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LANDSCAPE TRANSFORMATION AND LAND-USE DYNAMICS IN THE JAMMU REGION: A SPATIO-TEMPORAL ANALYSIS OF JAMMU DISTRICT, INDIA

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ABSTRACT

Land Use and Land Cover (LULC) constitute one of the most sensitive and observable expressions of the interaction between human activity and the physical environment, and its systematic monitoring are fundamental to sustainable regional planning. This study presents a spatio-temporal assessment of LULC change in Jammu district, Jammu and Kashmir, India, over the decade 2011–2021, using multi-temporal Landsat satellite imagery (Landsat 7 ETM+ for 2011 and Landsat 8 OLI/TIRS for 2021) obtained from the United States Geological Survey (USGS) Earth Explorer archive. Six thematic band composites were generated and classified through supervised Maximum Likelihood Classification (MLC) in a GIS environment into six land-cover classes — vegetation, agricultural land, built-up area, river bed, fallow land, and water bodies — following the USGS (Anderson et al., 1976) land-classification scheme. The classified layers were masked to the district boundary, and area statistics were compared between the two reference years to derive a quantitative change-detection matrix. The results reveal a pronounced landscape transformation: vegetation cover expanded from 40 per cent (940.38 km^2) of the district in 2011 to 57 per cent (1,341.29 km^2) in 2021, while agricultural land contracted sharply from 35 per cent (822.58 km^2) to 17 per cent (401.70 km^2) over the same period. Built-up area nearly doubled, rising from 5 per cent (121.38 km^2) to 9 per cent (217.36 km^2), reflecting rapid urban and infrastructural expansion around Jammu city and its peripheral towns, while fallow land declined from 15 per cent to 6 per cent and the river-bed class increased from 4 per cent to 10 per cent, most plausibly on account of hydrological and channel-migration processes along the Tawi and its tributaries. Water bodies remained a marginal but broadly stable 1 per cent of the district throughout. These findings depict a district in transition — from a predominantly agrarian, rural landscape toward one characterised by expanding green cover on the one hand and accelerating urbanisation on the other and they underscore the urgency of integrated, terrain-sensitive land-use planning that reconciles urban growth with the protection of agricultural and ecological resources. The study offers a replicable, GIS-based framework for monitoring land-use change in sub-Himalayan districts and provides an evidence base for future spatial planning in Jammu district and comparable regions of the north-western Himalayan foothills.

Keywords: Land Use/Land Cover, Remote Sensing, GIS, Landsat, Change Detection, Maximum Likelihood Classification, Urbanisation, Jammu District, Sustainable Land Management

INTRODUCTION

Land Use and Land Cover (LULC) are classical yet enduringly important concepts in geographic and environmental science, providing the conceptual bridge between the physical characteristics of the Earth's surface and the purposes for which humans

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exploit it. Land cover refers to the physical and biological characteristics of the surface vegetation, water, bare soil, and built structures — while land use denotes the purposes for which humans utilize that cover, whether through cultivation, settlement, industry, or conservation Chaves et al. (2020). LULC change (LULCC), in turn, captures the dynamics of this human–environment interaction, driven by anthropogenic processes such as deforestation, urbanization, and agricultural intensification, as well as by natural agents including floods, droughts, and wildfire. Because LULC data underpin policy on food security, climate-change adaptation, and natural-resource management, its accurate and repeated mapping has become indispensable to sustainable development planning Chaves et al. (2020).

Land is a finite and vital natural resource whose management directly conditions the well-being of present and future generations (Yar et al., 2022). Anthropogenic activity continuously reshapes the exchange of energy between the Earth's surface and the atmosphere through LULC change (Xiao & Weng, 2007), and the accelerating demand for land — driven by agriculture, urbanisation, deforestation, and population growth has intensified these modifications, often with adverse ecological consequences (Intergovernmental Panel on Climate Change, 2019). This is a particular concern in developing regions, where limited baseline knowledge of LULC dynamics constrains the ecosystem-service assessments and policy interventions needed for sustainable land management (Jombo et al., 2017; Musetsho et al., 2021).

The accuracy of LULC classification depends heavily on the choice of remote-sensing data and the complexity of the landscape under study (Lu & Weng, 2007; Manandhar et al., 2009). A range of sensors has historically been used for this purpose, from the Satellite pour l'Observation de la Terre (SPOT), prized for its high spatial resolution but constrained by narrower spectral range and higher cost (Song et al., 2011; Mhangara et al., 2020), to the Advanced Very High-Resolution Radiometer (AVHRR), valued for its broad, long-term coverage but limited by coarse spatial resolution (Liu et al., 2010; Lucas & Mitchell, 2017), and the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), which offers high spatial and spectral detail at the cost of limited temporal frequency (Liu & Weng, 2013; Veraverbeke & Hook, 2011). For large-area classification, MODIS remains widely used for its high temporal resolution, though its coarse spatial resolution restricts the discrimination of fine-scale classes (Lunetta et al., 2006; Mahmoudi et al., 2020; Schulz et al., 2017). The more recent availability of Sentinel-2 (10 m), Landsat 8, and Landsat 9 (30 m each) has substantially improved the practical accuracy achievable in district-level LULC mapping of the kind undertaken in this study.

Because Landsat imagery offers a uniquely long, consistent, and freely accessible archive, it has become the primary data source for extracting land-cover information in rapidly changing urban and peri-urban regions (Coulter et al., 2016; Johnson & Iizuka, 2016; Mack et al., 2017; Zhu et al., 2016). Much of this work has historically relied on mono-temporal imagery (Aslan & Koc-San, 2016; Godinho et al., 2016; Shahtahmassebi et al., 2017), which is vulnerable to the well-known problems of spectral confusion "the same object with different spectra" and "different objects with the same spectrum" that can compromise classification accuracy (Deng et al., 2018). Multi-temporal, Satellite Image Time Series (SITS) approaches mitigate this limitation and enhance the detection of landscape processes such as deforestation, agricultural expansion, and urban growth, even as classification itself remains a methodologically complex task shaped by sensor choice, algorithm selection, and landscape heterogeneity.

LAND USE / LAND COVER CLASSIFICATION SCHEME

The most widely adopted general-purpose classification scheme compatible with remote-sensing data remains that of Anderson et al. (1976), commonly referred to as the USGS classification scheme; most subsequent schemes represent modifications of this original framework. The present study adopts the USGS scheme, adapted to the physiographic and land-use characteristics of Jammu district, and recognizes the following broad land classes within the study area:

- Urban or built-up land: areas of intensive human use, including cities, towns, villages, strip development along highways, and transportation, power, and communication infrastructure, together with industrial, commercial, and institutional complexes.
- Agricultural land: land used primarily for the production of food and fibre, encompassing cropland and pasture, orchards, groves, nurseries, and ornamental horticultural areas.
- Forest / vegetation land: areas with a tree-crown density of 10 per cent or more, capable of producing timber or other wood products, and exerting a discernible influence on local climate and the water regime.
- Fallow / waste land: land of limited productive capacity in which less than one-third of the area carries vegetation cover, including salt flats, bare exposed rock, and temporarily uncultivated agricultural land.
- Water bodies: streams, canals, lakes, reservoirs, and other perennial surface-water features.
- River bed: the ground over which a river channel flows, including active and seasonally exposed floodplain surfaces.

REVIEW OF LITERATURE

A substantial and rapidly growing body of research has applied remote sensing and GIS techniques to LULC mapping and change detection across diverse physiographic and climatic settings. For clarity, the literature reviewed for this study is organised into five thematic clusters: (i) studies from the Jammu and Kashmir Himalayan region; (ii) comparative assessments of sensor performance and classification algorithms; (iii) machine-learning and deep-learning approaches to LULC classification; (iv) studies linking urban growth to land-surface temperature; and (v) applied environmental and resource-management studies employing LULC analysis.

