were identified and investigated, their impact on LST, NDVI, and NDBI, and determined correlation between LST, NDVI and NDBI. Taken 26 May 2021 Landsat 8 satellite data, ARC GIS 16.0 and ERDAS imagine 16.0 software were Used. The present study is focused on determining the Land use Land cover, Land surface Temperature, normalized difference vegetation index (NDVI), normalized difference and built-up index (NDBI), and correlation between LST, NDVI and NDBI for Kolar River catchment. This is classified into different land use/land cover (LU-LC) types using NDVI, NDBI and threshold values, iterative self – organizing data analysis technique and maximum likelihood classifier. A classification system composed of five classes – Agriculture, Forest, built-up area, water body, and bare soil, and build relationship of LST with the NDVI and NDBI over LULC.
The classified built-up areas showing maximum temperature 49.72 °C, high NDBI value 0.68 and low NDVI value -0.96, and water body have minimum temperature 22.84 °C degree, minimum NDBI value -0.83and minimum NDVI0.95 values. LST build a strong negative correlation with NDVI, and shows strong positive correlation with NDBI. Built-up area and bare land have maximum temperature due to increasing anthropogenic activities. Spatial variation of Land Surface Temperature, NDBI and NDVI in a particular land cover has been critically analysed and mapped.

Keywords: Remote Sensing and GIS, Land Use and Land Cover, LST, NDVI, NDBI and Thematic Maps

1. Introduction
The climate in and around cities and other built up areas is altered due to changes in LU/LC, and anthropogenic activities of urbanization. The most imperative problem in urban areas is increasing surface temperature due to alteration and conversion of vegetated surfaces to impervious surfaces. These changes affect the absorption of solar radiation, surface temperature, evaporation rates, storage of heat, wind turbulence and can drastically alter the conditions of the near-surface atmosphere over the cities. The temperature difference between urban and rural settings is normally called urban heat island (UHI). (Mallick J., 2008) [11]. Land surface temperature can provide important information about the surface physical properties and climate which plays a role in many environmental processes (Dousset & Gourmelon 2003; Weng, Lu & Schubring 2004) [3, 19]. The most important problem in the earth especially in urban areas is increasing surface temperature due to conversion of vegetated surfaces to impervious surfaces (Mallick *et al.*, 2008) [11], transformation of vegetated and wetland into agricultural land or bare waste land (Pal and Akoma., 2009) [13]. The degree of absorption of solar radiation, albedo, surface temperature, evaporation rates, transmission of heat to the soil, storage of heat, wind turbulence, can drastically change the conditions of the near-surface atmosphere over the cities (Mallick *et al.*, 2008) [11]. Land surface temperature (LST) is the skin temperature (Jeevalakshmi *et al.*, 2017) [8], and can be measured on the surface of bare soil, dense and scattered vegetation (Thakur and Gosavi, 2018) [17]. LST of the different surface area is different due to surface reflectance and roughness of different land use/land cover (LULC) types. Recently, due to rapid urbanization, the characteristics of land surface types are being changed. The presence of natural vegetation influenced a lot in the distribution of LST. Modify energy and water balance processes (Oke, 1987) [12] and also play vital role in many environmental processes (Weng *et al*., 2004) [19].

Along with other sorts of pollutants, land surface temperature will rise at rapid rate. Land surface temperature (LST) are related to changes in the spatial and temporal distributions of LULC (Anbazhagan and Paramasivam, 2016; Pramanik and Punia., 2020) [1, 15]. The LST negatively correlates with the NDVI and positive correlation with the normalized difference built-up index (NDBI) (Patil *et al*., 2018) [14]. These LULC changes and their effects are mostly discernible over regions having higher population density, industrialization, urbanization, deforestation, agricultural diversification etc. Thus, the most visible effect of anthropogenic activities regionally and locally is changes in the LULC which modifies the surface energy balance which in turn affects the surface temperature. LULC relates to the observable earth surface expressions, such as vegetation, geology, water resources and anthropogenic features which describes the Earth's physical condition in terms of the natural environment with man-made structures. (Singh *et al*., 2012) [16]. Land Surface Temperature show, a higher spectral variability occurs when the proportion of different land cover types is distributed more evenly, lower spectral variability occurs when less land cover types were found in a transect or one land cover type occupied the majority of the surface.

