Exploring the Effects of Land Use/Land Cover (LULC) Modifications and Land Surface Temperature (LST) in Pune, Maharashtra with Anticipated LULC for 2030

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Abstract

Land surface temperature (LST) is a crucial parameter influencing the thermal environment of urban and natural areas. Land use/land cover (LULC) patterns significantly impact LST, highlighting the need for a comprehensive understanding of their relationship. This study delves into the intricate interplay between LULC and LST in Pune city, India, employing a spatiotemporal analysis approach. The study utilizes satellite imagery from 2000, 2010, and 2022 to map LULC changes with Maximum likelihood, support vector machine and Random tree classification and their evaluation with accuracy and Kappa coefficient. Additionally, projected LULC for 2030 is prepared to assess future LST scenarios. Winter and summer LST data are analyzed to capture the seasonal dynamics of LST-LULC interactions. Pune has undergone significant LULC transformations, with the proportion of built-up areas increasing from 7% in 2000 to 47% in 2022, while barren land has decreased from 41% to 37%. Built-up areas exhibit consistently lower LST values during winter, while barren land tends to have the highest LST. In contrast, during summer, built-up and barren areas experience higher LST values, while water bodies and vegetation display relatively lower LST values due to their cooling effects. Mean LST in Pune has increased from 34.59°C in 2000 to 39.38°C in 2022, reflecting the changing thermal dynamics associated with LULC alterations. The expansion of built-up areas has contributed to temperature increases of up to 5.5°C in specific locations, highlighting the urban heat island effect. The study's findings emphasize the need for sustainable land use planning and development strategies to mitigate the adverse impacts of urbanization on LST. Policymakers, urban planners, and environmentalists can utilize these insights to develop informed land use policies, zoning regulations, and climate-smart urban development strategies.

Keywords: CA, LULC, LST, MLA, RF, SVM

1. Introduction

Urban sprawl refers to the uncontrolled and often unplanned expansion of urban areas into surrounding rural or undeveloped land. It is characterized by the outward growth of low-density residential and commercial developments, leading to the spread of urban infrastructure. Urban sprawl can have several impacts on the environment, and one notable effect is its influence on Land Surface Temperature (LST). The effect of urban sprawl on Land Surface Temperature is as explained below:

1. Heat Island Effect: Urban areas, especially those undergoing sprawl, often exhibit the Urban Heat Island (UHI) effect. This phenomenon is characterized by higher temperatures in urban areas compared to their rural surroundings. The increased concentration of impervious surfaces such as asphalt and concrete, along with reduced vegetation, leads to greater absorption and retention of solar radiation, contributing to elevated temperatures.

2. Changes in Thermal Inertia: The materials used in urban construction, such as concrete and asphalt, have higher thermal inertia compared to natural surfaces. Thermal inertia refers to a material's ability to store and release heat.

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Urban sprawl often introduces more of these high thermal inertia materials, which can lead to prolonged periods of elevated Land Surface Temperatures, especially during the nighttime.

3. Reduced Green Spaces: Urban sprawl typically leads to a reduction in green spaces such as parks and forests. These areas play a crucial role in regulating temperatures through shading and evapotranspiration. The loss of green spaces contributes to the overall warming of the urban environment, influencing Land Surface Temperature.

4. Impacts on Microclimates: Urban sprawl can create microclimates within a city, with variations in temperature across different areas. The areas with extensive impervious surfaces may experience higher Land Surface Temperatures, exacerbating the urban heat island effect.

5. Reduced air quality: The heat island effect can also trap pollutants near the ground, leading to a decrease in air quality. This can exacerbate respiratory problems and other health conditions.

6. Increased energy consumption: The higher temperatures in urban areas can increase the demand for air conditioning, which in turn increases energy consumption and contributes to greenhouse gas emissions.

Understanding the influence of urban sprawl on Land Surface Temperature is essential for assessing the environmental consequences of rapid urbanization. In this article, the relationship between land use changes and LST in Pune, India, is explored and the potential impact of projected land use changes for 2030 is analyzed. In this work, LULC with approximately decadal span i.e. 2000, 2010 and 2022 is carried out using Random Forest, Maximum Likelihood and Support Vector Machines.

A comparative study of all the three classification method is done to know the best performing classification method by taking user and producer accuracy and K coefficicent. Using Marov chain model the LULC map of 2030 is predicted. This study also focuses on analyzing LULC changes and its influence on LST in PMC and PCMC using Landsat satellite images for the same year. The surface temperature is analyzed for summer and winter season of city area. Overall, studying LULC and LST impact is important for understanding the complex relationship between human activities and the environment.

This knowledge can be used to develop strategies to create more sustainable and livable cities for future generations. Understanding these dynamics is essential for effective urban planning and sustainable development. This interpretation can be used to inform urban planning strategies aimed at mitigating heat-related challenges, promoting sustainable development, and enhancing the overall livability of expanding urban areas.

1.1 Study Area

Pune district is one of the most rapidly urbanizing districts in Maharashtra, India (Figure 1).

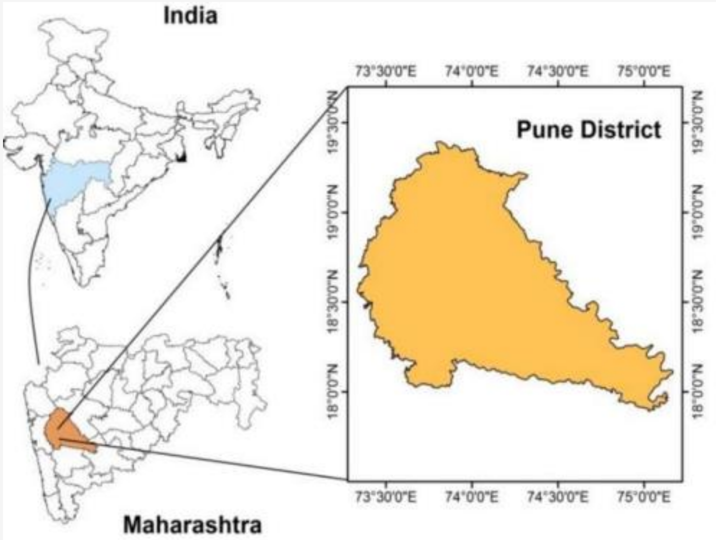

Figure 1: Map of Pune district

The district's urban population has grown at an average annual rate of 7.5% since 2001, and it is now home to over 45,000 hectares of built-up land. This rapid urbanization has been driven by a number of factors, including:

- Economic growth: Pune is a major center for information technology, manufacturing, and other industries. This economic growth has attracted a large influx of people to the city, which has led to an increase in demand for housing and other urban services.
- Infrastructure development: The development of new roads, highways, and other infrastructure has made it easier for people to live and work in Pune. This has also made it more attractive for businesses to invest in the city.
- Lack of planning: The rapid growth of Pune has outpaced the ability of city planners to keep up. This has led to a lack of proper planning and infrastructure, which has contributed to urban sprawl.

Urban sprawl has a number of negative consequences for Pune, including:

- Environmental damage: Urban sprawl leads to the loss of natural vegetation, which can contribute to soil erosion, water pollution, and air pollution.
- Social problems: Urban sprawl can lead to overcrowding, traffic congestion, and a lack of affordable housing.
- Economic costs: Urban sprawl can increase the cost of infrastructure and services, such as roads, schools, and hospitals.

There are a number of things that can be done to mitigate the effects of urban sprawl in Pune, after analyzing the current LULC pattern including:

- Promoting compact urban development: This involves concentrating development in existing urban areas rather than expanding into undeveloped areas.
- Preserving natural areas: Natural vegetation helps to cool the air and reduce pollution, so preserving trees and other natural areas in and around Pune can help to mitigate the effects of urban sprawl.
- Using public transportation: Public transportation can help to reduce traffic congestion and air pollution.
- Promoting mixed-use development: Mixed-use development combines residential, commercial, and office space in a single building or complex. This can reduce the need for people to travel long distances between home, work, and other destinations.

There is very limited or as such no research done so far in identifying impact of LULC on surface temperature which has adverse effect on human being. Being the metro city, urban planning need to done considering the LULC and LST pattern, so the study was taken to analyze the consequences way before the disaster.

2. Literature Reviews

In Pune, the rapid pace of urbanization has resulted in significant land use changes over the years. These changes have had a profound impact on the city's LST. As more agricultural and natural land is converted into urban areas, the city experiences an increase in impervious surfaces, such as roads, buildings, and parking lots. These surfaces tend to absorb and retain heat, leading to higher LST. Additionally, the loss of vegetation due to land use changes reduces the cooling effect of evapotranspiration, further exacerbating the urban heat island effect. When searched in scopus database, it is found that limited research has been done on identifying concentration of the land uses, coupled with the lack of green spaces, contributes to higher LST in densely populated areas.