STUDIES FROM THE JAMMU AND KASHMIR HIMALAYAN REGION

Regional evidence most directly relevant to the present study comes from within Jammu and Kashmir itself. Ganaie et al. (2014) examined spatial change in cropping land use across the erstwhile state of Jammu and Kashmir and found that, while net sown area increased by 3.36 per cent overall, the increase was considerably sharper in Jammu district specifically (19.73 per cent), even as it declined in Srinagar, Budgam, and Pulwama districts of the Kashmir valley — an early indication of the district-level land-use divergence that motivates the present decade-scale study. Alam et al. (2020) documented substantial LULC transformation in the Kashmir valley between 1992 and 2015 using Landsat imagery, reporting expansion of built-up, barren, marshy, plantation, and shrub classes alongside a decline in agriculture and water bodies, with forest and pasture cover following a fluctuating trajectory of initial decline followed by partial recovery. Jamal et al. (2020) similarly assessed LULC change in the wetland ecosystems of the Kashmir valley from 1994 to 2018, finding a significant decline in water bodies and marshy land alongside expansion of built-up, agricultural, and horticultural areas — with Wular Lake alone losing nearly 4,000 hectares of open water — underscoring the vulnerability of Himalayan wetlands to sustained anthropogenic pressure.

SENSOR COMPARISON AND CLASSIFIER-PERFORMANCE STUDIES

A second cluster of studies has focused on comparing the relative performance of different satellite sensors and classification algorithms for LULC mapping. Acar and Zengin (2023) found that Sentinel-2 and Landsat 8 classifications can diverge by as much as a factor of two for the same land-cover class, cautioning against uncritical cross-sensor comparison. Ghasempour et al. (2023) reported that Landsat 9 outperformed Landsat 8 in both overall accuracy (87.4 versus 82.0 per cent) and Kappa coefficient (0.83 versus 0.76) for LULC classification in Iğdır province, Türkiye, while Shahfahad et al. (2023) similarly found that Landsat OLI-2 improved on OLI in distinguishing vegetation density and surface features. Saralioglu et al. (2022) compared Support Vector Machine, K-Nearest Neighbours, LightGBM, and 3D-CNN classifiers for Landsat-8/9 imagery in Turkish forest- and agriculture-dominated landscapes, finding that the 3D-CNN approach minimised the characteristic "salt-and-pepper" classification noise and achieved the highest overall accuracy. Sekertekin et al. (2017) reported Kappa values of 0.78 for Sentinel-2 and 0.85 for Landsat-8 in a Turkish coastal setting, while Espinosa et al. (2019) found broadly comparable accuracy (87–88 per cent) between the two sensors in Mediterranean wetlands, with Sentinel-2 offering an edge in detecting small, linear features. Krivoguz et al. (2023) compared deep neural network, Random Forest, Support Vector Machine, and AdaBoost classifiers on historical Landsat-5 imagery of the Kerch Peninsula, finding the deep neural network most accurate (96.2 per cent) but least reliable for grassland and agricultural classes. Complementary methodological work by Srivastava et al. (2022), Keshavarzi et al. (2022), Dinanta et al. (2021), Rehman et al. (2021), and Gupta and Shukla (2020) has further refined classifier selection, topographic-correction procedures, and ancillary-variable integration for improving LULC accuracy in heterogeneous and mountainous terrain — considerations directly relevant to the topographically diverse landscape of Jammu district.

MACHINE-LEARNING AND DEEP-LEARNING APPROACHES

A rapidly expanding body of work applies machine-learning and deep-learning methods to LULC classification at scale. Abbas et al. (2025) used a Random Forest classifier within the Google Earth Engine (GEE) cloud platform to map LULC change across three districts of south Punjab, Pakistan, over a thirty-year period (2003–2033, incorporating projected classes), achieving over 90 per cent overall accuracy and a Kappa value of 0.9. Ganjirad et al. (2024) proposed a GEE-based framework fusing pixel- and object-based classification with ensemble machine-learning methods, achieving 94.92 per cent overall accuracy and demonstrating downstream utility for regional climate modelling. Boonpook et al. (2023) introduced LoopNet, a deep-learning semantic-segmentation architecture that outperformed both conventional classifiers (Maximum Likelihood, SVM, Random Forest) and baseline deep networks (SegNet, U-Net, PSPNet) on Landsat 8 imagery, achieving 89.84 per cent accuracy. Mirmazloumi et al. (2022) combined Sentinel-1/2 and Landsat-8 data with an Artificial Neural Network to generate a 10 m resolution LULC map of Europe (ELULC-10) at 95.38 per cent accuracy, while Johnson et al. (2016) demonstrated that noise-tolerant classifiers combined with SMOTE-based class balancing could achieve strong performance (84.0 per cent for Random Forest) even when trained on noisy, crowd sourced Open Street Map labels — a cost-efficient alternative to conventional ground-truthing.

URBAN GROWTH AND LAND-SURFACE TEMPERATURE STUDIES

A further cluster of studies links LULC change, particularly urban expansion, to land-surface temperature (LST) dynamics a theme of direct relevance to the sharp rise in built-up area documented for Jammu district in the present study. Farhan et al. (2024) found a 196.5 per cent increase in built-up area and a 30.4 per cent decline in vegetation in Lahore, Pakistan, over three decades, with a negative NDVI–LST correlation and a rising urban heat island ratio index. Mohiuddin and Mund (2024) documented LST variability of 20–69 °C in the rapidly urbanising periphery of Phnom Penh, Cambodia, closely tied to seasonal and LULC variation. Kamran et al. (2024) examined LULC and urban green-infrastructure change in Kuala Lumpur across three time points (1990, 2005, 2021), emphasising the value of integrating historical and projected LULC trends into urban ecosystem-service planning. Naikoo et al. (2020) reported a 326 per cent increase in built-up area and a 44 per cent rise in fallow land in Delhi NCR between 1990 and 2018, alongside a 12 per cent decline in agricultural land and a 34 per cent decline in vegetation — a pattern of simultaneous urban expansion and green-cover loss that contrasts instructively with the pattern of urban expansion accompanied by net vegetation gain documented for Jammu district in the present study. Latif et al. (2017) and Zhou et al. (2014) provide further methodological grounding for LST–LULC and built-up index analysis, respectively, while Kafi et al. (2014) documented comparably rapid urban growth in Bauchi, Nigeria, using supervised, unsupervised, and post-classification change-detection methods.

APPLIED ENVIRONMENTAL AND RESOURCE-MANAGEMENT STUDIES

A final cluster of studies illustrates the breadth of applied uses to which LULC mapping has been put internationally. These include assessments of ecologically fragile-area sustainability on the Loess Plateau, China (Yang et al., 2024); land-tax-driven LULC change in Bangkok (Orina et al., 2024); post-heat wave land-use shifts in the Jialing river region of Chongqing, China (Nascimento et al., 2022); deforestation dynamics in the Oba Hills forest reserve, Nigeria (Bukoye et al., 2023); a sixty-year reconstruction of LULC change in Iraqi Kurdistan combining CORONA and Landsat imagery (Saleem et al., 2018); biodiversity-conservation mapping in the Krau Wildlife Reserve, Malaysia (Shaharum et al., 2018); satellite-based agricultural drought assessment in Maharashtra, India (Gaikwad et al., 2018); water-pollution mapping of Burullus Lake, Egypt (Zeiny et al., 2017); land-cover classification of the Brazilian Cerrado (Mattos et al., 2017); a broad review of LULC classification challenges in Nigeria (Alegbeleye et al., 2017); and shifting-cultivation landscape dynamics in southern Cameroon (Yemefack et al., 2006). Collectively, this body of work confirms that GIS- and remote-sensing-based LULC mapping is now a mature, globally applied methodology capable of supporting a wide range of environmental, agricultural, and urban-planning applications and it is this established methodology that the present study applies, for the first time in a systematic decade-scale form, to Jammu district.

OBJECTIVES OF THE STUDY

The present study is guided by two specific objectives:

1) To compare, analyse, and interpret the changes in Land Use and Land Cover that have occurred in Jammu district between 2011 and 2021, using Landsat 7 ETM+ and Landsat 8 OLI/TIRS imagery respectively.
2) To perform an accurate and detailed land-use/land-cover classification for both reference years and to identify the principal factors associated with the observed LULC changes over the study period.