These days, a lot of people come together in the city rapidly because of the industrial development, so climatic changes such as a sudden rise in temperature; relative humidity and air pollution have been brought out all over the world. Especially, distinct difference of temperature between urban and rural, it depends on urban planning, construction of industry and pattern of green distribution, which is called urban heat island, is one of the biggest problems nowadays. Furthermore, previous studies were used to determine the spatial distribution of Land surface Temperature and relationship of estimated land surface temperature (LST) with normalized difference vegetation index (NDVI) and normalized difference built - up index (NDBI).

The specific objectives of the study are: (1) to determine the nature of LST in the Kolar River catchment, Sehore District of Madhya Pradesh from Landsat 8 image of May 2021; and (2) to compare the relationship of LST over NDVI and NDBI indices, i.e. normalized difference vegetation index (NDVI), normalized difference built-up index (NDBI), for the whole area.

The purpose of the study is the future environmental planning and Agriculture of Kolar River Catchment which is located near Bhopal capital of Madhya Pradesh. The satellite image helps a lot in this city planning. LST of the city is gradually increasing with time and it becomes a genuine research problem. Thermal remote sensing and land surface indices play a major contribution in this field as the LST of the city were primarily determined by the variation of the land surface composition. This paper was simply a case study based on the relationship between land surface temperature and land surface indices in Kolar River Catchment area, Madhya Pradesh, India.

2. Methodology

2.1 Study Area

The Kolar River is originated from Vindhya mountain ranges of Sehore district which is located in Madhya Pradesh of central India. It is right-bank tributary of Narmada River which is after origin; it flows in south-west direction and merges with Narmada River near Nasrullahganj in Raisen district. Its total drainage area is 1347 sq.km. Covering two districts of Madhya Pradesh i.e. Sehore and Raisen district. Geographically it is bounded by latitudes 22º 33" 30' N to 23º 7' 30" N and longitudes 770 2'30" E to 770 28'30" E. Kolar river catchment area lies at an elevation from 350 to 600 meters which is surrounded by tropical deciduous forest.

Data used oposheet number 55E/4, 55E/8, 55F/1, 55F/5, 55F/2 and 55F/6 of the study area, District resource map, ASTER DEM. Satellite data, ArcGIS 16.0 and ERDAS imagine16.0 software used to the preliminary data processing, extracting, mosaicking satellite images and image classification.