Urban expansion significantly alters land use, replacing vegetated areas with human-made structures, leading to an increase in land surface temperature (LST). Duhok City's rapid urban growth, driven by political and economic advancements, has exacerbated this issue. The impact of land use changes on LST using Landsat images from 1990, 2000, and 2016reveals that changes in land use/cover significantly contribute to the rise in LST. Barren land and built-up areas exhibit the highest temperatures, while water bodies and forests have the lowest temperatures. NDVI and NDWI negatively correlate with low temperatures, while NDBI and NDBAI positively correlate with high temperatures [1].

The vegetation fraction derived from a spectral mixture model was utilized as an alternative indicator of vegetation abundance in remote sensing of urban heat islands (UHIs). The results found that land surfacetemperature (LST) exhibiteda slightly stronger negative correlation with vegetation fraction compared to the Normalized Difference Vegetation Index (NDVI). Fractal analysis indicated that complexity increased with pixel aggregation, peaking around 120 m, and that spatial variability of texture in LST was positively correlated with NDVI and vegetation fraction. These results suggest that vegetation fraction provides more insights into the interplay between thermal and vegetation dynamics and their impact on UHI spatial patterns [2] and [13].

The studies of UHI phenomenon and the relationship between Land Use Land Cover (LULC) changes, urbanization, and the intensity of UHIs emphasize the need for sustainable land management practices, preservation of green areas, and effective urban planning strategies to mitigate the adverse effects of UHIs.In bustling Chittagong, Bangladesh, urbanization's impact on temperature takes center stage [3][8][9][10] and [11]. The Analysis of satellite datawith Artificial Nerual Network (ANN) reveals built-up areas scorching, greenery shrinking, and water cooling as the city expands. By 2050, predicted temperature hikes raise alarm bells, urging planners to design sustainable solutions to tame urban heat and build a cooler future [4].

The study of urban temperature changes in Lahore, Pakistan, the fastest-urbanizing city in South Asiareveals that Lahore city faces the global challenge of climate change, the study also explored how alterations in land use (buildings, vegetation, etc.) affect land surface temperature (LST) [5]. Analyzing satellite data from 1992 to 2020, the study reveals built-up areas sprawl at the cost of greenery, bare land, and water. This has sparked a significant 4.3°C temperature rise in built-up areas. Predicted further increases by 2030 underscore the urgency of addressing these LULC-driven climate impacts, particularly in vulnerable developing countries like Pakistan.

The impact of urban land change on land surface temperature (LST) and carbon storage (CS) in Guangzhou from 1989 to 2021 was conducted using the integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model, the existing scenario of CS from 1989 to 2021 was assessed. The Cellular Automata-Artificial Neural Network (CA-ANN) and Long Short-Term Memory [6].

LSTM based Whale Optimization Algorithm (WOA) are employed to predict future LULC, CS, and LST scenarios. Results reveal a 63% increase in urban areas, causing a significant rise in high LST (≥34 °C) areas and a considerable decrease in carbon storage. The study highlights that areas with lower temperatures have higher CS capacity, emphasizing the importance of considering CS in urban planning for sustainable and environmentally friendly cities. Surface urban heat islands (SUHI) on the urban thermal environment and the relationship between land surface temperature (LST), land use-land cover (LULC), and vegetation. Utilizing remote-sensing indices such as urban thermal field variance (UTFVI), surface urban heat island intensity (SUHII), and normalized difference vegetation index (NDVI) was conducted to explored the connections between these factors. LULC maps are classified using a CART machine learning classifier, revealing a decrease in vegetated areas and an increase in urban areas over the 20-year period. Overall, the study emphasizes the need for sustainable urban planning and environmental management [4] and [12].

The study of the impact of rapid urbanization on land surface temperature (LST) and the emergence of Urban Heat Islands (UHI) in Manipur's greater Imphal city, India shown thet the variability in LST correlates positively with Normalized Difference Built-up Index (NDBI) and negatively with Normalized Difference Vegetation Index (NDVI). The study underscores significant decadal changes in LST, providing insights for urban planning and environmental management in the Imphal area [14].

Google Earth Engine Cloud (GEE) was utilized to assess spatiotemporal changes in Land Use/Land Cover (LULC) categories and their impact on Land Surface Temperature (LST) in India. Random forest (RF) machine learning technique was used for LULC classification, the study predicts future scenarios for 2030 based on estimated change maps. The CA-ANN model forecasted LST and LULC maps for 2030. Findings indicate a 5.75% decrease in vegetation/open land, a 6.31% increase in built-up areas, and a minor 0.56% decrease in water body area from 2000 to 2020. The highest recorded temperature in 2020 is 47.65°C, showing a strong positive correlation between LST and Normalized Difference Built-up Index (NDBI). The predicted LST for 2030 ranges from 43°C to 47.65°C, encompassing green spaces, impervious surfaces, and surface water, providing valuable information for climate mitigation strategies [15].

The relationship between land use/land cover (LULC) and land surface temperature (LST) in Seoul was investigated by employing the explainable artificial intelligence (XAI) approach. Integrating XGBoost and SHAP models, the study maximizes LST prediction accuracy, identifying surrounding built-up and vegetation areas as significant factors influencing LST.The results provide valuable insights for assessing and monitoring the thermal environmental impact of urban planning and projects, aiding in the determination of policy priorities for improving the urban thermal environment [16].

Remote sensing and GIS technologies analyzed land use and land cover (LULC) changes, highlighting a substantial shift from vegetation and bare land to built-up areas (25.46% and 10.17%, respectively), driven by population growth[17]. Linear regression analysis revealed a positive correlation between LST and LULC indices (NDBI and NDVI), emphasizing the need for improved land use planning to mitigate the city's vulnerability to climate variability.

The extent of urbanization and its impact on amenities was assessed by using qualitative parameters and compares it with Indore, a planned city. It also examines climate differences between urban and suburban areas using satellite imagery. The study reveals significant urbanization and higher LST and AOD in urban areas, particularly in recent years. These findings provide valuable insights for urban planning and management, especially in vulnerable regions [18].

Urbanization in Prayagraj and Naples has led to increased land surface temperature and ecological vulnerability. Sustainable urban planning is needed to mitigate these negative impacts. The predicted built-up and bare-land areas in both cities will increase by 2030, while vegetation cover will decline. This highlights the need for proactive measures to protect vegetation cover and combat the urban heat island effect [19].

LULC changes and the Urban Thermal Field Variance Index (UTFVI) from 1990 to 2022 was examined to predict their distributions for 2030. LULC classification was performed using a supervised satellite image classification system, and the predictions were carried out using the cellular automata-artificial neural network (CA-ANN) algorithm. LST was calculated using the radiative transfer equation (RTE), and the same CA-ANN algorithm was employed to predict UTFVI for 2030 [20].

The impact of land use/land cover (LULC) changes on the urban thermal environment in Karachi from 2000 to 2020 was examined. The results found taht the built-up and bare land areas shown the highest land surface temperature (LST), while vegetation cover exhibited the lowest. The Normalized Difference Built-up Index (NDBI) strongly correlated with LST, indicating its influence on LST. Parks with substantial medium- and high-density vegetation regulate the thermal environment, while scattered vegetation patches have minimal impact. These findings can inform land use planning to mitigate UHI effects and promote sustainable urban growth [21].

Geospatial techniques were adopted to analyze the relationship between land use and land cover (LULC) changes, land surface temperature (LST), and UTCL. The findingsrevealed a significant decrease in agriculture and vegetation land cover classes, accompanied by an 8.3°C increase in mean LST [22]. Addiotnally, a negative correlation between vegetation cover and LST, indicating that vegetation loss contributes to increased LST. The study proposes raising local community awareness for environmental conservation and the establishment of urban green spaces to mitigate UHI and enhance urban thermal comfort [23].

A framework for examining the relationship between urban growth and LST using remote sensing data was developed by [24]. It also validates and applies the framework to 6th of October City to assess the impact of urban growth on LST. The results show that LST decreases as urbanization increases due to increased shading and green spaces. This suggests that urbanization does not pose a risk of UHI in new cities [24].

The relationship between spatial attributes of land use/land cover (LULC) classes and their impact on land surface temperature (LST) over built-up patches in 694 districts across India was investigated by using LULC data from 2005 and 2015 and MODIS LST maps, the study found that the average LST of built-up patches is influenced by spatial characteristics of built-up patches, particularly the Mean Perimeter-Area Ratio (para_mn) LSM. Other significant LSMs include Core-Area index (cai_mn), Euclidian Mean Neighborhood Distance (enn_mn), and Aggregation index (ai). Region-specific analyses revealed stronger relationships between LSMs and LST in the East and West regions of India. Shrub LULC alsoexhibiteda notable associationwith LSTpatterns of built-up patches [25]. These findings provide valuable insights for understanding the role of LULC in UHI mitigation strategies.

Urban heat island (UHI) effect using MODIS LST data was conducted to analyze diurnal, seasonal, and inter-annual UHI variability from 2003 to 2018. Land use land cover (LULC) changes were also assessed. The study identifies six driving factors of SUHI: built-up area, urban-rural evapotranspiration difference, black sky albedo, enhanced vegetation index, thermal inertia, and population. Pearson's correlation analysis reveals the influence of these factors on SUHI [26]. These findings highlight the complex interplay between climatic conditions, LULC, and UHI intensity.