DATABASE AND METHODOLOGY

DATA ACQUISITION

Satellite imagery for the study was obtained from the United States Geological Survey (USGS) Earth Explorer archive. Landsat 7 ETM+ imagery was used to characterise land cover for the 2011 reference year, and Landsat 8 OLI/TIRS imagery was used for the 2021 reference year, both selected for minimal cloud cover over the district during the peak dry-season window to maximise spectral separability between land-cover classes.

BAND COMPOSITE GENERATION

The individual spectral bands of each scene were combined into a multi-band composite using standard image-processing tools seven bands for Landsat 7 and eleven bands for Landsat 8 and the resulting composites were visually checked against standard RGB colour-coding conventions to verify correct band ordering prior to classification.

SUPERVISED IMAGE CLASSIFICATION

Supervised classification was adopted for both reference years. In this approach, representative training samples are digitised for each target land-cover class and used to train a classification algorithm, which then assigns every remaining pixel in the scene to the class whose spectral signature it most closely resembles. Training samples were developed for six land-cover classes: vegetation, agricultural land, built-up area, river bed, fallow land, and water bodies.

MAXIMUM LIKELIHOOD CLASSIFICATION (MLC)

Following the generation of training samples, Maximum Likelihood Classification (MLC) was applied as the supervised classification algorithm. MLC is a statistically grounded method that assigns each image pixel to the class for which the observed spectral response is most probable, under the assumption that the pixel values for each class follow a multivariate normal distribution. The parameters of these class-wise distributions — mean vectors and covariance matrices — are estimated directly from the user-supplied training samples, making MLC both computationally tractable and well suited to the moderate-resolution, multi-band Landsat data used in this study.

EXTRACTION OF THE STUDY AREA

A shape file of the Jammu district boundary was created by digitising the district's physical/administrative map and was subsequently used to mask (clip) the classified raster layer, isolating the district from the surrounding classified region for area computation and final cartographic presentation.

FINAL MAP PREPARATION

Each classified Land Use/Land Cover map was finalised with the addition of a scale bar, north arrow, legend, and latitude–longitude graticule, in keeping with standard cartographic convention, to yield the finished thematic outputs presented in Section 6.

Table 1

Table 1 Description of Land-Cover Classes Adopted for the Study (Adapted from the USGS Scheme)

S. No.	Land Class	General Description
1	Water Bodies	Areas covered by rivers, streams, lakes, and water channels.
2	Built-Up Area	Settlements, city/town concentrations, developed areas, and roads.
3	Agriculture	Irrigated agricultural area and agricultural fallow land.
4	Barren / Fallow Land	Areas devoid of vegetation: exposed sediments, exposed rock, degraded land.
5	Forest / Vegetation	Thick vegetation, groves of evergreen and deciduous trees, shrubs, and agroforestry.
6	River Bed	Active and seasonally exposed river-channel surfaces.

Source: adapted from Anderson et al. (1976) USGS land-classification scheme; class definitions after https://doi.org/10.22214/ijraset.2023.55129.

Table 2

Table 2 Landsat 7 and Landsat 8 Band Combinations used for Image Interpretation

Application	Landsat 7 Bands	Landsat 8 Bands	Usage
True Colour (Natural View)	3-2-1	4-3-2	Similar to human vision; general landscape observation.
False Colour (Vegetation)	4-3-2	5-4-3	Highlights vegetation; healthy vegetation appears red.
Colour Infrared (Agriculture)	4-5-3	5-6-4	Effective for assessing crop health and vegetation stress.
Urban Studies (Built-up)	7-4-2	7-6-4	Distinguishes urban areas from natural features.
Geology (Rock / Soil)	7-5-1	7-6-1	Highlights geological formations and soil variation.
Burn-Area Detection	7-4-2	7-6-5	Aids wildfire and burned-land analysis.
Water-Body Identification	5-6-4	6-7-5	Differentiates water bodies from land features.

Source: NASA Landsat Science, Landsat 7 Handbook (landsat.gsfc.nasa.gov).

METHODOLOGY FLOW CHART

The overall workflow adopted for the classification and change-detection procedure is summarised in Figure 1.

Figure1

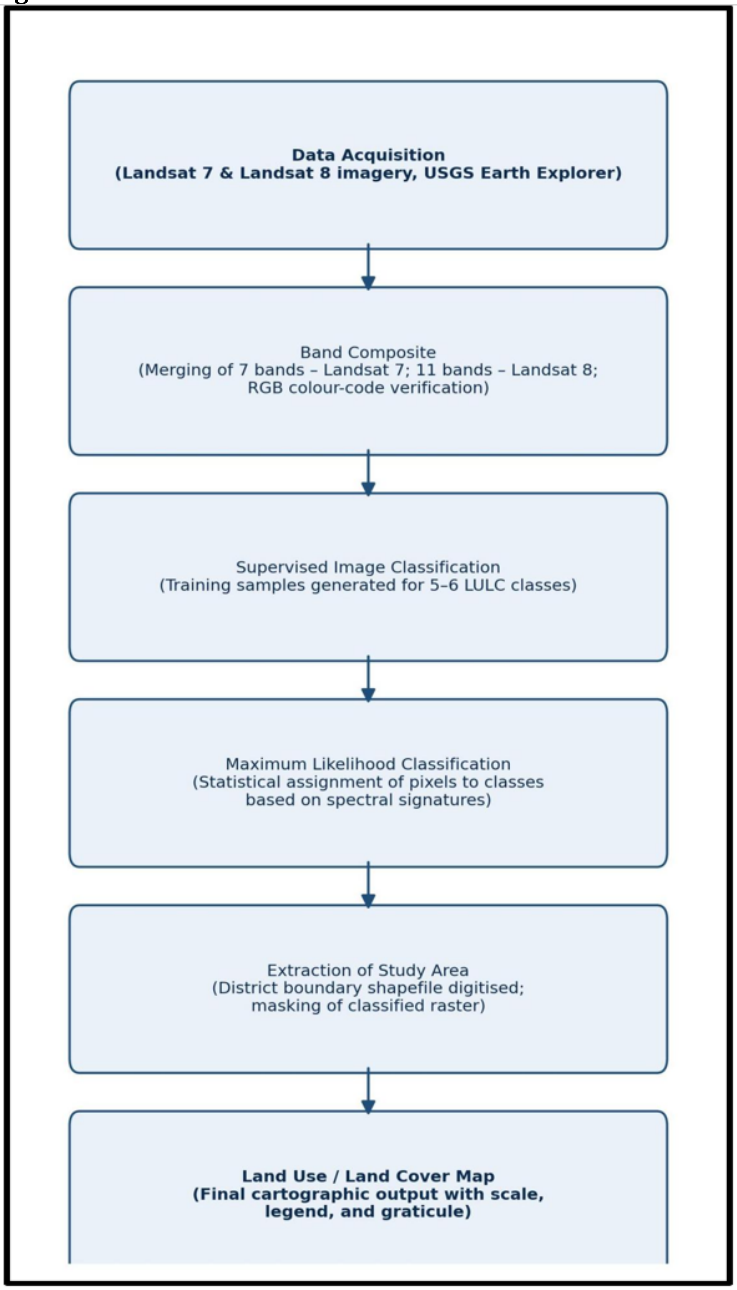

Figure 1 Flow Chart of the Methodology Adopted for LULC Classification and Change Detection

STUDY AREA

Jammu district, located in the Union Territory of Jammu and Kashmir, exhibits a strikingly diverse physiography encompassing alluvial plains, sub-Himalayan foothills, and middle-mountain tracts. The southern part of the district consists of fertile alluvial plains lying at an elevation of 300–400 m, adjacent to Punjab and Pakistan, where the Tawi River and its seasonal tributary streams (khads) sustain intensive agriculture. Moving northward, the terrain rises into the Shivalik Hills (400–800 m), characterised by steep slopes, rugged terrain, sparse scrub and acacia–pine vegetation, and soft, erosion-prone geology. Further north still, the landscape transitions into the foothills of the Pir Panjal Range (800–1,500 m), marked by deep valleys, dense pine, deodar, and oak forest, a cooler climate, and occasional winter snowfall. The Tawi River, originating from the Kali Kund Glacier, is the lifeline of Jammu city, while seasonal streams such as the Aik and Manawar Tawi supplement the district's drainage network. The district lies within Seismic Zone IV, rendering it moderately earthquake-prone owing to its location in a tectonically active zone, and this diverse physiography from fertile southern plains to forested northern hills — shapes the district's climate, agriculture, biodiversity, and settlement pattern in ways that are directly reflected in the LULC patterns documented later in this paper.