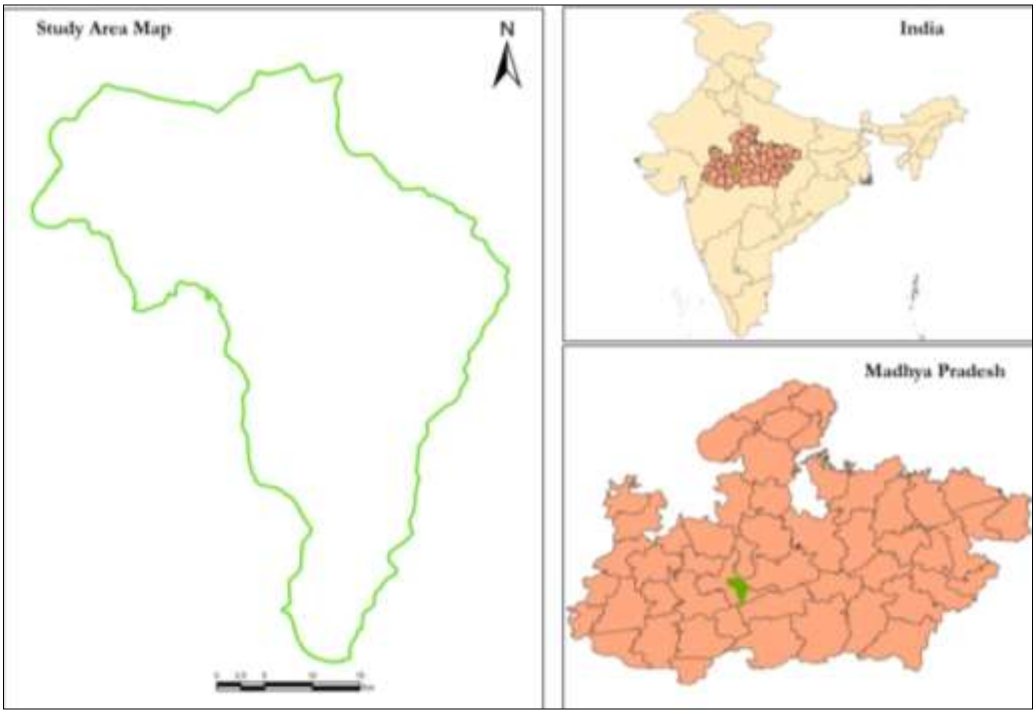

Fig 1: Location map of the study area

2.2 Dataset Preparation

The study area has been clipped from both two satellite images scene of less than 10% cloud coverage, collected from Earth explorer (USGS). Data sets has been projected in UTM projection with 44 zone and WGS 84 datum, Satellite images of 20021 (May) and 2021 (May) were taken to estimate the LST and utilized satellites images of the study areas described in Table 1.

Table 1: Satellite images Specification

Satellite	Date	Row/ Path	Sensor	Band	Resolution
Landsat	26 may 2021		OLI	4	30
				5	30
			TIR	10	100*30
	04 May 2021		OLI	4	30
				5	30
			TIR	10	100*30

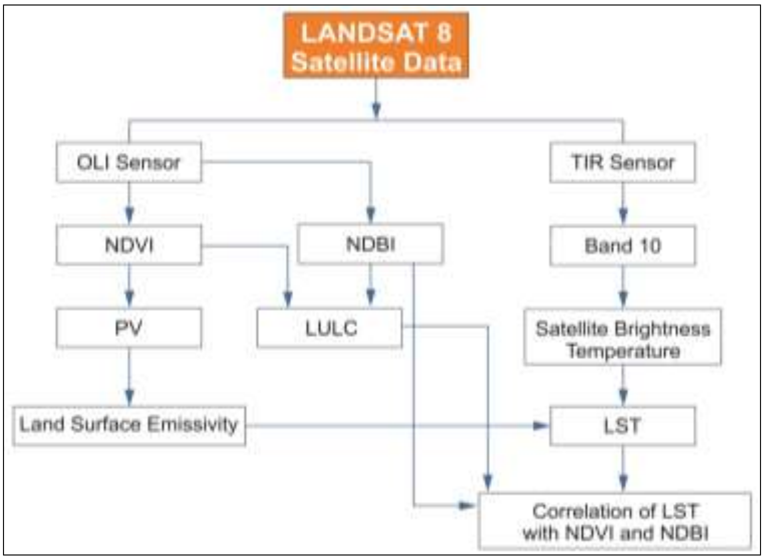

Fig 2: The flow chart of the study

2.3 Determination of NDVI and NDBI indices

The NDVI and NDBI values vary between -1 to +1 which helped for Land use Land covers were determined, with the help of normalized difference vegetation index (NDVI) and normalized difference and built - up index (NDBI) using threshold values, iterative self – organizing data analysis technique and maximum likelihood classifier.

NDVI = (NIR Band – Red band) / (NIR Band – Red band).................. (1)

NDBI = (SWIR Band – NIR Band) / (SWIR Band – NIR Band)........... (2)