Land use and land cover (LULC) changes in the coastal districts of Central Kerala, India, were analyzed using Landsat images from 1988, 2000, and 2017. The built-up area increased significantly from 1988 to 2017, accompanied by an increase in average land surface temperature (LST). The relationship between LST and NDBI as well as the impact of unplanned urbanization on the 2018 Kerala floods were investigated. The findings provide valuable insights for policymakers and planners to develop climate-resilient development strategies [27].

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The relationship between land use and land cover changes and urban heat island (UHI) development was studied in Khulna city, Bangladesh. The results found that the rapid reduction of green spaces and the expansion of built-up areas have significantly increased UHI intensity. The study also identified several implementation barriers that hinder the effectiveness of the city's UHI mitigation strategies. The authors propose a holistic approach to green space planning and local-scale adaptation measures to address the challenges of UHI in Khulna city [28].

An urban quality of life (UQoL) index map for Al Ain city in the United Arab Emirates was developed using remote sensing images, GIS vector datasets, and machine learning techniques. They integrated biophysical and infrastructure facility indicators using principal component analysis (PCA) and assigned weights based on the percentage of variance they explained. The results showed that greenness has a significant impact on the spatial distribution of UQoL in Al Ain city [29].

The relationship between LULC and LST over three decades were analyzed using satellite imagery and artificial neural networks. The results showed that built-up areas, waterbodies, and agricultural lands increased, while vegetation and bare lands decreased. Built-up areas experienced the highest temperatures, while waterbodies exhibited the lowest. Strong negative correlations were found between NDVI and MNDWI and LST, while NDBI and BSI showed positive correlations. LST predictions suggest that temperatures may reach critical levels by 2050 if current urbanization trends continue.

Rapid urbanization in major districts of Bangladesh has intensified urban heat islands (UHIs) during the winter dry period between 2000 and 2019. Remote sensing and geospatial analysis revealed that UHI intensities have increased in all districts except Rajshahi and Rangpur, coinciding with urban expansion. Large districts exhibit stronger UHIs compared to smaller ones. The hotspots of high UHIintensity were identified and they emphasized the need for suburbanization strategies to mitigate UHI and climate change effects [30]. The spatial and temporal patterns of urban expansion in Istanbul and Sydney was examined by using remote sensing data. Land surface temperature (LST) also increased with urban expansion. Landscape metrics revealed that urban growth in Istanbul was more fragmented, while Sydney's growth was more compact. These findings highlight the importance of urban planning to manage urban sprawl and its environmental impacts [31].

The the importance of preserving green cover to mitigate urban heat island effects in Lahore was highlighted. Lahore, Pakistan, has experienced rapid urbanization over the past three decades, leading to a significant loss of green cover and a corresponding increase in land surface temperature (LST). This study analyzed the impact of green cover reduction on LST and urban heat island (UHI) effects in Lahore. The results showed that built-up areas increased by 113.85% and green cover decreased by 392.78 km2 between 1990 and 2020. LST and UHI intensity were found to be positively correlated with built-up areas and negatively correlated with green cover [32].

The relationship between urban green spaces (UGS) and thermal variability was investiaged by using remote sensing and geospatial methods. The results showed that vegetated areas decreased by 8.62% between 2010 and 2020, while other land uses increased by 11.23%. The correlation between land surface temperature (LST) and normalized difference vegetation index (NDVI) decreased from 0.48 to 0.23, while the correlation between LST and normalized difference built-up index (NDBI) increased from 0.38 to 0.61.These findings highlight the importance of preserving UGS to mitigate urban heat island effects and promote sustainable urban planning [33].

The seasonal variations in LST and urban heat islands (UHIs) in Chandigarh from 2000 to 2020 was examined by using remotely sensed data and geospatial techniques. showed a 10.08% increase in built-up areas and a 4.5% decrease in vegetation over the study period. UHI intensities increased steadily in both summer and winter, with dense built-up areas exhibiting the highest UHI values. These findings highlight the role of land use changes in UHI formation and the need for sustainable urban planning practices [34].The urban heat island (UHI) effect in the Asansol and Kulti blocks ofIndia's Paschim Bardhaman district was examined, and Land use and land cover (LULC) dynamics were analyzed using remote sensing data from 1990 to 2020. The results showed a decline in vegetation, agricultural land, and grassland, while built-up areas expanded. LST increased significantly, with the highest increase observed in Mohanpur, Lohat, Ramnagar, Madhabpur, and Hansdiha. These findings highlight the need for sustainable urban planning practices to mitigate UHI effects [35].

The urban heat island (UHI) effect caused by land use land cover (LULC) changes in Jimma city, Ethiopia was investiaged. Landsat satellite data from 2000 and 2020 was used to analyze LULC, normalized difference vegetation index (NDVI), and normalized difference built-up index (NDBI). The results showed a slight decrease in vegetation cover from 12.3% in 2000 to 10.8% in 2020. A negative correlation was found between vegetation cover and mean LST. Mean LST increased from 24.5°C to 26.3°C between 2000 and 2020, and maximum UHI increased from 32.5°C to 34.7°C. These findings suggest that urban green spaces and open areas can help mitigate UHI effects [36].

The rise in Land surface temperature (LST) in Pune city, India from 1990 to 2019 due to changes in LULC shows that teh built-up areas expanded by 43.1%, while agriculture, scrubland, fallow land, water bodies, and vegetation decreased. Mean LST increased during the summer season (5.8%) and decreased during the winter season (12.4%). LST in agriculture, shrub land, water body, and fallow land increased over time, while LST in built-up areas decreased. LST in the surrounding rural area was 1.4°C lower than in the city, indicating an urban cool island effect [37].

The LULC changes from 2001 to 2019 in Pune District, Maharashtra was conducted by using satellite images. The study reveals a rise in built-up areas, from just 2% in 2001 to over 11% by 2019. While vegetation initially flourished, reaching 35% in 2009, it later receded to 27% by 2019. Water cover fluctuated slightly, while barren land saw a complex dance, declining initially but eventually returning to near 2001 levels. This satellite-eye view shows a dynamic landscape, urging closer investigation into the forces shaping Pune's future [38].

3. Land Use changes in Pune

Land use refers to the socioeconomic activities that humans undertake on a particular piece of land. These activities can range from agriculture and forestry to residential and commercial development. Land use is determined by a variety of factors, including physical constraints (such as soil fertility and water availability), economic conditions, and social preferences. Land cover, on the other hand, is the physical characteristics of the earth's surface as observed from the ground or from remote sensing platforms. Land cover can be classified into a variety of categories, such as forests, grasslands, wetlands, and urban areas. Land cover is determined by both natural factors (such as climate and topography) and human activities (such as deforestation and urbanization). LULC data is used for a variety of purposes, including:

- Urban planning: LULC data can be used to identify areas for future development, plan for transportation infrastructure, and assess the environmental impacts of urbanization.
- Natural resource management: LULC data can be used to identify and monitor changes in land use, assess the impacts of human activities on natural ecosystems, and develop conservation strategies.
- Climate change studies: LULC data can be used to assess the impacts of climate change on land use patterns and to develop mitigation and adaptation strategies.

In this work, LULC for the study are is obtained for the year 2000, 2010 and 2022 using Random Tree (RT), Maximum Likelihood (MLE) and Support vector machines (SVM) classification methods. The LANDSAT data was used for the year 200 2010 and 2022.The url link for datasource are https://bhuvan.nsrc.gov.in, https://www.usgs.gov, https://www.maps.google.com and data was taken for the duration between april and may of 2000, 2010 and 2022. Also using Markov model, the LULC for the year 2030 LULC is predicted. The categorized used for the LULC map are Built up, barren land, water and vegetation.

Figure 2 show the methodology adopted to get LULC map for the said year using three classifiers. Accuracy assessment and Kappa coefficient are evaluated to identify the best suited classifier. Further the change detection is done to understand the current growing pattern of the study area. Currently, Pune exhibits a mix of land use patterns, with a significant proportion dedicated to residential and commercial areas. The urban core experiences more pronounced heat islands due to the prevalence of concrete and asphalt surfaces. On the other hand, peri-urban areas still have patches of agricultural land and natural vegetation, which help mitigate the urban heat island effect to some extent. However, the ongoing urban sprawl poses a threat to these remaining green spaces.

3.1 LULC for the Year 2000

Figure 3 shows LULC map for the year 2000 with all three classifiers. The builtup land is more at the center of the district where the metropolitan city Pune is. The percentage change in land utilization has been shown in Figure 4 for the three methods in pie chart for easy understanding. Table 1 shows Land Cover Distribution of four classes in Area and Percentage for the year 2000.

3.2 LULC for the Year 2010

The Figure 5 shows LULC maps by three methods maximum likelihood, Random tree and support vector machine for the year 2010. The percentage change in land utilization has been shown in Figure 6 for the three methods in pie chart for easy understanding. Table 2 shows Land Cover Distribution of four classes in Area and Percentage for the year 2010.