THE OUTER PLAINS (ALLUVIAL PLAINS)

Located in the southern part of the district adjacent to Punjab and Pakistan, at an elevation of 300–400 m, this zone is flat to gently undulating and composed of fertile alluvial soil, dominated by seasonal streams (khads) including the Tawi River.

THE SHIVALIK HILLS (OUTER HILLS)

Lying immediately north of the plains at 400–800 m elevation, this zone is characterised by steep slopes, rugged terrain, and narrow valleys, with sparse scrub vegetation, acacia, and pine cover. The soft, loose geology of this zone renders it particularly susceptible to erosion and landslides.

THE MIDDLE HIMALAYAS (PIR PANJAL FOOTHILLS)

Extending into the northern part of the district toward the Pir Panjal Range at 800–1,500 m elevation, this zone is hilly, with deep valleys and forested slopes, cooler temperatures, significant monsoon rainfall, and occasional winter snowfall, supporting dense pine, deodar, and oak forest.

Figure 2

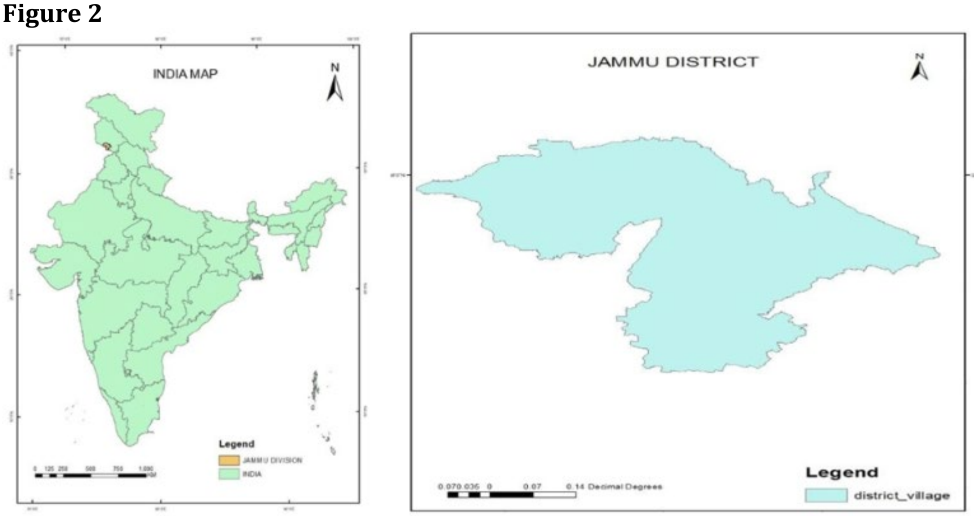

Figure 2 Location of Jammu District within the Jammu Division of the Union Territory of Jammu & Kashmir (left) and the District Boundary used for LULC Extraction (right)

The climate of Jammu district is predominantly sub-tropical, displaying considerable spatial variation across its diverse topography from the plains in the southwest to the Shivalik hills in the northeast and unfolding across four distinct seasons. Summers (May to early July) are hot and dry, with daytime temperatures exceeding 40 °C in the plains around Jammu, RS Pura, and Bishnah, driving high evaporation and dependence on irrigation. The monsoon (July–September) brings moderate to heavy rainfall, averaging around 1,100 mm annually, primarily from the southwest monsoon; this rainfall is vital for kharif cropping and groundwater recharge, but it also triggers flash floods and soil erosion, particularly in the hilly and foothill tracts drained by numerous seasonal khads. The post-monsoon period (October–November) sees a transition to moderate temperatures and declining rainfall, favouring rabi sowing, while winters (December–February) are cold and comparatively dry, with plains temperatures dropping to around 5 °C and lower still in higher-elevation tracts such as Nagrota, Dansal, and Akhnoor; occasional western disturbances bring light winter rainfall, and morning fog is common. This climatic contrast between the hot, irrigated plains and the cooler, rain-fed hills shapes not only agricultural practice but also settlement pattern and water-resource management, and the district increasingly faces the compounding pressures of heat waves, summer water scarcity, and more variable monsoon rainfall associated with climate change.

The soils of Jammu district vary considerably with topography, climate, and parent material. The low-lying plains particularly around RS Pura, Bishnah, and parts of Jammu tehsil — are dominated by fertile alluvial soils, deep and loamy to clayey in texture, formed by sediment deposition from the Tawi and Chenab rivers and well suited to rice, wheat, and vegetable cultivation. Moving toward the foothill or Kandi belt, soils become coarser and gravelly (piedmont soils), less fertile, with poor water retention and reliance on rain-fed pulses and millet cultivation. In the hilly Shivalik tracts around Akhnoor, Nagrota, and Dansal, red loamy soils prevail, moderately fertile and suited to horticulture and agro forestry but prone to erosion on steep slopes. Forest soils at higher altitudes are organically rich but scarcely used for cultivation, while salt-affected and degraded soils occur in patches in poorly drained parts of RS Pura and Bishnah. This diversity underscores both the district's agricultural potential and the need for sustainable soil-management practices, particularly in the erosion-prone piedmont and hill zones.

Jammu district is the most populous district in the Union Territory of Jammu and Kashmir, recording a total population of 1,529,958 at the 2011 Census, comprising 813,821 males and 716,137 females. The district shows an almost equal urban–rural split (765,013 urban against 764,945 rural residents), reflecting a balanced demographic structure. Jammu city, as the district headquarters and largest urban centre, forms the core of the JUA and houses over half the district's population, while Bari Brahmana, RS Pura, Akhnoor, and Nagrota constitute other rapidly developing urban centres driven by industrial and infrastructural growth. The rural population is dispersed across more than 1,100 villages, and the district records a comparatively high literacy rate of 83.45 per cent alongside a low sex ratio of 880 females per 1,000 males. Hinduism is the predominant religion, with smaller Muslim, Sikh, and other communities, and the district accommodates a significant migrant population, including displaced persons from Pakistan-occupied Jammu and Kashmir and West Pakistani refugees settled in border areas. Continued population growth, driven by urban expansion and migration, underlines the district's evolving role as a political, economic, and logistical hub of the wider Jammu region and provides essential demographic context for the sharp rise in built-up area documented in Section 6 of this paper. As the winter capital of Jammu and Kashmir, the JUA exhibits a diverse and pluralistic socio-religious composition. The Hindu population, predominantly of Dogra identity, forms the majority community, followed by significant Muslim and Sikh minorities the latter largely Punjabi Sikhs who settled in the region following the Partition of 1947 alongside smaller Christian, Buddhist, and Jain populations. This multi-religious composition is reflected in the cultural life of the city, with diverse festivals, religious practices, and places of worship coexisting across the urban and peri-urban landscape.

RESULTS: LAND USE AND LAND COVER OF JAMMU DISTRICT

Land Use and Land Cover (LULC) mapping captures both the physical characteristics of the Earth's surface — vegetation, water, bare soil, and built structures — and the ways in which humans utilise that surface for agriculture, settlement, industry, or recreation. Understanding the spatial distribution of LULC and how it changes over time is essential for urban planning, agriculture, forestry, water-resource management, and climate-change adaptation. In Jammu district, prior LULC evidence has pointed to rapid built-up expansion around Jammu city, a decline in agricultural land linked to urban encroachment, and pressure on forest cover in the Shivalik hills. Modern GIS and remote-sensing techniques, of the kind applied here, permit an accurate, up-to-date, and repeatable assessment of these dynamics; the results are presented below for the 2011 and 2021 reference years in turn, followed by a systematic comparative and change-detection analysis.