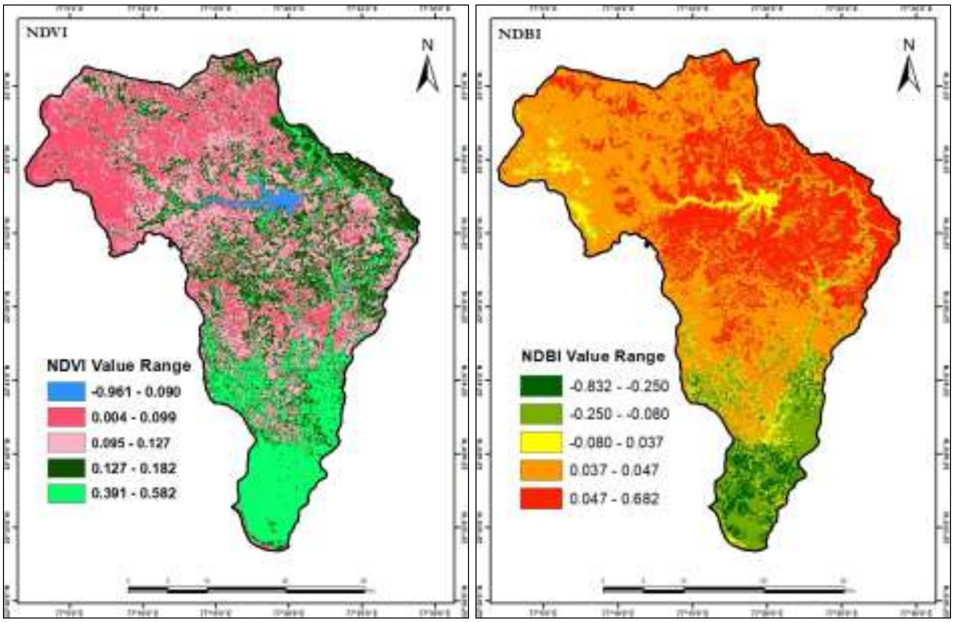

Fig 3: NDVI and NDBI maps of the study area

2.4 Land use Land Cover Pattern

The NDVI is the most common and widely used index for vegetation extraction which was applied in this study. NDBI was also applied in this study to detect the built-up area. These two indices can be applied to categorize different types of LU–LC by the suitable threshold values. To get more accurate classification, Boolean operators may be used on the spectral bands of the indices. For example, NDVI > 0.2 and NDBI < 0 may be used together to extract vegetation. Similarly, NDVI < 0 and NDBI < 0 may be used together to extract water bodies, whereas 0 < NDVI < 0.2 and NDBI > 0.1 may be used together to extract built-up area and bare land. But these threshold values may differ due to atmospheric conditions. These values may also be integrated for LU–LC classification. This classification was composed in five classes-Agriculture, Forest, built-up area, water body, and bare soil or open land. An iterative self-organizing data analysis technique classifier with the supervised classification method and the maximum likelihood classification were used later to get a better result in extracting the built-up area and bare land.

