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ORIGINAL ARTICLE

Transforming landscapes: mapping urbanization and forest cover degradation in Dehradun, Uttarakhand (2000–2020)

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Abstract
Urbanization is a rapidly intensifying global phenomenon, reshaping landscapes and altering ecosystems across regions. In India, the foothills of the Himalayas, particularly Dehradun, has witnessed significant transformations due to urban expansion. Rapid urbanization has given rise to various adverse consequences affecting the environment, economy, and the well-being of its inhabitants. Among these challenges, land-use change stands out as a significant issue linked to urbanization. This research investigates alterations in land use and land cover (LULC) during the period from 2000 to 2020 within the Dehradun District of Uttarakhand. Forest cover degradation is one of the main threats to the area. LULC changes are determined with an interval of 5 years, that is, 2000, 2005, 2010, 2015, and 2020. Remote sensing (RS) and Geographical information system (GIS) methods detect changes in urban and forested areas using a multi-temporal supervised classification approach for generating LULC maps. The classifications reveal significant changes in the study area from 2000 to 2020. It was found that there was a decline in dense vegetation by 9.00% and an increase in built-up area by 2.32%, which may be due to the increase in urbanization and industrialization across 20 years. The outcome of current research can help significantly improve future development initiatives within the study area and is essential for the effective implementation of Sustainable Development Goal 15. The spatial analysis techniques contribute to a deeper understanding of potential strategies for prioritizing land use policies aimed at restoration at the priority level. These insights can then be extrapolated to benefit other socio-environmental tropical forest systems.

Keywords Land use and land cover · LANDSAT satellite · Remote sensing · Supervised classification

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Abbreviations

LULC	Land Use Land Cover
LANDSAT	Land remote–sensing satellite
SDG	Sustainable Development Goal
RS	Remote Sensing
GIS	Geographical Information System
ETM	Enhanced Thematic Mapper
NIR	Near Infrared Band
IR	Infrared
TIR	Thermal Infrared
TM	Thematic Mapper
T1	Tier 1
L1TP	Level 1 Terrain Precision Correction
SOI	Survey of India
USGS\EE	United States Geological Survey Earth Explorer
MLC	Maximum likelihood classifier

Introduction

Remote Sensing (RS) refers to the scientific field that involves obtaining information or details about an object from a distance, without making physical contact. Using RS datasets, Land Use and Land Cover (LULC) maps are produced to examine and assess urban transformations driven by various factors within a given area of interest (Giri and C.P 2012). Land cover means the geographical area of that particular region, and Land use means how we use that area according to our needs (Lillesand et al. 2004). Adaptations across various categories should be considered to effectively strategize sustainable management of natural resources. Utilizing remote sensing and GIS methodologies offers reliable means for obtaining precise satellite data regarding changes in LULC in a timely manner (Arveti et al. 2016).

LULC plays a significant role in understanding the connections between human activities and the environment (Dewan et al. 2012; Wei et al. 2015). Over the past few years, there has been a swift transformation in land cover, especially in developing countries (Güneralp et al. 2015). Quick changes in land cover are generally indicated with the help of urban sprawl (Liu et al. 2014) and reduction in tree cover (Song and Zhang 2006), heading towards the deprivation of cultivable land (Lopez et al. 2001. These factors have a significant impact on urban environmental conditions, affecting aspects such as climate, biodiversity, shifts in weather patterns, and the dispersion of atmospheric particulate pollutants on both regional and global scales (Abdullah et al. 2007).

Several researchers have carried out extensive studies on change detection analysis in various regions. For example, Verma et al. (2022) examined the Chamoli area, while Chauhan et al. (2003) investigated the Sal forest within the Dehradun forest division, identifying significant shifts. Their findings revealed a 17.77% conversion of dense Sal forest to medium density, as well as a transition from dense Sal to miscellaneous forest types between 1976 and 1999. While Tiwari and Khanduri 2011 studied change detection in a doon valley in Dehradun, and they noted a reduction of 3.75% in the forested area and a 9.5% decrease in seasonal water bodies. Jana et al. (2020) analyzed Landsat images from 2000 to 2019 to assess how urban growth over time has affected green spaces and thermal patterns in the Doon valley. Patidar and Sankhla (2015) conducted a spatio-temporal analysis of LULC changes in Dehradun using remote sensing data. The study focuses on significant urban expansion and its impact on land use patterns. The most significant variation was found in built up areas with an increase of 112.4% over nine years in the time period of 2000–2009; these studies are mainly focused on urban area and has not covered the whole Dehradun district. One of the major importance of study is that it helps in implementation of SDG 15 which focuses on "Life on Land." By monitoring and analyzing changes in LULC patterns, one can gain valuable insights into the health of terrestrial ecosystems and the impact of human activities on biodiversity in the Dehradun district (Blanco et al. 2024).