LAND USE AND LAND COVER OF JAMMU DISTRICT, 2011
Figure 3

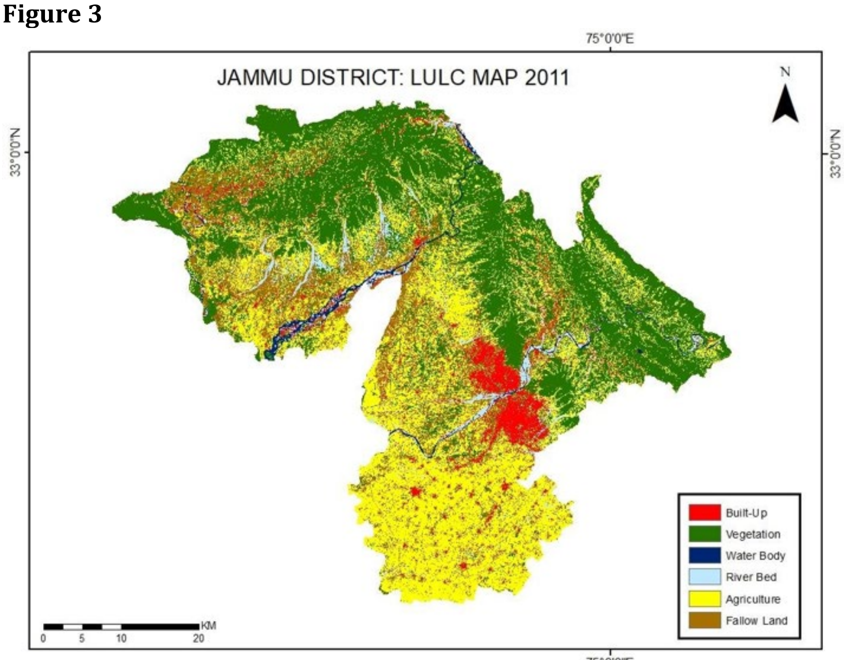

Figure 3 Land Use and Land Cover of Jammu District, 2011 (Derived from Landsat 7 ETM+ Imagery)

Table 3

Table 3 LULC Class-Wise Area and Share of Jammu District, 2011

Class	Area (sq. km)	Share (%)
Agricultural Land	822.58	35
Built-Up Area	121.38	5
Fallow Land	348.54	15
River Bed	98.25	4
Vegetation	940.38	40
Water Body	30.43	1
Total	2,361.58	100

The 2011 LULC profile of Jammu district reveals vegetation as the single dominant land-cover category, occupying approximately 40 per cent of the total district area — a substantial presence of natural green cover, forest, and shrub land that plays a central role in maintaining the district's ecological balance. Agricultural land follows closely at 35 per cent of the total area, reflecting the district's continued dependence on agrarian practice and rural livelihoods in 2011, while fallow land (15 per cent) represents areas previously cultivated but left uncultivated during the reference period, potentially owing to seasonal or soil-related factors. Built-up areas comprised a comparatively modest 5 per cent, indicative of moderate urbanisation concentrated principally around Jammu city, while the river-bed class (4 per cent) captured dry or partially active river channels, and water bodies occupied only 1 per cent of the district, reflecting limited perennial surface-water availability. Overall, the 2011 LULC profile depicts a predominantly vegetative and agrarian landscape with nascent pockets of urban growth an important baseline against which the 2021 transformation, presented next, can be measured.

LAND USE AND LAND COVER OF JAMMU DISTRICT, 2021
Figure 4

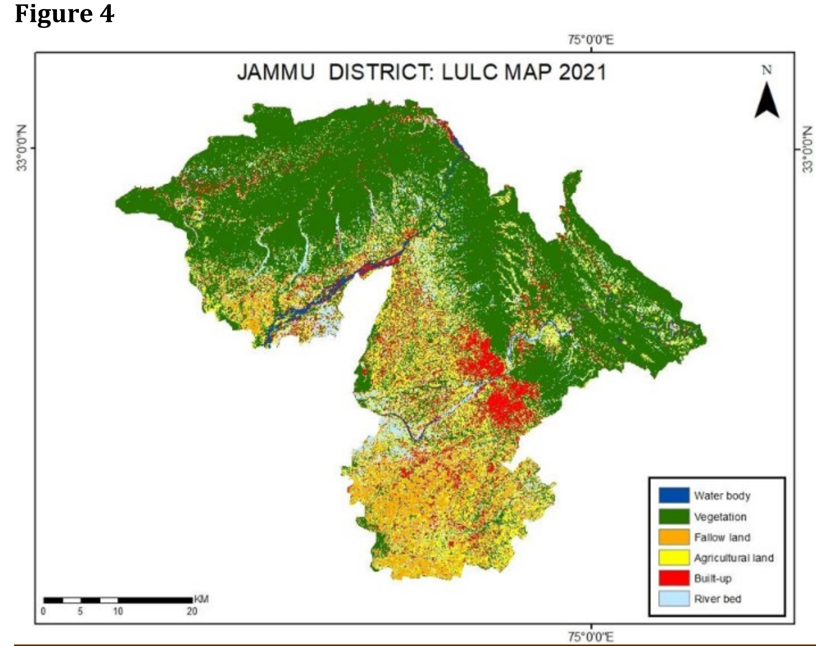

Figure 4 Land Use and Land Cover of Jammu district, 2021 (Derived from Landsat 8 OLI/TIRS Imagery)

Table 4

Table 4 LULC Class-Wise Area and Share of Jammu District, 2021

Class	Area (sq. km)	Share (%)
Agricultural Land	401.70	17
Built-Up Area	217.36	9
Fallow Land	142.60	6
River Bed	224.51	10
Vegetation	1,341.29	57
Water Body	34.14	1
Total	2,361.62	100

By 2021, the LULC profile of Jammu district had shifted markedly. Vegetation now dominates the landscape, occupying approximately 57 per cent of the total geographical area — an extensive expansion of natural green space that plays a heightened role in ecological balance, biodiversity support, and local climate regulation. Agricultural land, by contrast, had contracted to just 17 per cent of the total area, indicating a substantial reduction in the district's agrarian footprint, quite plausibly linked to urbanisation and to shifting rural land-use priorities over the preceding decade. Built-up areas expanded to 9 per cent, reflecting a clear trend of urban growth, infrastructural development, and rising population density, particularly in and around Jammu city and its adjoining towns — indicative of a broader transition toward a more urban-oriented economy and lifestyle. The river-bed class expanded to 10 per cent of the district, representing active and seasonal river channels, floodplains, and dry riverbeds subject to seasonal variation and central to the district's hydrological system, while fallow land declined to 6 per cent, potentially reflecting soil degradation, land-use conversion, or temporary withdrawal from cultivation. Water bodies remained essentially unchanged at 1 per cent of the district area, continuing to reflect limited surface-water availability but persisting as a stable, if minor, resource for drinking water, irrigation, and ecosystem function.

COMPARATIVE ANALYSIS OF LULC, JAMMU DISTRICT (2011–2021)

To visualise the class-wise transformation of the district's landscape directly, individual thematic maps for each of the six LULC classes were prepared for both 2011 and 2021 and are presented side by side in Figures 5–10 below.

Figure 5

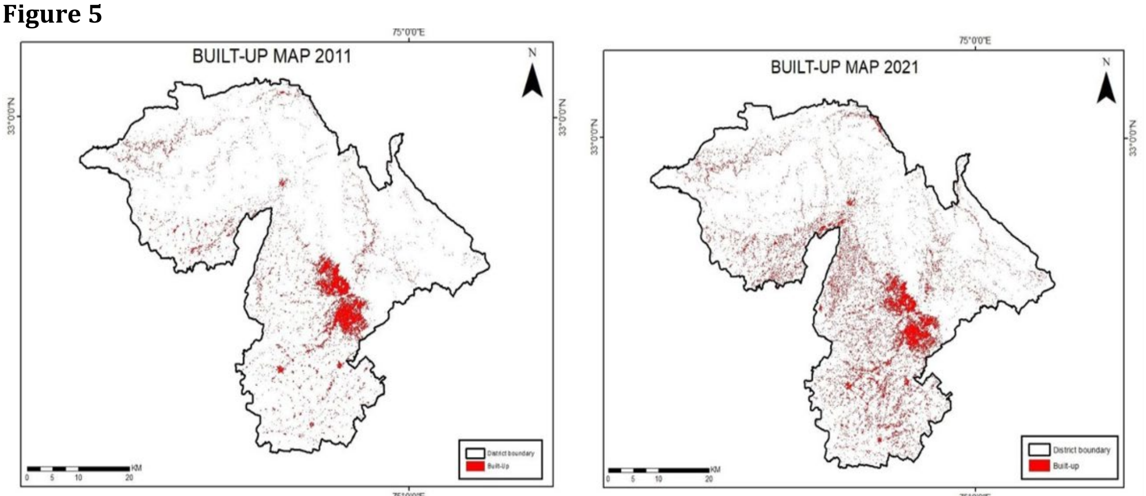

Figure 5 Built-up Area of Jammu District, 2011 (Left) and 2021 (Right)

Figure 5 makes visually explicit the concentrated, rapid densification of built-up land around Jammu city and Bari Brahmana between 2011 and 2021, with the built-up footprint nearly doubling in area over the decade and showing clear outward (peripheral) expansion along the main transport corridors radiating from the city.