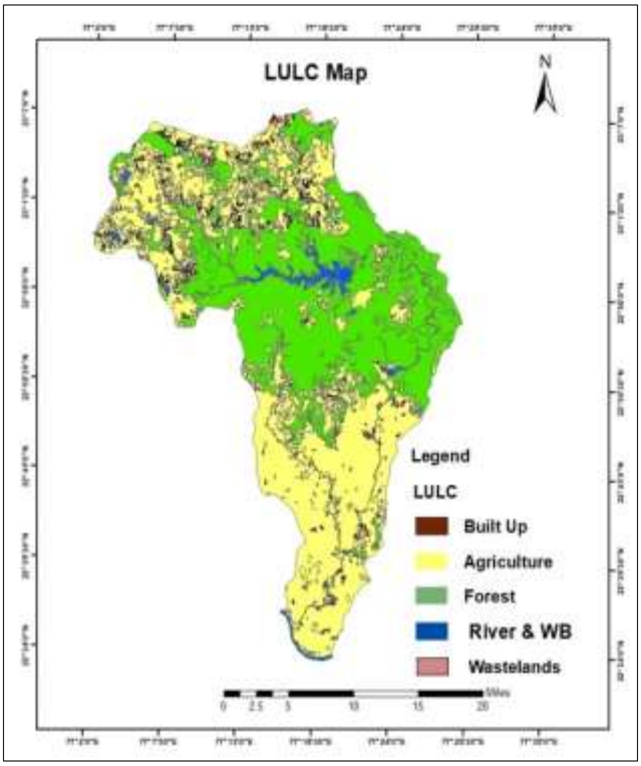

Fig 4: LULC map of the study area

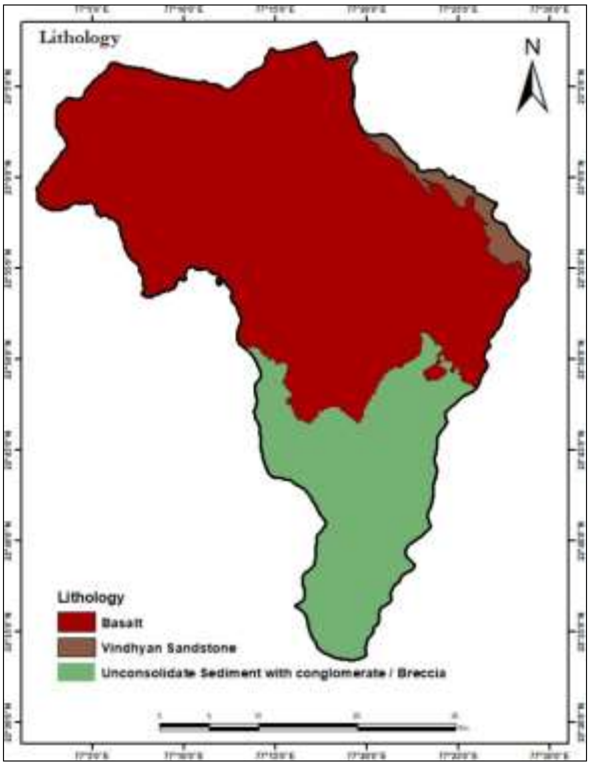

Fig 5: Litho logical map of the study area

2.5 Geological Formation

This part is occupied by Deccan Basalts. The rest part has red-yellow mixed soils derived from sandstone, shale, gneiss. The alluvial soils are found along the river courses. The higher elevations i.e. the hilly regions have a cover of murum, which is made up of small rounded pieces of weathered trap. The Vindhyans and Bijawars have a thin cover of sandy loams. The soils in granitic area are clayey. The schist has a thin capping of loam with lot of quartz grains. The alluvium is derived from hill slopes by numerous streams and watercourses.

2.6 Accuracy Assessment

LULC data verified in the same time period, a comparison was made between more than 300 random sampling points and their corresponding point on Google Earth images to verify the LULC classifications. This classification method used for this research provide good accuracy as the validity rates are more than 85% for the study area.

2.7 Retrieving Land Surface Temperature from thermal images

LST was retrieved from the Landsat 8 satellite images of OLI and TIRS sensors area using raster calculator and Arc GIS software.

In the present study, LST was derived from Landsat TIR data by using the mono window algorithm where ground emissivity, atmospheric transmittance, and effective mean atmospheric temperature are the three required parameters. At first, the original TIR bands 100 m resolution are resampled into 30 m for further application (Guha S. *et al.*, 2020) [5]. The entire procedure is included in the following equations:

$L\lambda$ = Radiance Multi Band*DN + Radiance Add Band

Where, $L\lambda$ is the spectral radiance in Wm−2 sr−1 mm−1

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

Where, BT is the Satellite brightness temperature, $L\lambda$ is the spectral radiance in Wm−2 sr−1 mm−1; K2 and K1 are calibration constants. For Landsat 8 data, K1 is 774.89, K2 is 1321.08 (Wm−2 sr−1 mm−1).

PV= square ((NDVI - NDVImin) / (NDVImax - NDVImin))

Where, NDVImin is the minimum NDVI value (0.2) for bare soil pixel and NDVImax is the maximum NDVI value (0.5) for healthy vegetation pixel.

ε = 0:004*Pv +0.986

Where, ε is the land surface emissivity.
LST = BT / (1 + λ* BT / 14388) * Ln (Land Surface Emissivity)

Where, LST is Land Surface Temperature, BT is satellite Brightness Temperature and λ is wave length of band 10.