Table 1: Land Cover distribution of four classes in area and percentage for 2000 year

Methods	**Random Tree**		**Maximum Likelihood**		**Support Vector Machine**	
Particulars	Percentage (%)	Area (km2)	Percentage (%)	Area (km2)	Percentage (%)	Area (km2)
Barren-Land	40.77	6,360.2985	38.29	5,972.227	39.09	6,097.3827
Water bodies	3.45	538.356	3.65	568.9837	3.65	568.9837
Built-up	6.76	1,054.357	7.08	1,104.1734	7.08	1,104.1734
Vegetation	49.02	7,645.598	50.99	7,953.2677	50.19	7,828.33
Total	100	15,598.61	100	15,598.65	100	15,598.87

Table 2: Land Cover distribution of four classes in area and percentage for 2010 year

Methods	**Random Tree**		**Maximum Likelihood**		**Support Vector Machine**	
Particulars	Percentage (%)	Area (km^2)	Percentage (%)	Area (km^2)	Percentage (%)	Area (km^2)
Barren-Land	38.69	6,035.3985	39.072619	6,094.8871	38.85	6,060.5985
Water bodies	3.54	551.99	3.5574666	554.9246	3.56	555.3206
Built-up	9.33	1,454.889	9.4375425	1,472.15	9.31	1,452.7486
Vegetation	48.44	7556.599	47.932075	7,476.8621	48.27	7,530.2048
Total	100	15,598.877	100	15,598.87	100	15,598.873

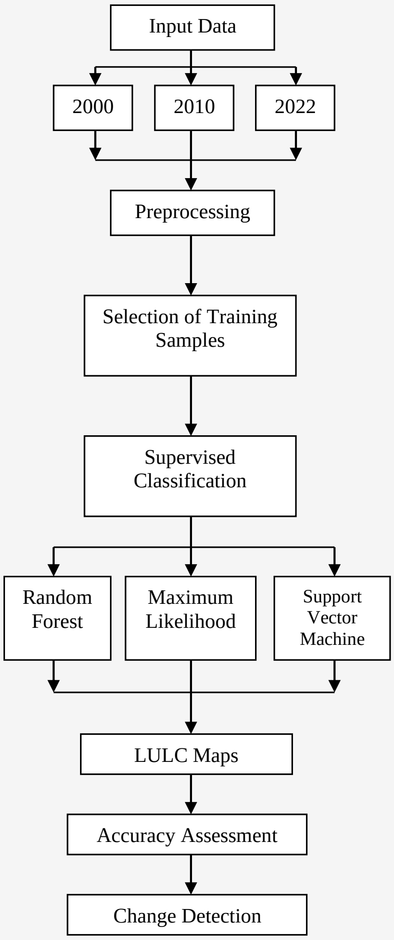

Figure 2: Methodology for LULC mapping

3.3 LULC for the Year 2022

The Figure 7 shows LULC maps by three methods maximum likelihood, Random tree and support vector machine for the year 2022. The percentage change in land utilization has been shown in Figure 8 for the three methods in pie chart for easy understanding. Table 3 shows Land Cover Distribution of four classes in Area and Percentage for the year 2022.

3.4 Accuracy and Kappa Calculation

The accuracy and kappa coefficient calculated is shown in Tables 4 and 5 respectively for 2000, 2010 and 2022 for maximum likelihood, support vector machine and random tree method. Maximum likelihood classifier has proven to be the best for classifier for LULC however the duration for which data was captured and testing sample size prominently governs the accuracy and Kappa value. In the future study, the testing dataset will be used on large scale for more accurate analysis and classifier suitability prediction.

3.5 Projected LULC Map of 2030

A prediction of 2030 LULC map of the Pune district in done by using MOLUSCE model as shown in Figure 9. The Model takes trained LULC.tif files as input along with the land use categories included in it to be predicted. .The data includes map of Pune district from years 2000, 2010 and 2022 including the spatial distribution of land use categories of each time period for the maximum likelihood classification. Based on the data, a table is created which represents the change (δ) of transition from one land use category to another over time. A transition probability matrix is developed to project future land use changes which starts with an initial land use distribution, and iteratively apply the transition potential modelling and uses neural network transition curve to simulate land use changes over multiple time steps. Land Cover Distribution of four classes in Area and Percentage for Year 2030 is shown in Table 6. The percentage changes in land utilization from the year 2022 to the predicted year 2030 is shown in Table 7.

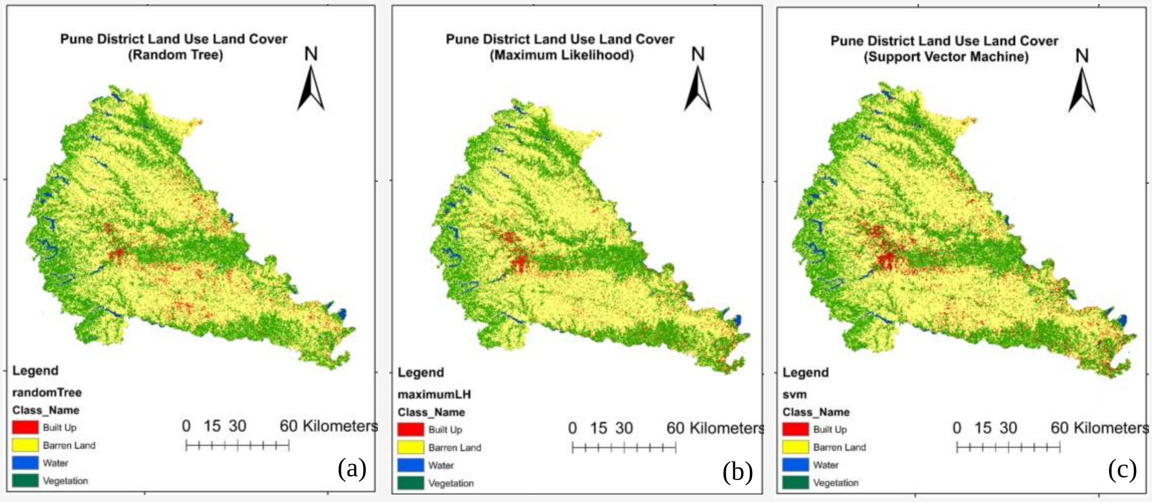

Figure 3: LULC of Pune district in 2000 using different classifiers (a) RT, (b) MLE and (c) SVM

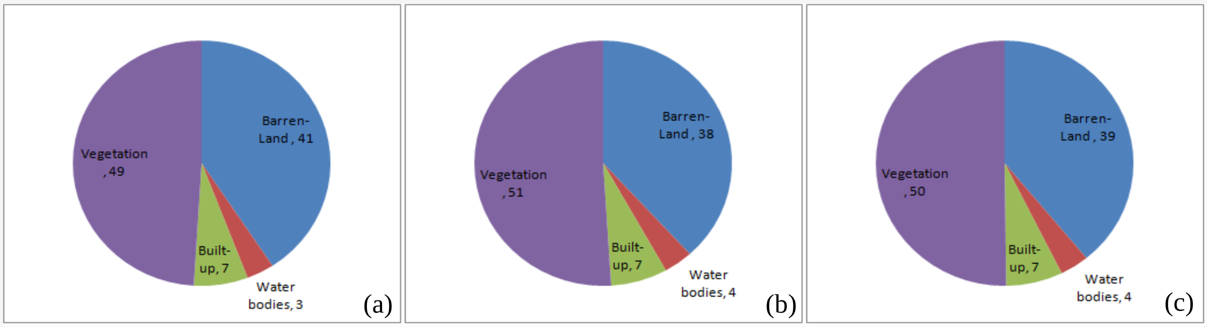

Figure 4: Percentage of LULC of Pune district in 2000 using different classifiers
(a) RT, (b) MLE and (c) SVM

Table 3: Land Cover distribution of four classes in area and percentage for 2022 year

Methods	**Random Tree**		**Maximum Likelihood**		**Support Vector Machine**	
Particulars	Percentage (%)	Area (km^2)	Percentage (%)	Area (km^2)	Percentage (%)	Area (km^2)
Barren-Land	36.0	5,618.78	38.0	5,917.66	36.9	5,759.49
Water bodies	3.4	528.18	3.4	522.6	3.6	560.14
Built-up	42.0	6,540.9	47.2	7,353.67	46.5	7,249.38
Vegetation	18.6	2,905.18	11.5	1,799.11	13.0	2,024.03
Total	100	15,593.04	100	15,593.04	100	15,593.04