Figure 6

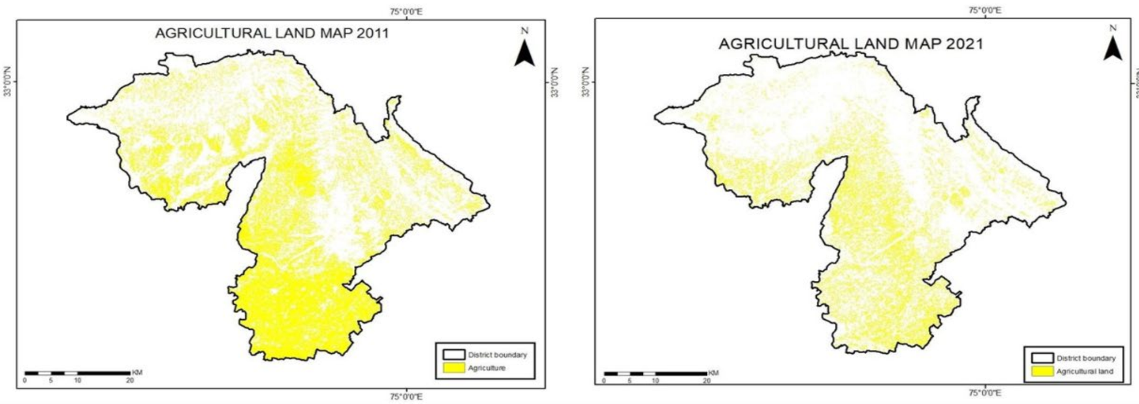

Figure 6 Agricultural Land of Jammu District, 2011 (Left) and 2021 (Right)

Figure 6 illustrates the marked contraction of agricultural land across the district, particularly in the southern plains around RS Pura and Bishnah, where cultivated land visibly gives way to a combination of urban encroachment and reclassified vegetation/fallow cover by 2021.

Figure 7

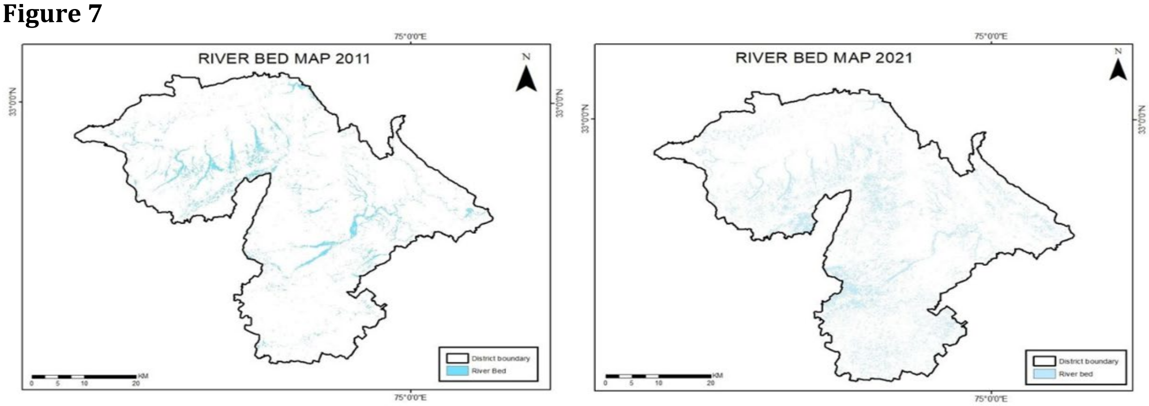

Figure 7 River-Bed Extent of Jammu District, 2011 (Left) and 2021 (Right)

Figure 7 shows a visible expansion of the mapped river-bed class along the Tawi and Chenab corridors, consistent with hydrological and channel-migration processes, seasonal flooding, and possibly with improved spectral separability of exposed riverbed sediment in the 2021 Landsat 8 imagery relative to the 2011 Landsat 7 scene.

Figure 8

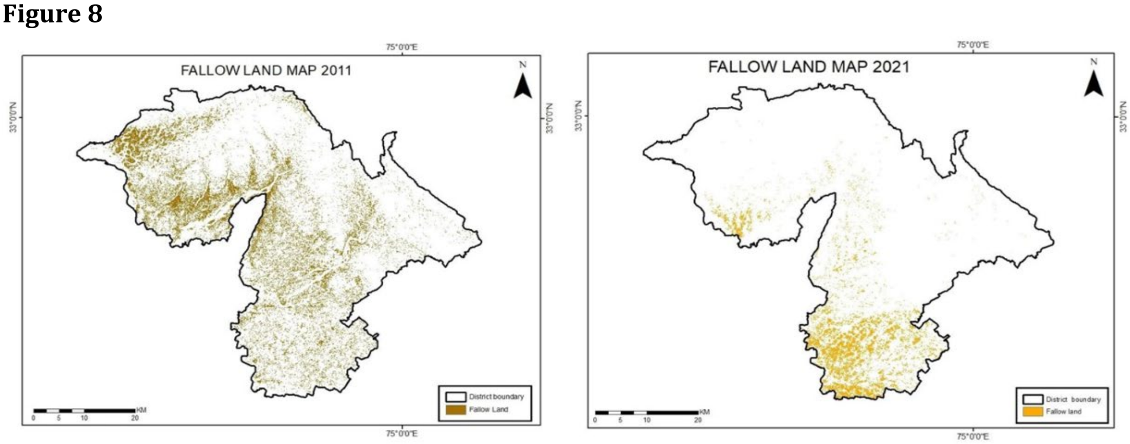

Figure 8 Fallow Land of Jammu District, 2011 (Left) and 2021 (Right)

Figure 8 shows a substantial reduction in fallow land, concentrated particularly in the northern and central parts of the district, consistent with either the reclassification of previously fallow tracts into vegetation cover or their conversion to built-up and agricultural use.

Figure 9

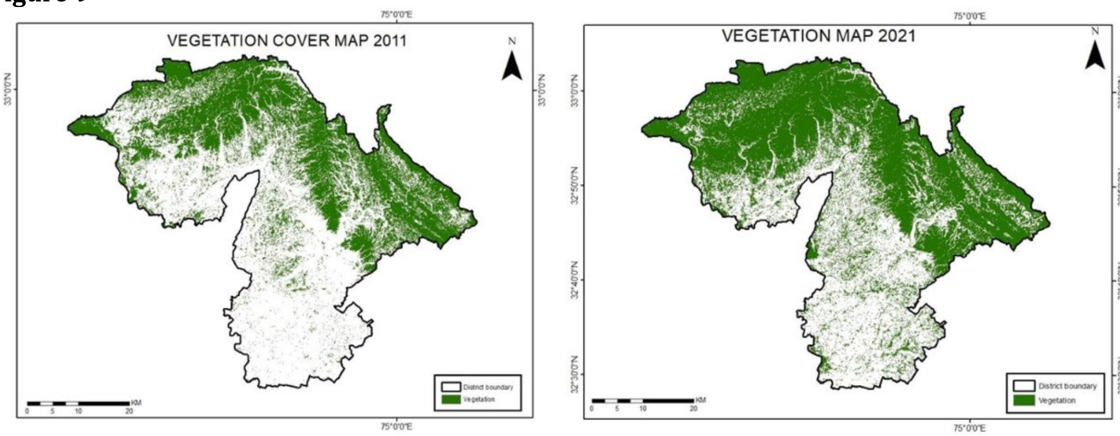

Figure 9 Vegetation Cover of Jammu District, 2011 (Left) and 2021 (Right)

Figure 9 documents the extensive densification and areal expansion of vegetation cover across the district, most pronounced in the central and northern hill tracts, and consistent with the dramatic rise in the vegetation class's district-wide share from 40 to 57 per cent.