Dehradun district is surrounded by national parks, protected areas, and wildlife sanctuaries, making it an environmental sensitive zone. Forest present from the Himalayas to the plains can be found in different parts of the state due to topographical and climatic variability (Sharma et al. 2017). The district is undergoing significant urbanization and infrastructure development, leading to transformations in its natural landscapes (Kumar et al. 2013). Additionally, due to its proximity to the fragile Himalayan ecosystem, the area is particularly susceptible to environmental shifts (Josh et al. 2011). Therefore, it is essential to monitor the urban growth and its impact on land cover, particularly the transformation of forest area into urban space, to ensure sustainable development in the region. Due to aforementioned reasons, we have taken Dehradun district as our study area. It is observed that the study area has encounter a drastic change over time due to urbanization which is affecting the geography of the area. Forest degradation and uncontrolled urbanization are major threats to this Eco-sensitive zone. Forest degradation leads to various negative impacts, including increased trees mortality (Laurance 1991), changes in plant and animal population (Cushman 2006), and disruptions in seed dispersal (Cramer et al. 2007). Additionally, greater access to interior forests has resulted in intensified hunting and resource extraction (Peres 2001), as well as the conversion of forests into agricultural areas (Kaimowitz and Angelsen 1998). Urbanization, when managed haphazardly and occurring swiftly without a structured approach, can result in substantial environmental impacts, altering demographic characteristics and reshaping the urban landscape, particularly land and water. Hence, it is imperative to gain a thorough comprehension of alterations in land cover resulting from urbanization to effectively tackle environmental shifts and promote sustainability. This holds particularly accurate as the majority of recently developed regions have experienced substantial transformations throughout the years. Furthermore, these metropolitan regions account for a significant portion of global energy consumption and contribute to severe environmental issues, leading to the deterioration of ecosystems due to pollution in the forms of air, water, and land contamination (Yan et al. 2016; Battista and Vollaro 2017).

GIS and RS have covered a huge scale of environmental, integrated environmental assessment, and agricultural

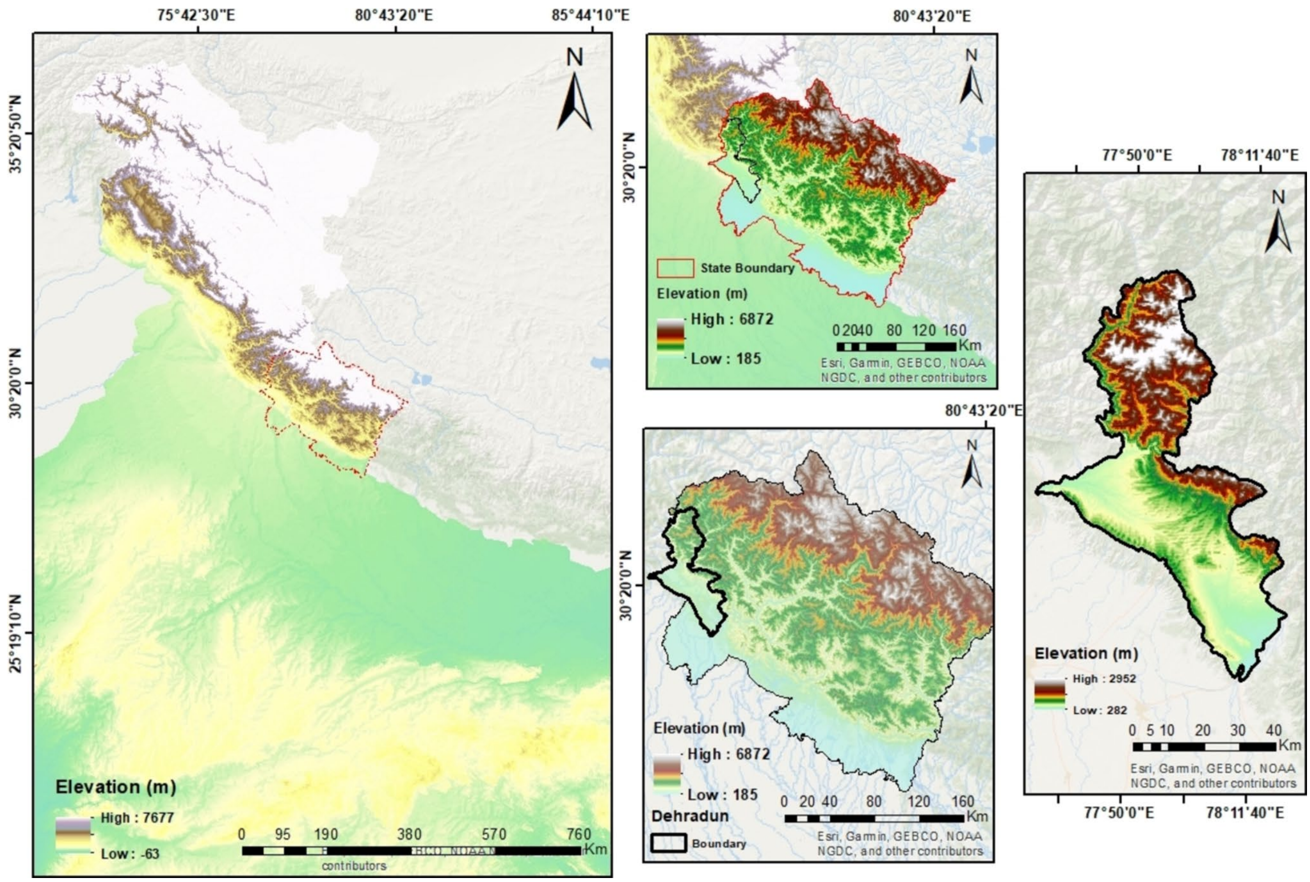


Fig. 1 Elevation map of study area Dehradun district, Uttarakhand, India

applications (Mallupattu and Reddy 2013). The utilization of satellite data has been expanded to harness the growing volume of spatial information, in conjunction with GIS, for enhanced analytical capabilities. Among these, human being has resulted in notable changes (Birhane et al. 2019), however, the transformation of LULC and its resources could have been harnessed to a great extent to fulfill societal, cultural, spiritual, and material requirements. Furthermore, these shifts in LULC can be attributed to various climatic, socioeconomic, and political factors (Kafi et al. 2014).