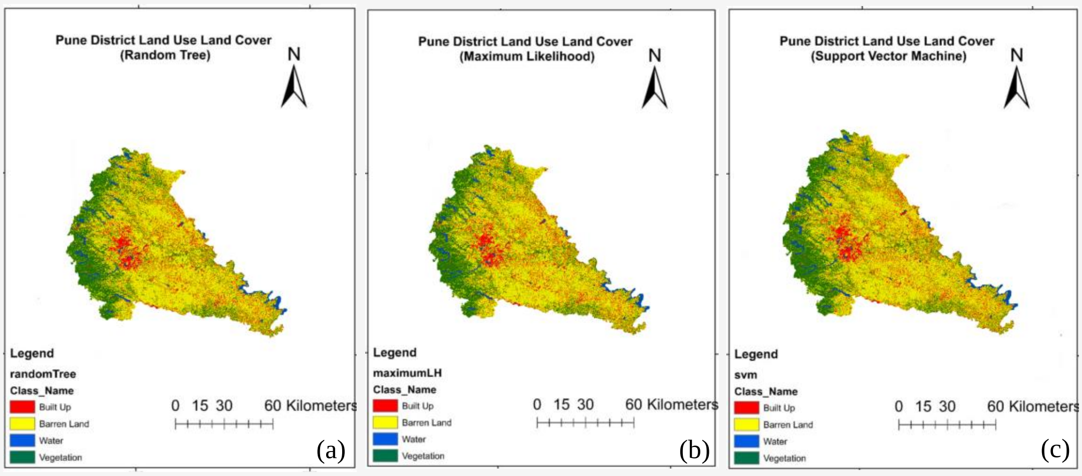

Figure 5: LULC of Pune district in 2010 using different classifiers (a) RT, (b) MLE, and (c) SVM

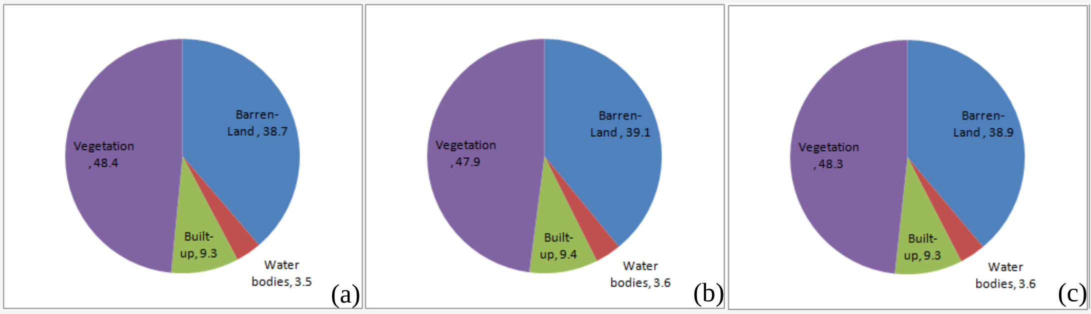

Figure 6: Percentage of LULC of Pune district in 2010 using different classifiers (a) RT, (b) MLE, and (c) SVM

Table 4:Accuracy and kappa coefficient assessment for 2000, 2010 and 2022 year

Classified Data	Barren Land	Water bodies	Built up	Vegetation	Barren Land	Water bodies	Built up	Vegetation	Barren Land	Water bodies	Built up	Vegetation
	Year 2000 RT				Year 2000 MLE				Year 2000 SVM			
User Accuracy	86.66	85.71	100	87.5	85.71	78.57	87.5	93.33	100	85.71	100	82.35
Producer Accuracy	92.85	85.71	100	93.33	80	84.61	93.33	87.5	86.66	85.71	93.33	87.5
Kappa Coefficient	0.7216				0.7124				0.7014			
	Year 2010 RT				Year 2010 MLE				Year 2010 SVM			
User Accuracy	78.57	71.42	94.11	57.14	78.57	71.42	94.11	57.14	78.57	71.42	94.11	57.14
Producer Accuracy	64.7	83.33	88.38	66.66	64.7	83.33	88.38	66.66	64.7	83.33	88.38	66.66
Kappa Coefficient	0.6824				0.7054				0.7238			
	Year 2022 RT				Year 2022 MLE				Year 2022 SVM			
User Accuracy	92.85	84.61	94.11	93.33	92.85	84.61	94.11	93.33	86.66	92.3	94.11	100
Producer Accuracy	86.66	91.66	100	87.5	86.66	91.66	100	87.5	92.85	100	94.11	87.5
Kappa Coefficient	0.7846				0.8042				0.788			

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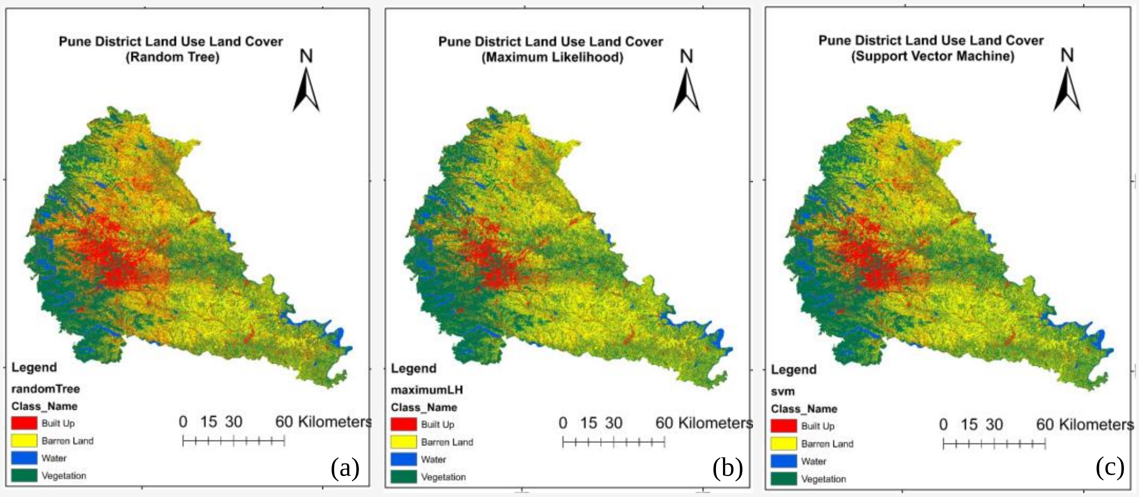

Figure 7: LULC of Pune district in 2022 using different classifiers (a) RT, (b) MLE and (c) SVM

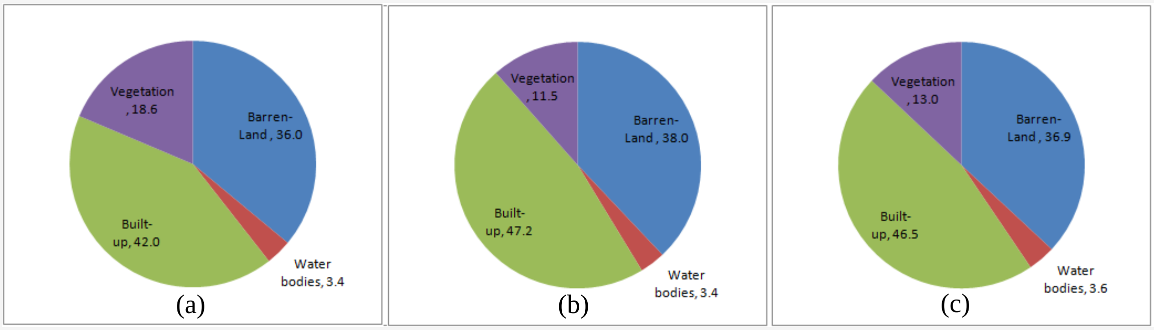

Figure 8: Percentage of LULC of Pune district in 2022 using different classifiers (a) RT, (b) MLE, and (c) SVM

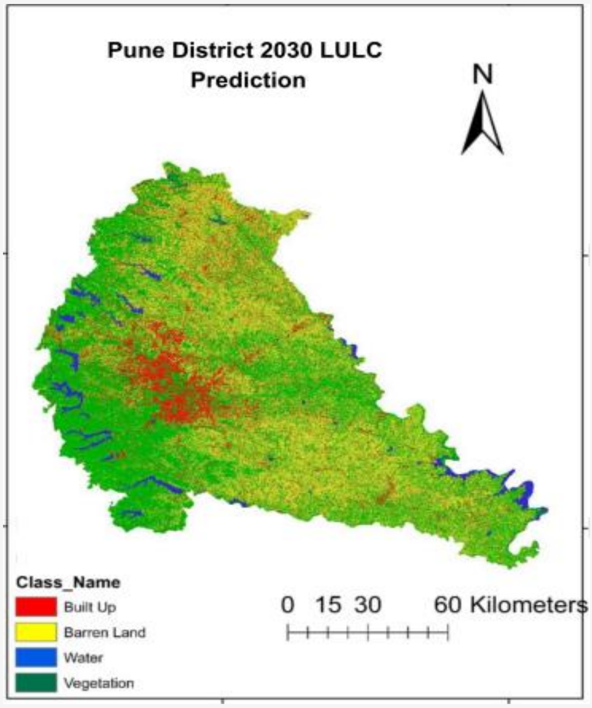

Figure 9: A predicted LULC maps of Pune district for the year 2030

Table 5: Kappa coefficient year 2000, 2010, and 2022

Year	Random Forest	Maximum Likelihood	Support Vector Machine
2000	0.7216	0.7124	0.7014
2010	0.6824	0.7054	0.7238
2022	0.7846	0.8042	0.7880

Table 6: Land Cover distribution of four classes in area and percentage for year 2030

Parameter	Pixel Count	Area (km^2)	Percentage [%]
Barrenland	43,953,502	4,395.3502	28.18
Water	52,2783	522.5783	3.34
Vegetation	73,507,298	7,350.7298	47.10
Builtup	33,243,830	3,324.383	21.38
Total	151,227,413	15,593.0413	100.00

Table 7: Changes in LULC Map from year 2022 to year 2030

Parameter	Year 2022		Year 2030		Percentage Change
	Pixel Count	Area (km^2)	Pixel Count	Area (km^2)	
Barren Land	59,176,623	5,917.66	43,953,502	4,395.3502	-9.76
Water	5,225,976	522.6	522,783	522.5783	-0.00019
Vegetation	73,536,713	7,353.67	73,507,298	7,350.7298	-0.01
Builtup	17,991,103	1,799.11	6,759,113	3,324.383	9.78
Total	155,930,415	15,593.04	124,742,696	15,593.0413	

4. Land Surface Temperature (LST)

Accurately estimating LST values for different years required careful selection of specific bands from Landsat 5, Landsat 7, and Landsat 8 satellites.