Figure 10

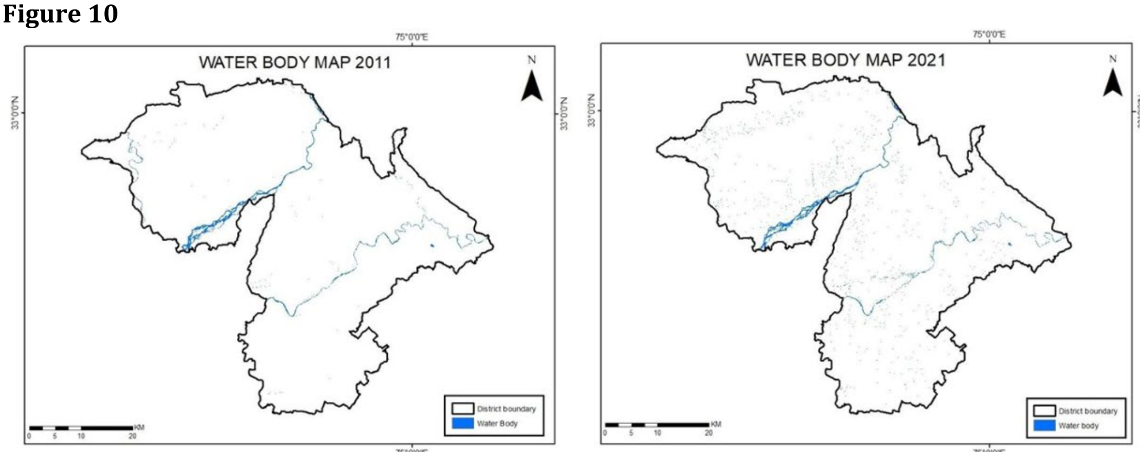

Figure 10 Water-Body Extent of Jammu District, 2011 (Left) and 2021 (Right)

Figure 10 shows the district's water bodies remaining spatially concentrated along the same principal river corridors in both years, consistent with the broadly stable 1 per cent district-wide share recorded for this class.

LULC CHANGE DETECTION, JAMMU DISTRICT (2011–2021)

The comparative analysis of Land Use and Land Cover in Jammu district between 2011 and 2021 reveals substantial transformation in the region's land dynamics, summarised quantitatively in Table 5 and Figure 11 below.

Table 5

Table 5 LULC Change-Detection Matrix, Jammu District, 2011–2021

LULC Class	2011 Area (sq. km)	2011 (%)	2021 Area (sq. km)	2021 (%)	Change (sq. km)	Change (%)
Vegetation	940.38	40	1,341.29	57	+400.91	+17
Agricultural Land	822.58	35	401.70	17	-420.88	-18

Built-up Area	121.38	5	217.36	9	+95.98	+4
Fallow Land	348.54	15	142.60	6	-205.94	-9
River Bed	98.25	4	224.51	10	+126.26	+6
Water Bodies	30.43	1	34.14	1	+3.71	~0

Figure 11

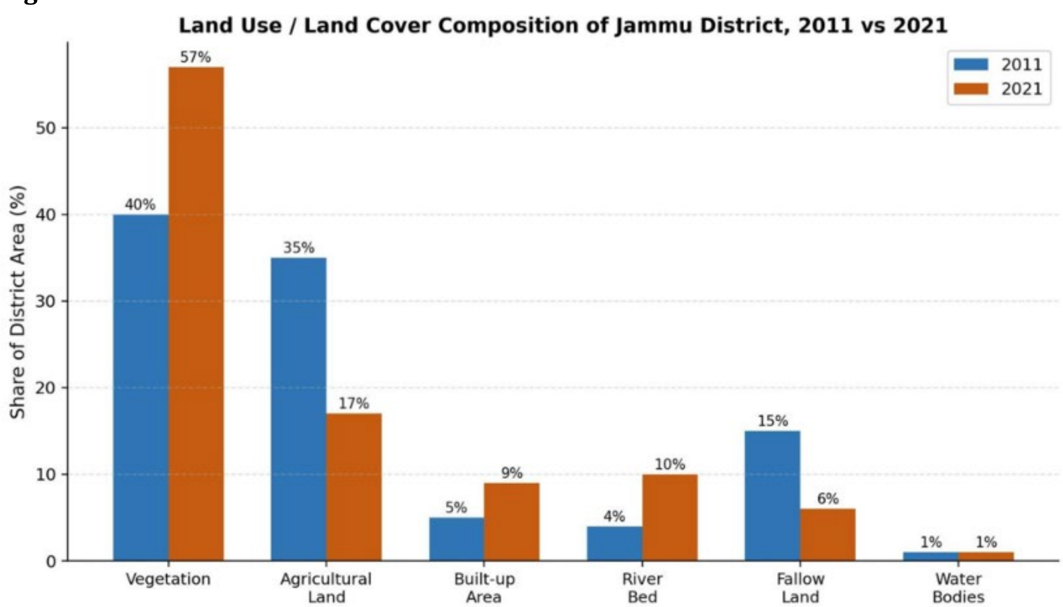

Figure 11 Comparative bar chart of LULC class shares, Jammu district, 2011 vs. 2021

Most notably, vegetation cover increased dramatically, from 940.38 km^2 (40 per cent) in 2011 to 1,341.29 km^2 (57 per cent) in 2021 — a net gain of 400.91 km^2, indicating a positive ecological shift possibly attributable to afforestation initiatives, natural vegetation regeneration, or the reclassification of marginal land. Conversely, agricultural land declined sharply, from 822.58 km^2 (35 per cent) to 401.70 km^2 (17 per cent) — a net loss of 420.88 km^2, suggesting a substantial reduction in agrarian activity that may reflect urban encroachment, changing rural livelihoods, land fragmentation, or declining soil productivity. Built-up area nearly doubled, rising from 121.38 km^2 (5 per cent) to 217.36 km^2 (9 per cent), a net gain of 95.98 km^2 reflecting rapid urbanisation, infrastructure development, and population pressure, particularly around Jammu city and its peripheral zones. Fallow land fell from 348.54 km^2 (15 per cent) to 142.60 km^2 (6 per cent), a net decline of 205.94 km^2, possibly indicating conversion to permanent vegetation cover or more intensive land utilisation. A notable and somewhat counter-intuitive shift is observed in the river-bed category, which expanded from 98.25 km^2 (4 per cent) to 224.51 km^2 (10 per cent) — a net gain of 126.26 km^2, potentially reflecting geomorphological change, sediment deposition, or hydrological alteration linked to climatic variability, though sensor-related differences between the Landsat 7 and Landsat 8 scenes cannot be entirely ruled out as a contributing factor (see Section 9, Discussion). Water bodies showed only a marginal increase, from 30.43 km^2 to 34.14 km^2, maintaining an essentially stable 1 per cent district-wide share throughout. Taken together, these changes depict a landscape transitioning from a predominantly agricultural and rural character toward one marked simultaneously by ecological regeneration and accelerating urbanisation — a duality that carries important implications for land-management policy, discussed further below.