While numerous studies have been conducted on LULC changes over Dehradun, none have encompassed the entire district, which plays a crucial role in shaping these transformations. Thus, the uniqueness of study lies in its comprehensive approach to analyze the entire Dehradun district. Additionally, our study adopts a 5-year interval LULC analysis, allowing us to closely monitor and reveal the changes occurring within each five-year period. This periodic assessment provides valuable insights into the temporal dynamics of LULC alterations, offering a clearer understanding of how the landscape evolved over time.

Study area

Dehradun district is right in the center of the beautiful Himalayas and Shivalik range. This district is surrounded by two of most powerful rivers of India, i.e. the sacred Ganges River flows in from the eastern side, while the Yamuna River approaches from the west. The Doon Valley has eight towns Dehradun, Herbertpur, Vikas Nagar, Doiwala, Rishikesh, Saharpur, Raiwala, and Subhash Nagar (Maps of India 2013). The Dehradun district in the Doon Valley is guarded by the Himalayas from the north side, while ranges of Shivalik are guarding it from the south (Fig. 1). The whole Dehradun is bifurcated into two main parts known as Dehradun city, which the Himalayas and the Shivalik surround, and the other one is Jaunsar Bavar which is located north of Dehradun, shares its boundary with Uttarkashi District and with Tehri and Pauri from the west side. The city shares borders with the Yamuna River and Sirmaus (Himachal Pradesh), and from the south direction, it shares boundaries with the Haridwar and Saharanpur districts of Uttar Pradesh.

The total area of Dehradun district is 3088.00 hectares at an average elevation of 640 m above sea level. It is located between the latitudes of 29.58–31.2 degrees north and the longitude of 77.34–78.18 degrees east. As it is located at the base of the Himalayas, it has a temperate climate throughout the year. Vegetation of this area is mainly tropical moist deciduous with trees like the Sal forest (Shhorea robusta).

This holy state shelters an area of 53,483 sq km., having beautiful valleys of flowers and different mountains like Nanda Devi and others. Dehradun serves as the interim capital of Uttarakhand. The district, with its adjacent beauty, can be described as heaven on earth. The biodiversity-rich area has floral vegetation, forest cover, healthy and pristine ecosystem. This area has many wildlife sanctuaries due to the presence of green forests. The rise in anthropogenic activities and increase in population over time has led to urbanization, resulting in a reduction of forest cover, land area, and aquatic bodies.

Methodology and Data used

The different LANDSAT images are identified and analyzed for creating LULC maps of different years. For the year 2000, 2005 LANDSAT-5 data has been used. In this, Enhanced Thematic Mapper is used, which is denoted as "ETM+". The instrument is capable of providing high-resolution image information. It has 8 bands from which we have used bands 4 (NIR), 3 (Red), and 2 (Green) to generate false color composite (FCC). The image has visible, NIR (Near Infrared bands) and two short-wave infra-red (IR) with one TIR (Thermal Infrared). In this data, land surface phenology, the science package denotes the processing level with both surface temperature and surface reflectance band.

For 2010, LANDSAT-5 data have been used for the LULC information in which the TM instrument is used, denoted as Thematic Mapper - the main function is to give high resolution and vegetation observation. It has 7 bands from which we have used bands 4 (NIR), 3 (Red), and 2 (Green) to generate false color composite (FCC). For years 2015 and 2020, the LANDSAT-8 dataset has been used for map creation. It has 11 bands from which we use band 5(NIR), 4(Red), 3(Green) to generate false color composite (FCC).

One image captures the entire Dehradun district in all three Landsat datasets from November, a month when the area typically experiences minimal or no cloud cover. The spatial resolution is 30×30 m while temporal resolution is 16 days of all 3 LANDSAT as shown in Table 1. This data is of 1 tier (T1) which means it belongs to the highest quality. The T1 also has real-time which is real-time including Level 1 Terrain Precision Correction (L1TP) processed data having well-characterized radiometry and is better calibrated (Fig. 2).

The base map is created using the Survey of India (SOI) Toposheet on 1: 50,000 scale, which mentions the Dehradun records maps from the Uttarakhand government. In QGIS, the base map is digitized, and the proper attribute is used. LULC cover classes are detected and classified using RS data of various resolutions as prescribed by the National Remote Sensing Centre (NRSC) for the assigned years. All Landsat data was downloaded from the United States Geological Survey Earth Explorer (USGS/EE)(https://earthexplorer.usgs.gov/). A numeric image interpretation technique is used for the supervised classification of satellite data using QGIS.

Image classification–This involves partitioning an image into distinct, non-overlapping regions based on specific criteria in computer vision. Image classification process uses sample pixels from a representative image to train software, which then classifies all other pixels based on these training sets. The user selects input classes and defines pixel grouping limits, while also specifying the number of image categories. Supervised classification provides accurate class mapping but relies heavily on the expertise of the image analyst (Sengur et al. 2019).