2000: Landsat 5 and Thermal Band 6

For the year 2000, we utilized Landsat 5 imagery and extracted data from Band 6. This thermal infrared band captures radiation emitted by the Earth's surface, making it ideal for estimating LST. By utilizing Band 6, we gained valuable insights into the thermal characteristics of the study area for that particular year.

2010: Landsat 7 and Thermal Band 6

For the year 2010, we employed Landsat 7 imagery and extracted data from Band 6. This band provides thermal information in the thermal infrared region, enabling us to accurately estimate LST. Using Band 6 from Landsat 7, we were able to investigate the thermal dynamics and variations in land surface temperatures during that specific year.

2022: Landsat 8 and Thermal Bands 10 and 11

For the most recent year, we employed Landsat 8 imagery to estimate LST values. However, instead of using Band 6, we utilized Bands 10 and 11. These bands are part of the Thermal Infrared Sensor (TIRS) on Landsat 8 and are specifically designed for measuring land surface temperatures. Bands 10 and 11 capture the emitted thermal radiation with different wavelengths, enabling more accurate estimation of LST.

The calculation of LST from thermal images obtained from Landsat 5, Landsat 7, and Landsat 8 satellites was conducted with a meticulous and comprehensive approach, ensuring high scientific standards and reliable temperature estimation. By meticulously following conversion steps specific to each satellite, incorporating the influence of vegetation through NDVI, considering Land Surface Emissivity, and utilizing appropriate radiative transfer equations, the LST values obtained hold significance for researchers in understanding the thermal behavior of the land surface.

4.1 Algorithm for LST Estimation

Objective: To estimate LST values from Landsat satellite imagery for the years 2000, 2010, and 2022.

1. Data Acquisition: Acquire Landsat satellite imagery for the years 2000, 2010, and 2022.
2. Band Selection: Select the appropriate thermal bands for each satellite:
    - Landsat 5 and Landsat 7: Band 6
    - Landsat 8: Band 10

3. Radiance Conversion: Convert the Digital Number (DN) values from the satellite to radiance for Landsat 5 and Landsat 7 using the corresponding conversion coefficients.
4. Brightness Temperature Calculation: Convert the radiance values to Brightness Temperature (BT) derived from the spectral radiance assuming a blackbody emitter in Kelvin using band-specific thermal calibration coefficients.
5. Celsius Conversion: Convert the BT values to Celsius (°C) by subtracting 273.15.
6. Normalized Difference Vegetation Index (NDVI) (used to quantify the health and density of vegetation) calculation: Calculate the NDVI using the Red and Near-Infrared bands of the Landsat imagery.
7. Proportion of Vegetation (PV) Calculation: Compute the PV that normalizes and squares the NDVI values.
8. Land Surface Emissivity (ε) (measure of how easily the land releases its stored heat as infrared radiation) Determination: Determine the ε based on empirical models or field measurements appropriate for the study area.
9. LST Calculation: Employ the radiative transfer equation, along with the BT values, wavelength of emitted radiance, and E, to calculate the LST.
10. LULC Impact Analysis: Analyze the LST data to investigate the influence of LULC changes on surface temperature patterns.

The flowchart below shown in figure 10 outlines the process of deriving LST from thermal images captured by satellite sensors such as Landsat 5 and 8. The steps involve converting digital numbers to radiance values, calculating BT, converting BT to Celsius, and finally obtaining the LST. This information is crucial for applications like environmental monitoring, agriculture, and urban heat island studies. The flowchart in Figure 11 illustrates the steps involved in estimating LST and related parameters. It includes the conversion of digital numbers to radiance, calculation of BT, determination of NDVI, estimation of ε, and finally, the computation of LST using BT and ε values. These steps are crucial for understanding and analyzing LST dynamics in various applications such as vegetation health monitoring and land surface temperature mapping.

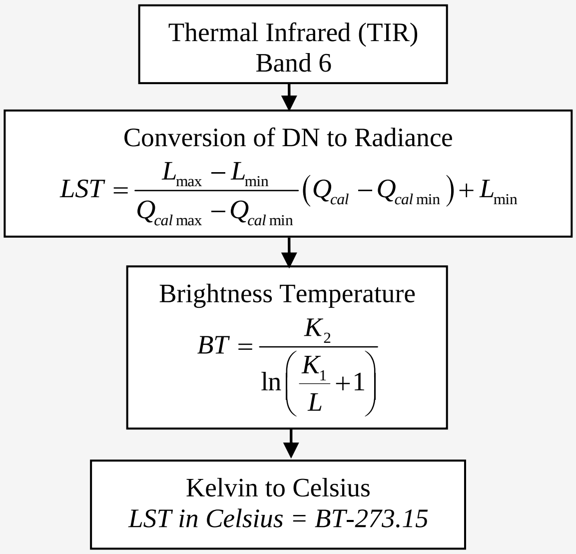

Figure 10: Flowchart of LST for Landsat 5 and 7

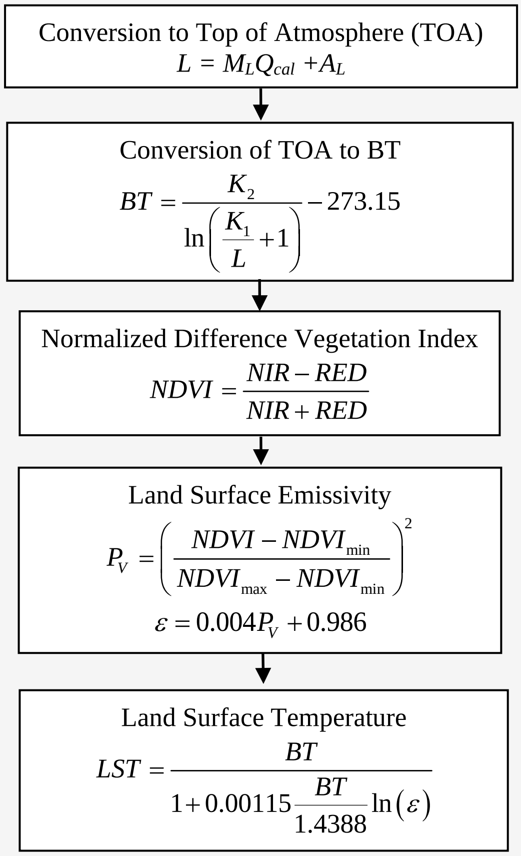

Figure 11: Flowchart of LST for Landsat 8

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Where *Lmax* is the maximum radiance in the unit of $Wm^{-2}\ m^{-1}\mu sr^{-1}$, *Lmin* is the minimum radiance ($Wm^{-2}\ m^{-1}\mu sr^{-1}$), *Qcal* is the *DN* value of pixel, *Qcalmax* is the maximum *DN* value of pixels, *Qcalmin* is the minimum *DN* value of pixels, K_1 and K_2 are the thermal constants of TIR band 10, NIR is the near infrared band value of a pixel, *R* is the red band value of the same pixel, M_L is the band-specific multiplicative rescaling factor from the metadata, *L* is the band-specific additive scaling factor from the metadata.