DISCUSSION

The decade-scale LULC transformation documented for Jammu district — a near-doubling of built-up area concentrated tightly around Jammu city and its peripheral towns, set against a sharp contraction of agricultural land and a substantial expansion of vegetation cover — is consistent with, and extends, the wider literature on land-use dynamics in the Jammu and Kashmir Himalaya. Ganaie et al. (2014), examining cropping-pattern change across the erstwhile state of Jammu and Kashmir, found that net sown area increased far more sharply in Jammu district (19.73 per cent) than in the Kashmir valley districts of Srinagar, Budgam, and Pulwama during the period they examined — an early indication that Jammu district's land-use trajectory has long diverged from that of the valley. The present study suggests that this divergence has, over the subsequent decade, taken a further turn: rather than continued agricultural intensification, the 2011–2021 period is characterised instead by agricultural contraction, driven principally by urban expansion around the district's industrial-urban core. This pattern echoes findings from Alam et al. (2020) and Jamal et al. (2020) in the neighbouring Kashmir valley, both of whom documented simultaneous built-up expansion and agricultural/wetland decline over comparable multi-decadal windows, suggesting that this urbanisation-driven land-use transition is a broader feature of the Jammu and Kashmir Himalaya rather than a phenomenon unique to Jammu district.

This district-level urban–rural land-use divergence also resonates with a growing body of geospatial research on socio-economic and infrastructural disparity within Jammu Province more broadly. Babu, Sharma, and Tandup (2025), mapping the distribution of basic amenities across neighbouring Samba district using GPS-referenced geo-tagging and Euclidean buffer analysis in ArcGIS, found a pronounced core–periphery gradient in which police stations, health centres, banking infrastructure, and fire services cluster tightly along the National Highway corridor and around the Samba–Bari Brahmana industrial-urban node, while the northern hill tracts and southern border belt remain comparatively underserved. The built-up expansion documented in the present study — concentrated almost entirely around Jammu city and its immediate periphery rather than spreading evenly across the district — is consistent with precisely this kind of core-oriented development pattern, in which infrastructure, population, and economic activity concentrate along well-connected corridors even as more remote tracts change comparatively little. Sharma, Babu, and Tandup (2026a), applying a twelve-indicator composite social-inequality index across the seventeen tehsils of Doda district, likewise documented a durable core–periphery structure in which literacy, employment, and gender-balance outcomes are markedly better in accessible, lower-altitude tehsils such as Bhaderwah, Assar, and Gundna than in remote, high-altitude tehsils such as Phigsoo, Bhella, and Mohalla reinforcing the broader inference, consistent with the LULC pattern found here, that terrain and connectivity are fundamental structuring forces behind uneven land-use and development outcomes across the wider Jammu Himalaya.

The methodological approach adopted in this study multi-temporal Landsat classification and GIS-based change detection also parallels a wider programme of remote-sensing-based environmental monitoring being undertaken across Jammu Province. Sharma, Babu, and Tandup (2026b), using an analogous Landsat time-series and on-screen GIS digitisation methodology, documented a 38.5 per cent contraction in snow-covered area in neighbouring Kishtwar district between 2000 and 2025, attributed to rising winter temperatures, a shift from snow to rainfall at lower elevations, and land-use pressure in high-altitude catchments. Read together with the present findings, this suggests a wider pattern of environmental and land-cover transformation across the Jammu Himalaya — ranging from lowland urbanisation and agricultural contraction in Jammu district itself to high-altitude cryospheric retreat in Kishtwar that is increasingly amenable to systematic documentation through freely available Landsat archives and standard GIS classification and change-detection procedures of the kind applied here.

The observed expansion of vegetation cover from 40 to 57 per cent of the district merits particular scrutiny. While this could reflect genuine afforestation or natural regeneration consistent with state-level forestry and green-cover initiatives in Jammu and Kashmir over the study period it may also, in part, reflect the reclassification of formerly fallow or sparsely cultivated land into the vegetation class, particularly given the near-simultaneous, and numerically comparable, decline in fallow land (from 15 to 6 per cent). Some portion of the apparent gain in vegetation and in river-bed extent may also be attributable to differences in spectral and radiometric characteristics between the Landsat 7 ETM+ sensor used for the 2011 baseline and the Landsat 8 OLI/TIRS sensor used for 2021, a limitation common to two-date Landsat comparisons noted elsewhere in the literature (Acar & Zengin, 2023; Ghasempour et al., 2023). Nonetheless, the consistency of the overall direction of change vegetation gain, agricultural loss, and built-up expansion across independently classified imagery, and its agreement with comparable findings from Delhi NCR (Naikoo et al., 2020) and the Kashmir valley (Alam et al., 2020; Jamal et al., 2020), lends confidence to the substantive conclusion that Jammu district has undergone a genuine and significant land-use transformation over the study decade.

CONCLUSION AND POLICY RECOMMENDATIONS

The analysis of Land Use and Land Cover in Jammu district between 2011 and 2021 highlights substantial transformation in the district's land dynamics. Over the span of a decade, vegetation cover emerged as the dominant land category, increasing from 40 to 57 per cent of the total area, indicating a positive ecological shift likely driven by afforestation, natural regeneration, or improved land-conservation practice. This gain in green cover, however, coincides with a dramatic decline in agricultural land, which shrank from 35 to just 17 per cent — a reduction that raises legitimate concern for the sustainability of traditional livelihoods, food security, and rural land-use practice in the district. Simultaneously, built-up areas expanded considerably, from 5 to 9 per cent, highlighting rapid urbanisation and infrastructural growth, particularly around Jammu city and its adjoining towns, indicative of increasing population pressure, migration, and economic transition. Fallow land declined notably, from 15 to 6 per cent, suggesting either intensified land use or conversion into vegetation or built-up categories, while the river-bed class increased markedly, from 4 to 10 per cent, potentially reflecting hydrological shifts, seasonal flooding, or erosion-related processes. Water bodies remained relatively stable, maintaining a consistent 1 per cent share of the district's total area throughout.

This evolving land-use pattern underscores the need for integrated and sustainable land-management strategies in Jammu district. Policymakers and planners must address the dual challenge of accommodating continued urban growth while safeguarding ecological systems and supporting agricultural sustainability; careful monitoring, effective regulation, and long-term planning are essential to ensure balanced development and environmental resilience going forward. On this basis, the following recommendations are offered:

- **Planned and Regulated Urban Expansion:** Enforce strict zoning laws and adopt smart urban-planning practice to prevent haphazard growth and to protect agricultural and environmentally sensitive land.
- **Protection of Agricultural Land:** Introduce land-conservation policy, financial incentives for farmers, and modern farming techniques to prevent the large-scale conversion of farmland into urban settlement.
- **Green Infrastructure Development:** Promote afforestation, urban green belts, and rooftop gardens to mitigate deforestation, air pollution, and rising urban temperatures.
- **Sustainable Water Management:** Implement rainwater harvesting, groundwater-recharge projects, and wetland restoration to address declining water bodies and to secure water supply for both urban and rural populations.
- **Utilisation of Open Land for Productive Use:** Convert vacant open land into eco-friendly public spaces, community parks, urban forest, and sustainable housing to enhance land productivity and urban live ability.
- **Climate-Resilient Infrastructure:** Incorporate disaster-resistant construction, flood-management systems, and sustainable drainage networks to mitigate the risks associated with climate change and extreme weather events.
- **Eco-Friendly and Smart Urbanisation:** Encourage green building design, energy-efficient infrastructure, and sustainable public transport to reduce the carbon footprint of urban development.
- **Public Awareness and Community Participation:** Engage local communities, stakeholders, and environmental organisations to build awareness of sustainable land-use planning and resource conservation.
- **Balanced Land-Use Policy:** Develop an integrated land-use strategy that harmonises urban expansion, agricultural preservation, and ecological conservation while fostering continued economic development.
- **Technology-Driven Monitoring and Policy Implementation:** Utilise GIS-based mapping, remote sensing, and real-time monitoring systems to track ongoing land-cover change and to implement corrective measures in a timely and effective manner.

More broadly, this study demonstrates the value of a replicable, Landsat- and GIS-based classification and change-detection framework for diagnosing land-use transformation at the district scale a framework that, read alongside comparable recent work on service accessibility in Samba district (Babu, Sharma, & Tandup, 2025), social inequality in Doda district (Sharma, Babu, & Tandup, 2026a), and cryospheric change in Kishtwar district (Sharma, Babu, & Tandup, 2026b), points toward the value of a systematic, province-wide geospatial monitoring programme spanning the plains, foothills, and high mountains of the Jammu region alike.

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