Supervised classification is a technique used to assign class labels to networks of cells within a matrix GIS database. This approach involves the initial ranking of cell values to identify and categorize them into distinct classes or clusters (Abburu and Golla 2015). The term "supervised classification" is used because the process requires human intervention to interpret satellite or airborne imagery. This methodology delineates clusters of grid cells with similar spectral reflectance values (Lillesand et al. 2004).

Maximum likelihood / Bayesian classifier

The maximum likelihood is the strongest supervised monitored classifier currently in use (Ahmad et al. 2012). This method uses probability theory as an answer to the classification problem. This probabilistic approach helps in distinguishing between classes with overlapping spectral signatures by providing a measure of confidence in the classification results (Lillesand et al. 2004). This method uses statistical data such as mean, covariance and variances from selected class signatures to classify unknown pixels. This allows it to account for within-class variability and improve classification accuracy (Jensen 2005). This technique is based on Bayes' theorem, assuming the data is linearly or normally distributed in multidimensional space. Each class is defined by a covariance matrix and a mean vector, which are applied to each pixel. To assign pixels to the most similar landcover class, statistical probabilities are computed, and pixels are classified according to the highest probability under preset weightage (Srivastava et al. 2012), this type of classification is called as maximum likelihood classsification (MLC). When classes vary significantly in size and shape in spectral space, this method generates class assignments that are more accurate

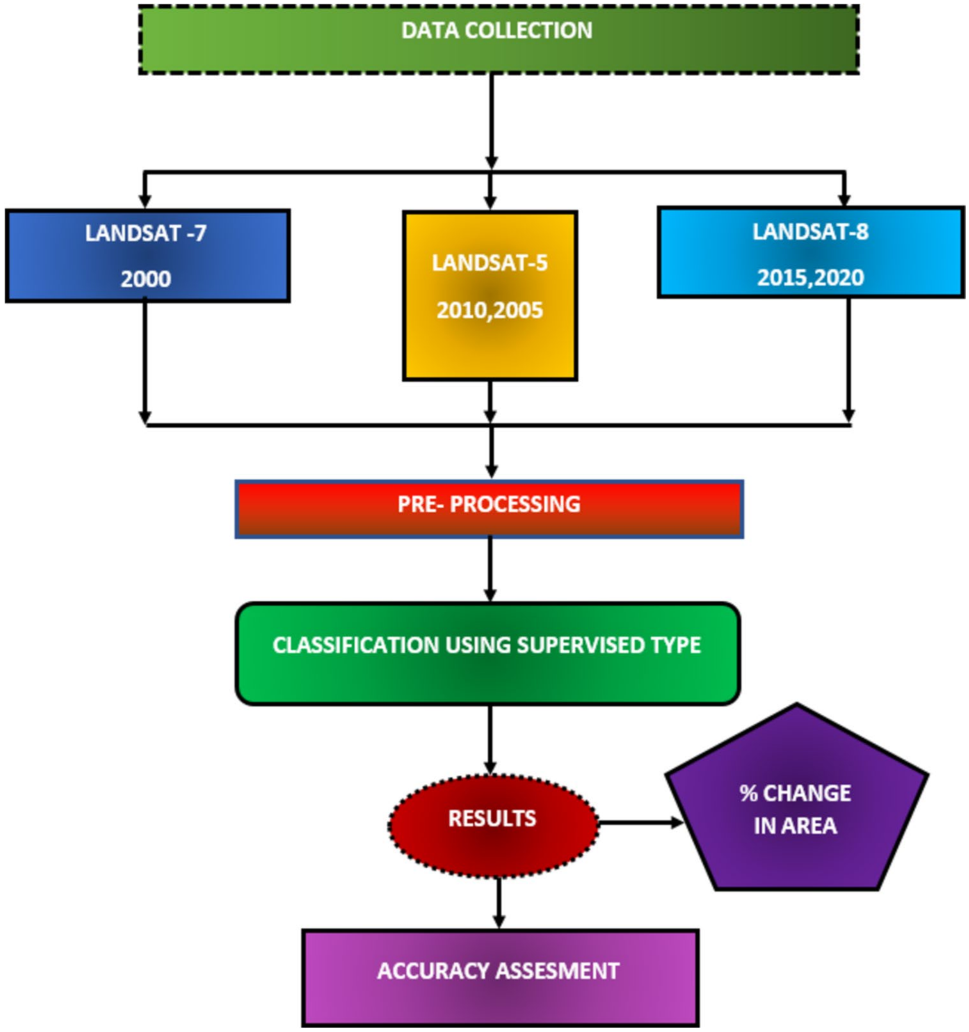


Fig. 2 Methodology for LULC classification and change detection flow

Table 1 Details of satellite data

Acquisition year	Satellite/sensor	Resolution (m)
2000	LANDSAT 5 TM	30
2005	LANDSAT 5 TM	30
2010	LANDSAT 7 ETM + LEVEL 2	30
2015	LANDSAT 8 OLI/TIRS LEVEL 2	30
2020	LANDSAT 8 OLI/TIRS LEVEL 2	30

than the minimum distance from the means method. It must be noted, however, that some classes are not conventional elements of the ground stage.