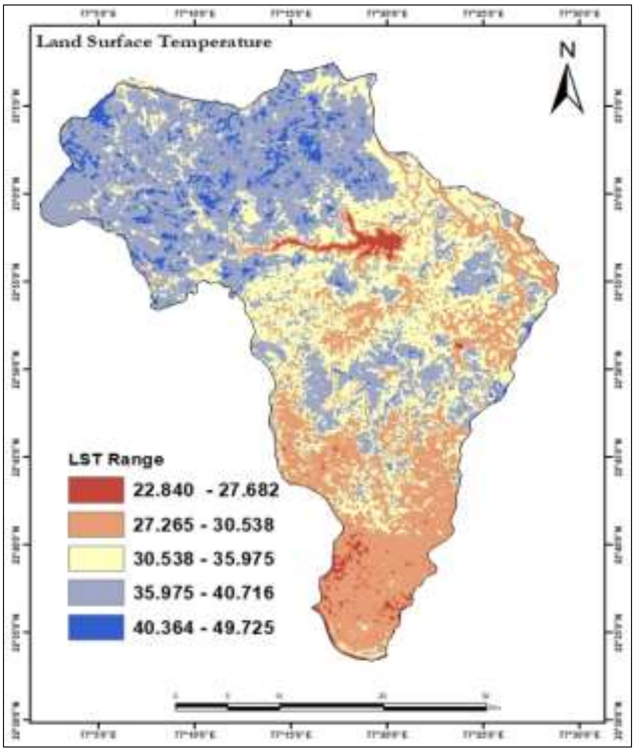

Fig 6: LST map of the study area

3. Analysis and Interpretation between LST over LULC, NDVI and NDBI

A number of research scholars recently attempted to build the LST-NDVI correlation (Varshney A., 2019) [18]. Some previous attempts were spatiotemporal in nature and were mainly conducted on the big cities like Tokyo, Shanghai, Chongqing, Shijiazhuang, Rome, Shiraz, Melbourne, Bangkok, Monte Hermoso, Beijing, Islamabad, etc. But, the discussion based on the LST-NDVI correlation in an Indian city in premonsoon season was rare.

The descriptive statistics relationship of LST over NDVI and NDBI values for Kolar River Catchment area presents in Table 2. Land Surface Temperature distribution was classified into appropriate ranges and colour-coded to generate a thermal distribution map of LST over the study area.

The present study is focused on determining the Land use Land cover, Land surface Temperature, normalized difference vegetation index (NDVI), normalized difference and built - up index (NDBI), and correlation between LST, NDVI and NDBI for Kolar River catchment. This is classified into different land use/land cover (LU – LC) types using NDVI, NDBI and threshold values, iterative self – organizing data analysis technique and maximum likelihood classifier. A classification system composed of five classes – Agriculture, Forest, built-up area, water body, and bare soil, and build relationship of LST with the NDVI and NDBI over LULC

The classified built-up areas showing maximum temperature 49.72 °C, high NDBI value 0.68 and low NDVI value -0.96, and water body have minimum temperature 22.84 °C, minimum NDBI value -0.83 and minimum NDVI -0.95 values. LST build a strong negative correlation with NDVI, and shows strong positive correlation with NDBI. Built-up area and bare land have maximum temperature due to increasing anthropogenic activities. Spatial variation of Land Surface Temperature, NDBI and NDVI in a particular land cover has been critically analysed and mapped.