4.2 The Relationship between Land Use Changes and LST in Pune City

In Pune, the rapid pace of urbanization has resulted in significant land use changes over the years. These changes have had a profound impact on the city's LST. As more agricultural and natural land is converted into urban areas, the city experiences an increase in impervious surfaces, such as roads, buildings, and parking lots. These surfaces tend to absorb and retain heat, leading to higher LST. Additionally, the loss of vegetation due to land use changes reduces the cooling effect of evapotranspiration, further exacerbating the urban heat island effect. Currently, Pune exhibits a mix of land use patterns, with a significant proportion dedicated to residential and commercial areas. The concentration of these land uses, coupled with the lack of green spaces, contributes to higher LST in densely populated areas. The urban core experiences more pronounced heat islands due to the prevalence of concrete and asphalt surfaces. On the other hand, peri-urban areas still have patches of agricultural land and natural vegetation, which help mitigate the urban heat island effect to some extent. However, the ongoing urban sprawl poses a threat to these remaining green spaces. The relation of LULC and LST has been analyzed here for the PMC and PCMC area i.e. city place. The results of the study examining the impact of LULC on LST in Pune Municipal Corporation (PMC) and Pimpri Chinchwad Municipal Corporation (PCMC) areas reveal significant implications for urban climate. The figure 12 clearly shows the rapid urabn sprwaling in PMC and PCMC area from 2000 to 2022. The built up land is increased over the barren lands and vegetation at a vast speed. The white region is not the study area and does not represent any class of land use. The city area induling PMC and PCMC was clipped from Pune district.

4.3 Wintertime LST Variations in PCMC and PMC

An analysis of winter season LST changes in the PCMC and PMC area for the years 2000, 2010, and 2022 shown in Figures 13 and 14 provides intriguing insights into the thermal dynamics of different land cover classes.

Built-up Areas: Oases of Coolth

Among the land cover classes, built-up areas consistently exhibit the lowest temperatures during the winter season. This phenomenon can be attributed to the inherent characteristics of urban environments. Concrete and asphalt, the primary building blocks of urban landscapes, possess lower heat retention capabilities compared to natural land covers. Additionally, built-up areas often have a higher density of structures, casting shadows and reducing direct sunlight exposure, thereby limiting heat absorption. These factors collectively contribute to the cooler winter microclimates observed in built-up areas.

Water Bodies: Bastions of Thermal Stability

Water bodies, including rivers, lakes, and ponds, also demonstrate relatively lower temperatures during the winter season. Water's superior specific heat capacity allows it to retain heat for extended periods. As a result, water bodies act as heat sinks, absorbing and releasing heat at a slower rate, leading to lower winter temperatures. The remarkable stability in water body temperatures over the studied years suggests that these aquatic ecosystems have maintained their thermal characteristics despite the changing environment.

Vegetation: Diminishing Thermal Regulation

Vegetation, encompassing forests, parks, and agricultural areas, generally experiences lower temperatures compared to barren land during the winter season. Vegetation provides shade, reducing solar radiation absorption, and promotes evaporative cooling through transpiration. These processes contribute to lower land surface temperatures. However, the figure indicates a decreasing trend in vegetation temperatures over the years. This decline could be attributed to various factors, including land-use changes, deforestation, or alterations in vegetation cover, which may have resulted in reduced thermal regulation by vegetation during the winter season.

Barren Land: A Paradox of Cooling Temperatures

In contrast, barren land, characterized by the absence of vegetation or limited plant cover, exhibits the highest temperatures among all land cover classes during the winter season. The lack of vegetation leads to higher solar radiation absorption and limited cooling effects, resulting in elevated land surface temperatures. However, the figure reveals a surprising decreasing trend in barren land temperatures over the studied years. This decline suggests potential changes in land management practices, land cover transformations or reclamation efforts that have contributed to relatively cooler temperatures in barren areas.

Table 8 represents the Winter Season LST variation in degrees Celsius across the PCMC and PMC area from 2000 to 2022 for different land cover classes. In 2000, the LST for Waterbodies was 20.12°C, which increased to 21.03°C in 2010 and slightly further to 21.20°C in 2022. For Built-Up areas, the LST was 25.19°C in 2000, which increased to 26.45°C in 2010 and then decreased to 22.25°C in 2022. Vegetation had an LST of 27.36°C in 2000, which decreased to 26.97°C in 2010 and further to 24.68°C in 2022. Lastly, Barren Land had an LST of 31.23°C in 2000, which decreased to 29.46°C in 2010 and further to 27.27°C in 2022.

4.4 *Decoding Summertime LST Dynamics in PCMC and PMC*

A comprehensive examination of summer season Land Surface Temperature (LST) changes in the PCMC and PMC area for the years 2000, 2010, and 2022 shown in Figures 15 and 16 unveils the intricate thermal behavior of different land cover classes during the summer months.

Barren Land: Blazing Heat

Among the land cover classes, barren land consistently exhibits the highest temperatures during the summer season. This phenomenon stems from the absence of vegetation, which leads to increased solar radiation absorption and limited evaporative cooling. As a result, barren land experiences elevated land surface temperatures. The scorching temperatures observed in barren land areas indicate the potential for these regions to face heat stress and increased thermal discomfort during the summer months.

Built-up Areas: A Rising Thermal Tide

Built-up areas demonstrate an alarming upward trend in LST from 2000 to 2022. This can be attributed to the rapid urbanization and expansion of infrastructure within the PCMC and PMC areas. As built-up areas expand, the landscape becomes dominated by impervious surfaces such as concrete and asphalt, which possess higher heat retention capacities. Additionally, the construction of buildings and infrastructure can contribute to the formation of urban heat islands, where temperatures within built-up areas are significantly higher than their surrounding rural counterparts. These factors collectively contribute to the observed increase in LST within built-up areas over the studied period.

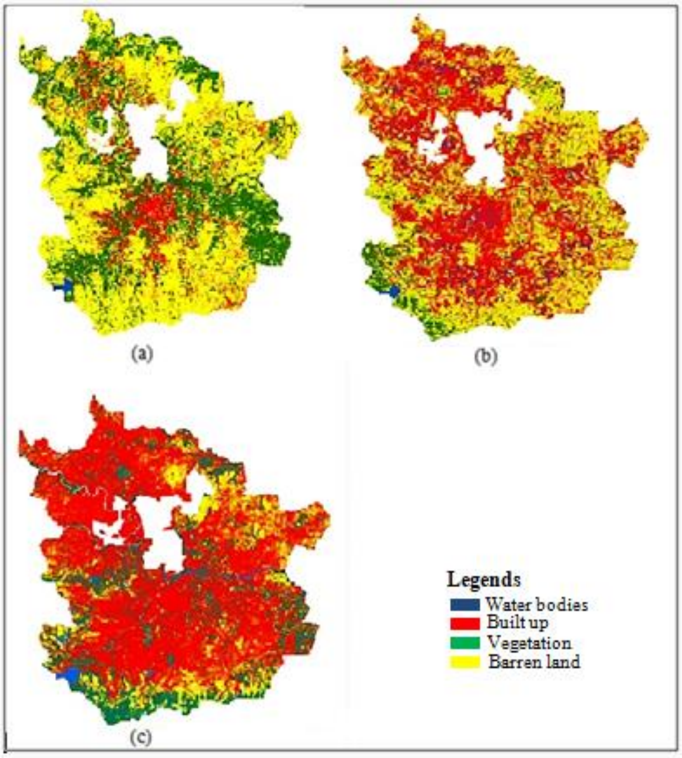

Figure 12: Dynamic LULC changes over PCMC and PMC (a) 2000, (b) 2010 and (c) 2022

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Table 8: Winter season LST variation (°C) across PCMC and PMC area for LULC classes

LULC Class	2000	2010	2022
Water bodies	20.12	21.03	21.2
Built-Up	25.19	26.45	22.25
Vegetation	27.36	26.97	24.68
Barren Land	31.23	29.46	27.27

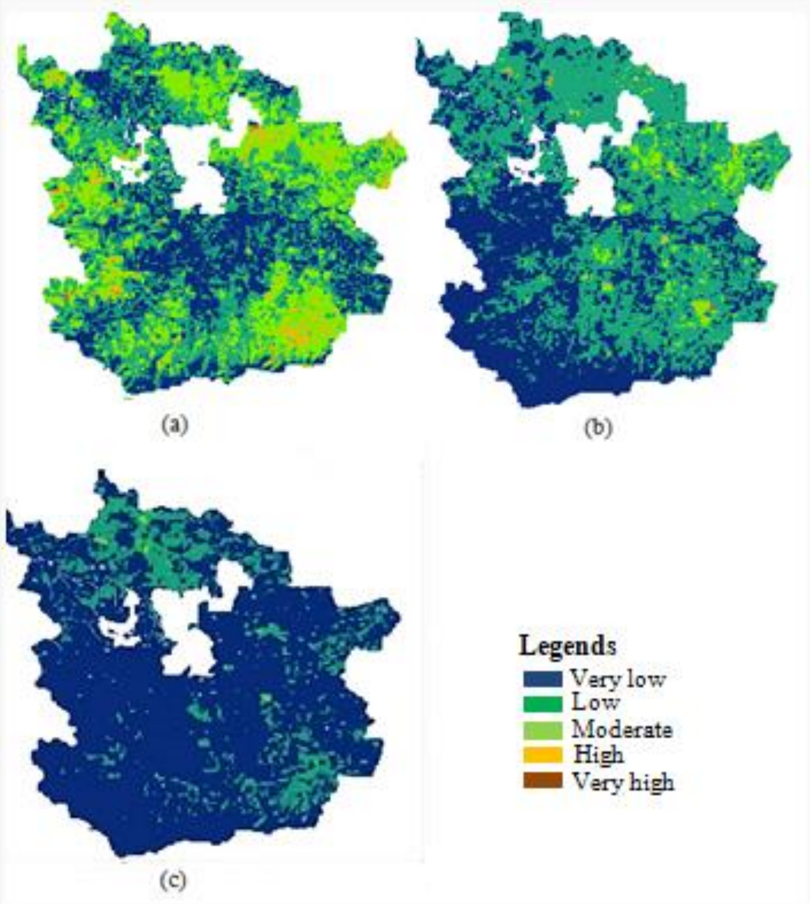

Figure 13: Winter season LST changes in the PCMC and PMC (a) 2000, (b) 2010, and (c) 2022