Estimation of change in area percentage of different classes between 2000–2020

$$\text{Change in area}\% = \frac{\text{Change in Area } 2020_i - \text{Change in area } 2000_i}{\text{Total area } 2000} \times 100 \quad (1)$$

Here, the area is changed according to different classes (Mariye et al. 2022).

Accuracy assessment

LULC maps derived from satellite imagery encompass various categories and levels of error, making accuracy assessments essential for establishing reliable evidence. Satellite data have increasingly gained importance in studies at global, regional, and local scales, playing a critical role in informing key decisions globally (Kyriakidis et al. 2004). Thus, validating the accuracy of remote sensing data is crucial for evaluating these decisions. Additionally, classification accuracy is frequently employed as a vital cartographic tool (Cihlar 2000).

$$\text{Accuracy} = \frac{\text{Number of correct Prediction}}{\text{Total number of Prediction}} \quad (2)$$

The equation measures the percentage of correct predictions out of total no. of predictions following (Kubat 2017).

The accuracy of the projected LULC maps was also evaluated using the Kappa coefficient which ranges from − 1 to + 1 (Congalton and green 2009). (Eq. (3)):

$$\text{Kappa} = \left(P_o - P_e\right)/\left(1 - P_e\right) \quad (3)$$

where,

P_e = Percentage of predicted agreements,

P_o = Proportion of actual agreements.

The accuracy was evaluated by comparing the classified values with ground truth data from Google Earth Pro. For each year, 100 random points were plotted for every class across the study area. These points were projected in Google Earth Pro, and their actual class was determined. It was found that accuracy is 85.19%, 89.22%, 89.53%, 91.25%, 93.90% and kappa is 0.830, 0.873, 0.879, 0.899, 0.916 for the respective years shown in Fig. 3. This difference in accuracy assessment across the years may be due to different LANDSAT data.

Results and discussion

LULC classification

The spatial distribution of distinct LULC categories through temporal intervals from 2000 to 2020 is presented in Fig. 4. Through the Map, we can easily identify the rise in built-up and decline in dense vegetation over 20 years.

Figure 5 and Table 2 illustrates the changes in land area across various LULC classes for the years 2000, 2005, 2010, 2015, and 2020. In 2000, dense vegetation covered 1227.51 km², the largest area among all classes, while other categories included 494.92 km² of vegetation, 551.21 km² of agricultural land, 35.43 km² of built-up land, 676.96 km² of barren land, and 84.66 km² of water bodies. By 2020, dense vegetation had decreased to 951.13 km², while vegetation increased to 618.03 km², agricultural land to 597.13 km², built-up areas to 106.81 km², barren land to 717.91 km², and water bodies reduced to 79.01 km². These

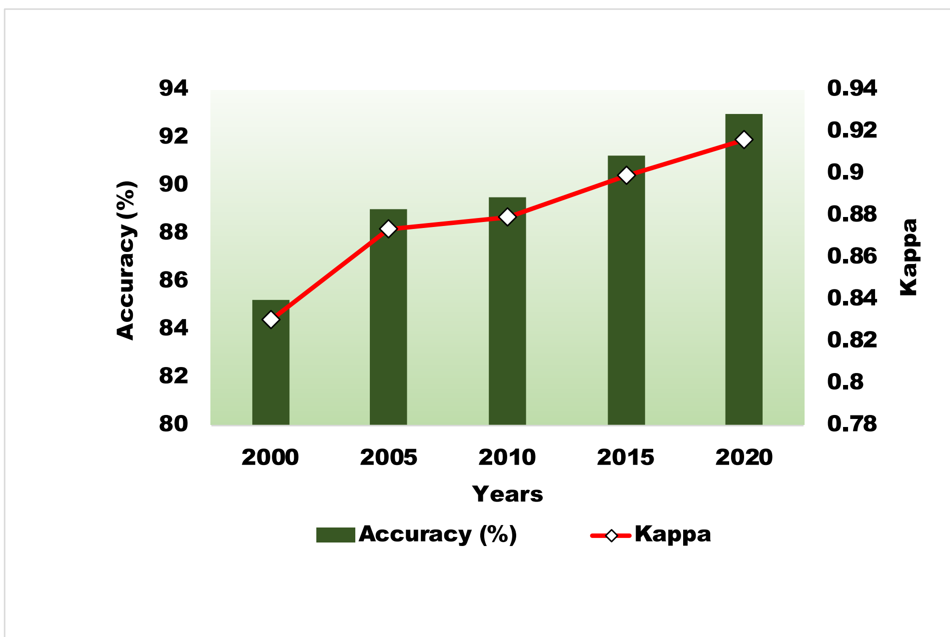


Fig. 3 Accuracy percentage and Kappa from year 2000 to 2020

Table 2 Area statistics (km^2)

Year	Dense vegetation	Barren land	Water body	Built-up	Vegetation	Agriculture
2000	1227.81	676.96	84.66	35.43	494.92	551.21
2005	1141.46	649.17	183.26	77.55	583.71	435.86
2010	1090.09	598.27	95.81	92.09	463.85	727.20
2015	1048.88	616.06	127.08	104.00	638.45	535.80
2020	951.13	717.91	79.01	106.81	618.03	597.13