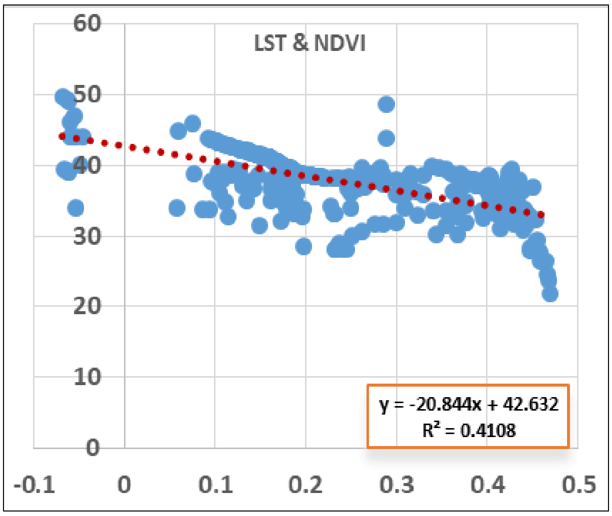

Fig 7: Correlation of LST and NDVI

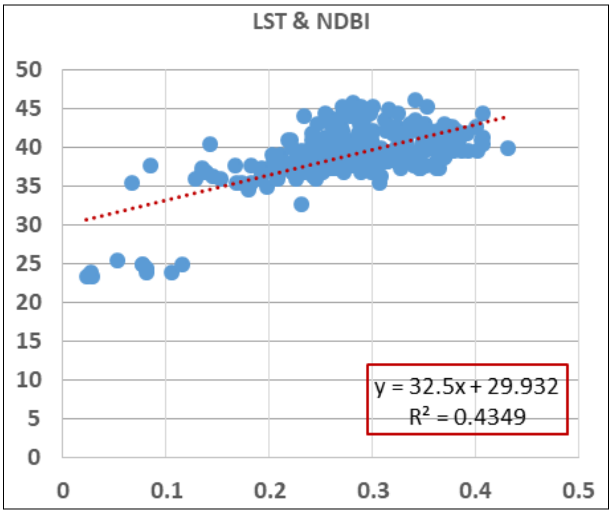

Fig 8: Correlation of LST and NDBI

4. Results and Discussion

Land Surface Temperature Distribution over NDVI and NDBI values analysed with in Kolar River Catchment area. LST distribution was classified into appropriate ranges and colour-coded to generate a thermal pattern distribution map of LST over the study area. A little hetero- genetic in LST was observed due to the LU–LC dynamics.

The classified built-up areas showing maximum temperature 49.72 °C, high NDBI value 0.68 and low NDVI value -0.96, and water body have minimum temperature 22.84 °C, minimum NDBI value -0.83 and minimum NDVI -0.95 values. LST build a strong negative correlation with NDVI, and shows strong positive correlation with NDBI. Built-up area and bare land have maximum temperature due to increasing anthropogenic activities. Spatial variation of Land Surface Temperature, NDBI and NDVI in a particular land cover has been critically analysed and mapped.

4.1 Relationship of LST on NDVI and NDBI
It is very interesting fact that LST distribution is very closely related to the distribution of NDVI and NDBI. Generally, LST is negatively related to NDVI and positively related to NDBI. But, this relationship may be varied due to spatial resolution, latitudinal extension or seasonal variation. NDVI and NDBI are the two LU–LC indices those are highly dependent on the LU–LC types in any region. Normally, high NDVI values indicate the presence of green vegetation and high NDBI values indicate the presence of built-up area and bare land. Basically, LST increases with the increase in built-up area and bare land whereas it decreases with the increase in forest, cropland, wetland and water bodies.
The linear regression trend analysis of NDVI (Figure 5) for the year 2021 shows the strong negative correlation between LST and NDVI value. Figure 5 indicates that surface temperature decreases with the increase of NDVI values that means with the increase of low dense vegetation areas. The coefficient of determination value found of NDVI 0.4108 and NDBI 0.434 for the year 2021.

5. Conclusion
Present study of Kolar River catchment on land use land cover/ Land cover and Land Surface Temperature showing rapid change in the LULC and Land Surface Temperature as there is high growth in the Waste land & built up areas. Waste land have occupied the Agriculture lands and forest are while forest has reduced marginally and water body is showing almost stagnant condition over time. If this trend of growth continues then most of the Agriculture areas will be occupied by Waste land and in near future which may create a threat to environment. Bare land and built-up area are mostly responsible for high LST generation. The presence of vegetation and water bodies reduces the LST level. Furthermore, the relationships between LST–NDVI and LST–NDBI were interpreted quantitatively by linear regression analysis at the pixel level. For whole study area, LST shows strong negative correlation with NDVI; and strong positive correlation with NDBI. It may be due to the presence of more heterogeneous landscapes within the study area.
The result of the present study is significant for future environmental planning for the city. Most of the low NDVI and high NDBI zones indicate high LST because maximum area cover Bare land & built up area, and indicated low Land Surface Temperature on high NDVI and low NDBI indices. It means the area with more green vegetation and wet soil represents low LST. Thus, the portion of vegetation and soil must be increased to reduce the thermal stress of the city. For better sustainability, a large amount of urban plantation is needed along the roadside and residential area. The present water bodies and green areas inside study area boundary must be preserved for providing a better life. NDBI shows a strong positive relationship with LST. It means the built-up area and bare or fallow land is responsible for high LST. Thus, the major commercial and industrial sectors should be moved into the outskirts of the city to make the residential zones less polluted. The green building materials like earthen materials, wood, bamboo, natural clay, earth bags, natural fibre, etc. should be introduced on a large scale for new construction.

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