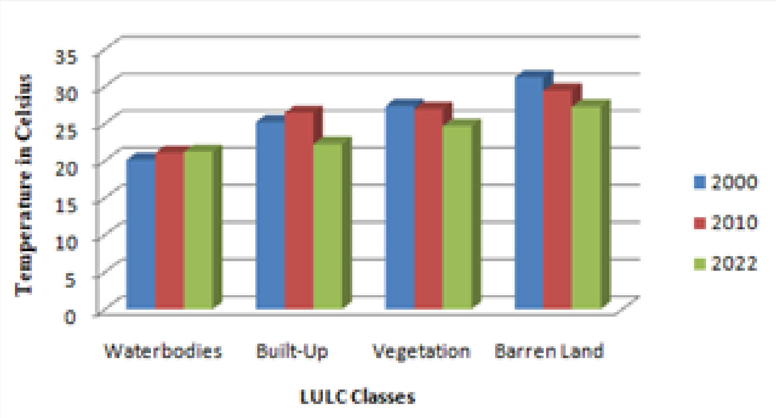

Figure 14: Winter season LST variation across PCMC and PMC area from for different Land Cover classes

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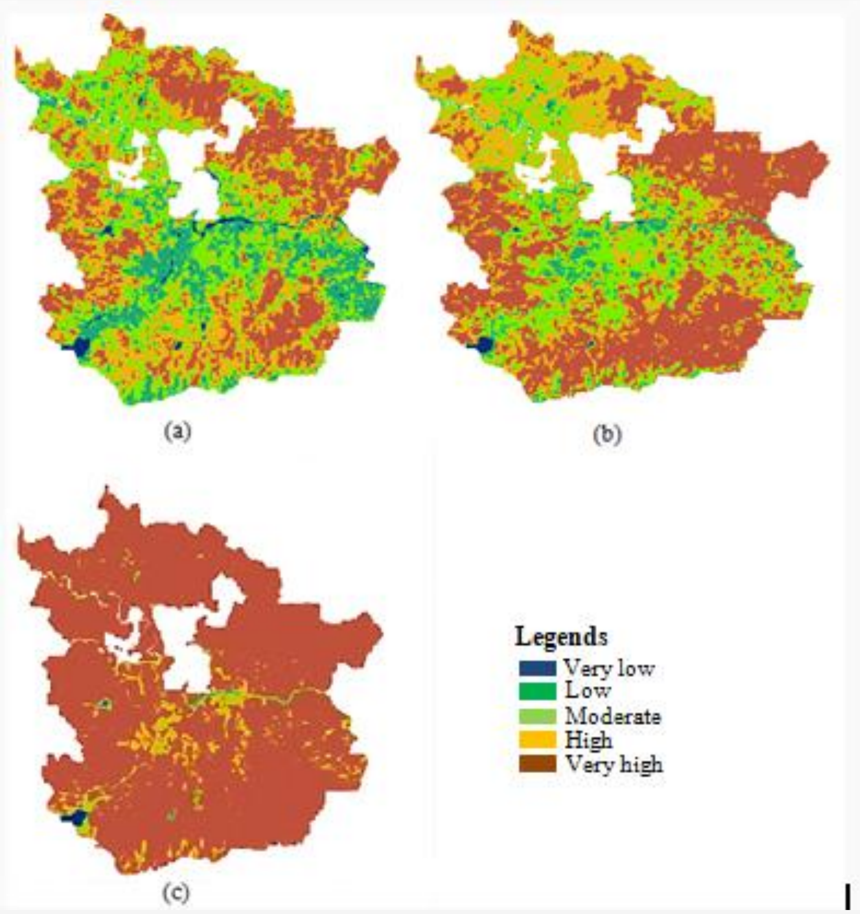

Figure 15: Summer ceason LST changes in the PCMC and PMC (a) 2000, (b) 2010, and (c) 2022

Table 9: Summer season LST variation (°C) across PCMC and PMC area for LULC classes

LULC Class	2000	2010	2022
Water bodies	30.49	35.31	35
Built-Up	32.78	33.82	40
Vegetation	32.57	34.36	36.81
Barren Land	38.25	40.6	41.33

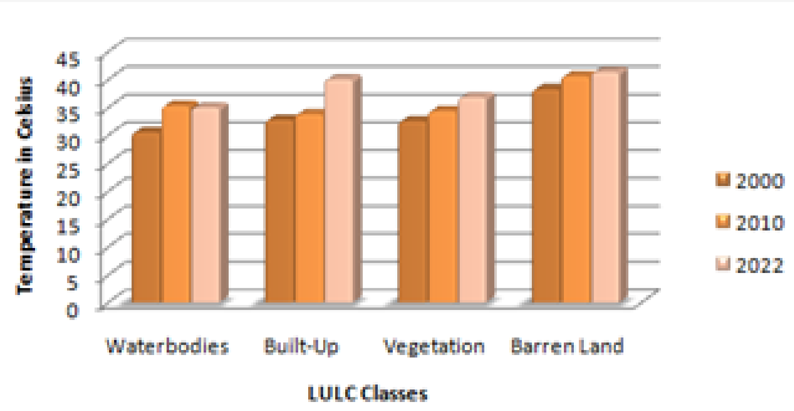

Figure 16: Summer season LST Variation across PCMC and PMC srea from for different Land Cover classes

Water Bodies: Oases of Thermal Stability
Water bodies, including rivers, lakes, and ponds, generally exhibit lower temperatures compared to other land cover classes during the summer season. Water possesses a high specific heat capacity, enabling it to act as a heat sink, absorbing and storing thermal energy. Consequently, water bodies tend to moderate temperature fluctuations and provide a cooling effect to the surrounding areas. The stable LST values for water bodies across the analyzed years suggest that these aquatic ecosystems have maintained their thermal characteristics. This stability could be attributed to their natural water circulation patterns and the presence of vegetation along their banks. Table 9 represents the variation in LST during the summer season from 2000 to 2022 across different land cover classes in the PCMC and PMC areas. In 2000, the Waterbodies recorded an LST of 30.49°C, which increased to 35.31°C in 2010 and slightly decreased to 35.00°C in 2022. The Built-Up areas had an LST of 32.78°C in 2000, slightly increased to 33.82°C in 2010, and experienced a significant increase to 40.00°C in 2022. The Vegetation areas had an LST of 32.57°C in 2000, slightly increased to 34.36°C in 2010, and further increased to 36.81°C in 2022. The Barren Land recorded an LST of 38.25°C in 2000, increased to 40.60°C in 2010, and further increased to 41.33°C in 2022.

5. Conclusion

Land use and land cover change (LULC) has a significant influence on land surface temperature (LST), particularly in urban areas. This study investigates the impact of LULC changes on LST in the Pune Municipal Corporation (PMC) and Pimpri Chinchwad Municipal Corporation (PCMC) areas of India. Key findings of the study include:

- Built-up areas experienced the most significant LULC change, increasing from 3% in 2000 to 18.63% in 2022.
- Barren land decreased from 58% to 36.03%, reflecting the conversion of natural landscapes to urban areas.
- Vegetation initially increased from 36% to 44% in 2010 but subsequently declined to 41.95% in 2022, indicating possible deforestation or land degradation.
- LULC changes have direct implications for LST. Built-up areas have comparatively lower LST in winter but higher LST in summer compared to other land cover types.
- Water bodies and vegetation exhibit relatively lower LST due to their cooling effects.
- Mean LST values increased from 34.59°C in 2000 to 39.38°C in 2022, reflecting the changing thermal dynamics associated with LULC alterations.
- The expansion of built-up areas has contributed to temperature increases of up to 5.5°C in specific locations, highlighting the urban heat island effect.

Implications:
The findings of this study emphasize the need for sustainable land use planning and development strategies to mitigate the adverse impacts of urbanization on LST. Policymakers, urban planners, and environmentalists can utilize these insights to develop informed land use policies, zoning regulations, and climate-smart urban development strategies. Based on projections of LULC, Pune is expected to undergo significant land use changes by 2030. The expansion of residential and commercial areas, along with the construction of new infrastructure, will further intensify the urban heat island effect. As the city continues to grow, the demand for land for housing, industries, and other developments will lead to the conversion of more agricultural and natural land. These changes will result in increased LST and a further reduction in the cooling effect of vegetation.

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