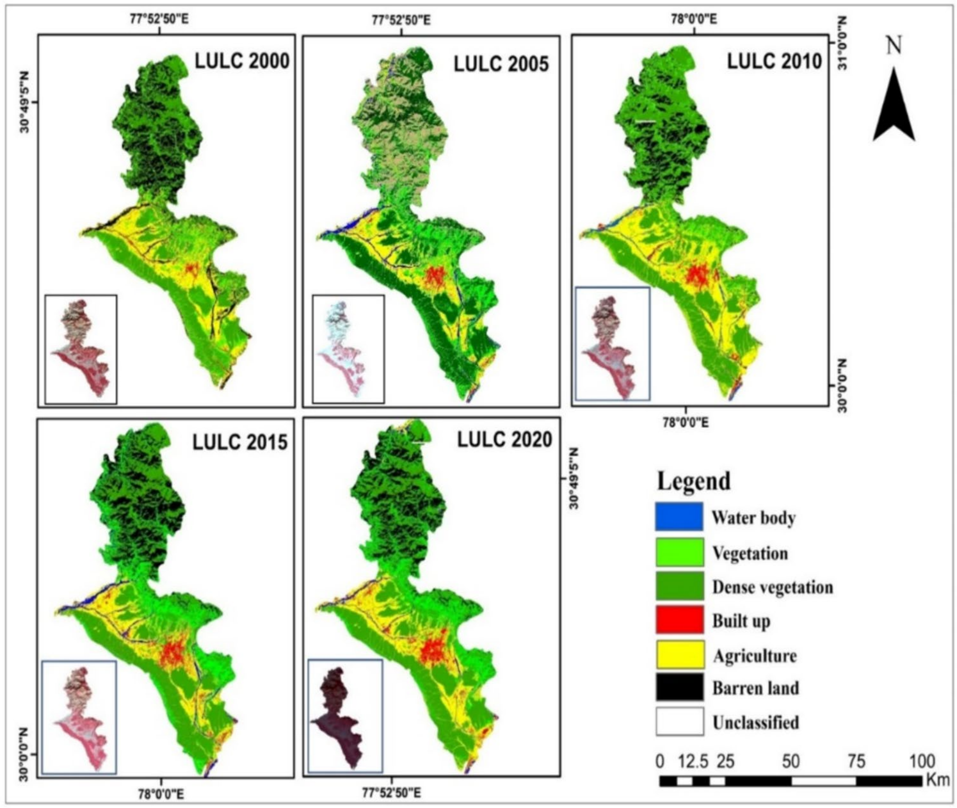


Fig. 4 Changes in land use and land cover for the years 2000, 2005, 2010, 2015, and 2020 for different classes

results suggest significant temporal variations in LULC over the period from 2000 to 2020. Notably, dense vegetation, barren land, agriculture, and water bodies showed a decline, whereas built-up areas and vegetation increased, likely driven by human activities such as encroachments and rapid, unplanned urbanization. The apparent fluctuation in vegetation cover between 2005 and 2010 may be attributed to recurring forest fires in those years (Hussain et al. 2018).

Analysis of change detection (2000–2020)

The GIS environment was utilized to assess and categorize land use changes in the classified maps from both 2000 and 2020 (Fig. 6). The distribution of percentages across various land use categories is presented in two columns. The first column represents data from the year 2000, indicating that out of the total area, the highest portion, 39.38%, was covered by dense vegetation. Additionally, 16.12% was occupied by vegetation, 17.95% was designated for agricultural use, 1.15% was allocated for urban/built-up areas, 22.04% was categorized as barren land, and 2.76% was occupied by water bodies.

On the other hand, the second column displays information from Fig. 6b in the year 2020. In this year, the distribution of land use and land cover was as follows: 30.38% was covered by dense vegetation, 20.13% was covered by vegetation, 19.45% was utilized for agricultural purposes, 3.48% was designated as urban/built-up areas, 23.38% was classified as barren land, and 2.57% was occupied by water bodies. In Fig. 6c, the change map illustrates the transitions within the time interval of 2000–2020 for each class. This depiction employs the colours red and yellow: red signifies the year 2000, whereas yellow symbolizes the year 2020. It was found that from the year 2000 to 2020, dense vegetation, agriculture, and water body is decreased by 9.01%, 4.01%, and 0.19%, while built-up, barren Land and vegetation is increased by 2.33%, 1.34% and 4.03% respectively shown in the figure.

Conclusions

The research conducted in the Dehradun district of Uttarakhand highlights usage of LANDSAT satellite data to classify land, is a useful way to understand how the land has changed. The shifts in LULC have happened quickly. Urbanization is a major reason for these changes, as shown by a huge increase in urban/built-up areas from 1.15 to 3.48%. Also, more land is now used for farming which is 17.7–19.45% well explained in the results. Barren Land has also increased from 22.04 to 23.38 a bit. Over time, Built-up areas have expanded, as noted by Joshi et al. (2019). The outcomes demonstrated that human activities have notably contributed to alterations in LULC, underscoring the issue of

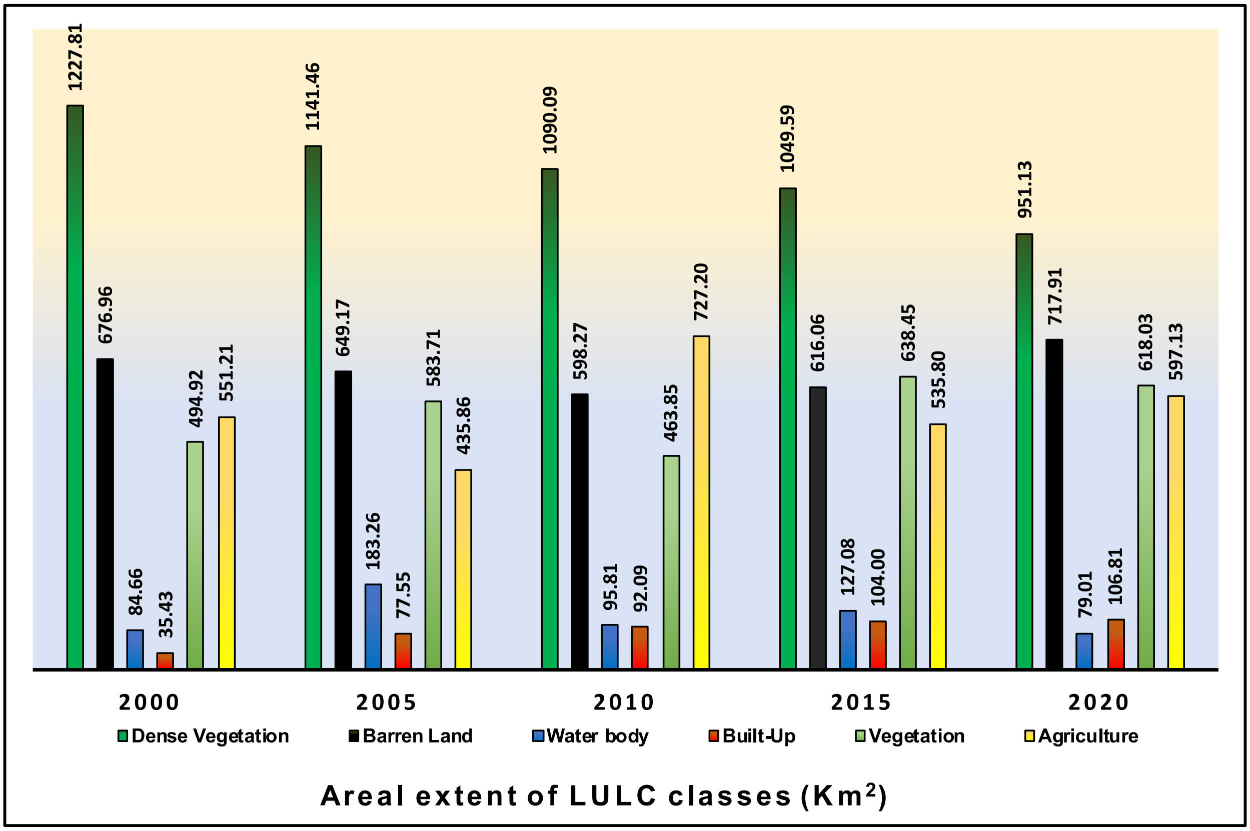
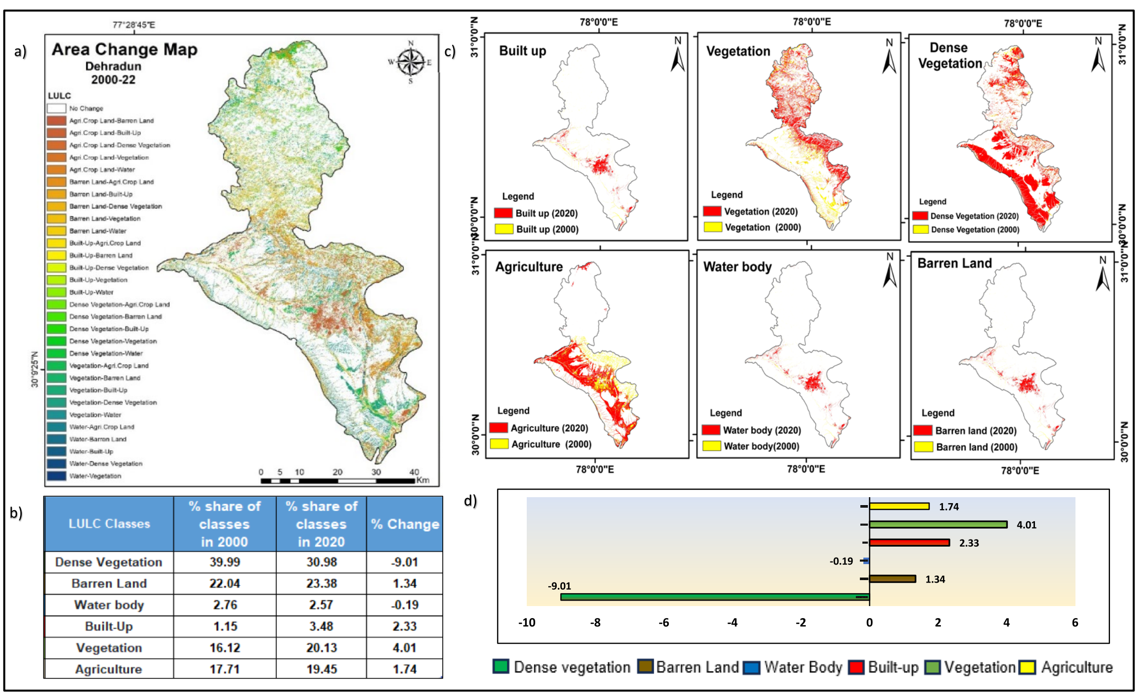


Fig. 5 Different classes and areas from 2000 to 2020



LULC Classes	% share of classes in 2000	% share of classes in 2020	% Change
Dense Vegetation	39.99	30.98	-9.01
Barren Land	22.04	23.38	1.34
Water body	2.76	2.57	-0.19
Built-Up	1.15	3.48	2.33
Vegetation	16.12	20.13	4.01
Agriculture	17.71	19.45	1.74

Fig. 6 Illustration of **a** Land use and land cover change map of Dehradun, **b** percentage share of classes in 2000–2020, **c** Change map between the time interval 2000–2020 and **d** LULC change in percent for Dehradun

unsustainable land-use practices in the research area, which is a noteworthy environmental concern. The substantial growth of built-up areas is primarily determined by urban growth and the migration of individuals from rural to urban areas. has led to a disorganized and fragmented expansion of settlements into productive agricultural lands.

As a suggestion, it's important to carefully handle the transformation of agricultural and open/scrub lands in Dehradun, especially when converting them into residential, commercial, or industrial areas. Policymakers have the opportunity to design a comprehensive and sustainable development plan for the entire area. This research makes a substantial contribution to the realization of SDG 15, which seeks to protect, restore, and promote the sustainable utilization of terrestrial ecosystems, efficiently manage forests, combat desertification, mitigate and reverse land degradation, and halt the loss of biodiversity. The findings from the LULC assessment over Dehradun from 2000 to 2020 have several critical policy implications for Dehradun. First, the rapid increase in built-up areas points to the urgent need for comprehensive urban planning and stricter zoning regulations to manage unplanned urban sprawl. Effective urban policies can prevent further encroachment into forests and agricultural land. Second, the decline in dense vegetation underscores the importance of reinforcing forest conservation measures, such as afforestation and reforestation, while also enforcing strict penalties for illegal encroachment into forest lands. Third, with agricultural land shrinking, there is a pressing need for policies that safeguard farmlands and promote sustainable farming practices to balance urban development with food security. Fourth, the reduction in water bodies highlights the necessity for better water resource management, including restoring natural water systems and adopting sustainable water practices, such as rainwater harvesting. Lastly, ensuring that Environmental Impact Assessments (EIAs) are mandatory for all development projects will help evaluate the effects of urbanization on natural ecosystems, enabling informed decisions to minimize degradation. These combined efforts can guide Dehradun toward sustainable urbanization and environmental conservation. In recent past the government of Uttarakhand has taken several steps to address the challenges posed by urbanization and environmental degradation. For better urban planning and zoning, initiatives like the Smart Cities Mission and the Uttarakhand Urban and Regional Development Plan Formulation and Implementation guidelines have been introduced to ensure systematic growth and regulate land use. To protect and restore forest cover, efforts such as the Compensatory Afforestation Fund Management and Planning Authority (CAMPA) and the Green India Mission have been implemented, focusing on afforestation and forest conservation. The decline in agricultural land has been countered by promoting sustainable farming practices through schemes like the Pradhan Mantri Krishi Sinchayee Yojana (PMKSY) and the Paramparagat Krishi Vikas Yojana (PKVY), which emphasize water efficiency and organic farming. In response to water body degradation, programs such as the Atal Bhujal Yojana and Jal Shakti Abhiyan have been introduced, focusing on groundwater management, rainwater harvesting, and the rejuvenation of traditional water resources. All these initiatives, along with the introduction of additional policies mentioned above in 5 points, along with regular monitoring and evaluation. Consistent oversight and timely updates to these strategies will ensure better execution and progress. One potential limitation is the resolution of the dataset. Utilizing higher-resolution data can significantly enhance the accuracy of classification, enabling a more precise distinction between different pixels. Additionally, quantifying the variations in climate variables across various LULC classes would provide deeper insights into the interactions between LULC changes and climate dynamics. This comprehensive approach significantly enhances the effective execution of Sustainable Development Goal (SDG) 15, which focuses on the protection, restoration, and sustainable use of terrestrial ecosystems.The results offer valuable and up-to-date information that can guide smart policymaking and sustainable development for land use in Dehradun over the long run.

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Author contributions Rahul Jaiswal, Ajay Sharma and Sunita Verma conceptualized this research, methodology, software, validation, visualization and designed experiments; Rahul Jaiswal and Ajay Sharma participated in the design and interpretation of the data and performed experiments and analysis; Rahul Jaiswal and Sunita Verma writing—the original draft; Divya Prakash, Ayesha Chaudhary—interpretation of data, review and editing.

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Data availability The data used in this study can be requested from the corresponding author upon reasonable request.

Declarations

Conflict of interest The authors declare no competing interests.

Ethical approval All authors have read, understood, and have complied as applicable with the statement on “Ethical responsibilities of Authors” as found in the Instructions for Authors.

Consent to participate Not applicable.

Consent for publication Not applicable.

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