Spatiotemporal dynamics of land use and land cover in Chitradurga taluk, Karnataka, India (2013–2021): a Landsat-based change-detection assessment

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Abstract:
Land use and land cover (LULC) change is a primary driver of regional hydrological alteration, biodiversity loss and food-security risk, yet the semi-arid plateau districts of peninsular India remain under-documented despite rapid agrarian and urban transition. This study quantifies LULC change in Chitradurga taluk, a drought-prone steppe district in central Karnataka, between 2013 and 2021. Cloud-free Landsat 8 OLI imagery for both epochs was classified into seven LULC categories—agriculture, barren land, built-up, fallow land, vegetation, water bodies and wetland—using a maximum-likelihood supervised classification, supported by unsupervised clustering and Google Earth reference data. Classification quality was evaluated against ground-reference points using a confusion-matrix approach. The classifications achieved overall accuracies of 80% (2013) and 84% (2021), with Cohen's kappa coefficients of 0.76 and 0.61, respectively. Post-classification comparison revealed pronounced redistribution of the landscape over the nine-year period: built-up area expanded more than threefold, from 117.66 km² (8.51%) to 390.76 km² (28.26%), while fallow land contracted from 702.72 km² (50.82%) to 380.95 km² (27.55%) and barren land declined from 96.06 km² to 8.72 km². Vegetation and agriculture increased moderately, whereas water bodies and wetlands remained near-constant. The transition matrix indicates that built-up expansion was supplied mainly by the conversion of fallow and vegetated land, signalling intensifying urbanisation and land-resource pressure. These findings provide a quantitative baseline to inform district-level land-use planning and watershed management under semi-arid conditions.

Keywords: land use and land cover; change detection; supervised classification; accuracy assessment; kappa coefficient; Landsat 8; semi-arid India.

1. Introduction

Land is a finite resource whose surface expression is reshaped continuously by human activity and natural process. Expanding populations and intensifying economic demand convert agricultural, vegetated and open land into settlements and infrastructure, altering the partitioning of water, soil and biological resources at regional scale (Lambin & Meyfroidt, 2011). Because changes in land use modify evapotranspiration, groundwater recharge and surface runoff, LULC dynamics are now treated as a central diagnostic of environmental change and a foundation for natural-resource governance (Foley et al., 2005).

The terms land use and land cover describe related but distinct properties of the Earth's surface. Land cover denotes the biophysical material present—vegetation, water, soil and built material—whereas land use denotes the human purpose to which that cover is put. Distinguishing the two, and tracking how each evolves, requires accurate and repeatable observation. Satellite remote sensing provides the synoptic, multi-temporal and multispectral record needed for this task, and digital image classification translates that record into thematic LULC maps in which every pixel is assigned to a defined category (Anderson et al., 1976; Congalton & Green, 2019).

Change detection—the comparison of co-registered images of the same area acquired at different dates—converts these maps into a quantitative account of landscape transformation (Singh, 1989). Post-classification comparison is widely adopted because it identifies not only where change occurred but the specific nature of each transition, yielding a "from–to" change matrix (Lu et al., 2004). Recent applications across South Asia and Africa confirm that Landsat-based supervised classification reliably resolves multi-decadal LULC trajectories at district scale (Hassan et al., 2016; Hishe et al., 2024).

Despite this maturity, the semi-arid plateau districts of interior peninsular India remain comparatively under-studied, even though they face acute and competing pressures: recurrent drought, groundwater depletion, agrarian distress and rapid peri-urban growth. Chitradurga taluk in central Karnataka exemplifies this setting. A district-scale, quantitative baseline of its land-cover trajectory is needed to support evidence-based land and water planning, yet none has been reported for the most recent decade of accelerated change.

This study addresses that gap. Its objectives are threefold: (i) to map LULC in Chitradurga taluk for 2013 and 2021 from Landsat 8 imagery using complementary unsupervised and supervised classification; (ii) to evaluate classification reliability through overall, user's and producer's accuracy and the kappa coefficient; and (iii) to quantify the magnitude, direction and class-to-class pathways of LULC change over the period. Establishing where and how the landscape is being reconfigured is a prerequisite for targeting interventions that sustain agricultural land and scarce water resources in this drought-prone region.

2. Materials and Methods

2.1 Study area

Chitradurga taluk is the administrative headquarters of Chitradurga district, situated in the Vedavati (Hagari) river valley of central Karnataka, southern India, near 14.225°N, 76.398°E (Figure 1). The terrain is an undulating plateau with a mean elevation of about 732 m above sea level. The climate is semi-arid (steppe), with a mean annual temperature near 25.3°C and low mean annual rainfall of approximately 576 mm, which constrains rain-fed agriculture and groundwater recharge. At the 2011 Census the urban population was about 125,000, with a literacy rate of 76%. The taluk analysed here covers approximately 1,383 km². Its combination of chronic water scarcity, predominantly agrarian land use and expanding settlement makes it a representative test case for semi-arid LULC monitoring.

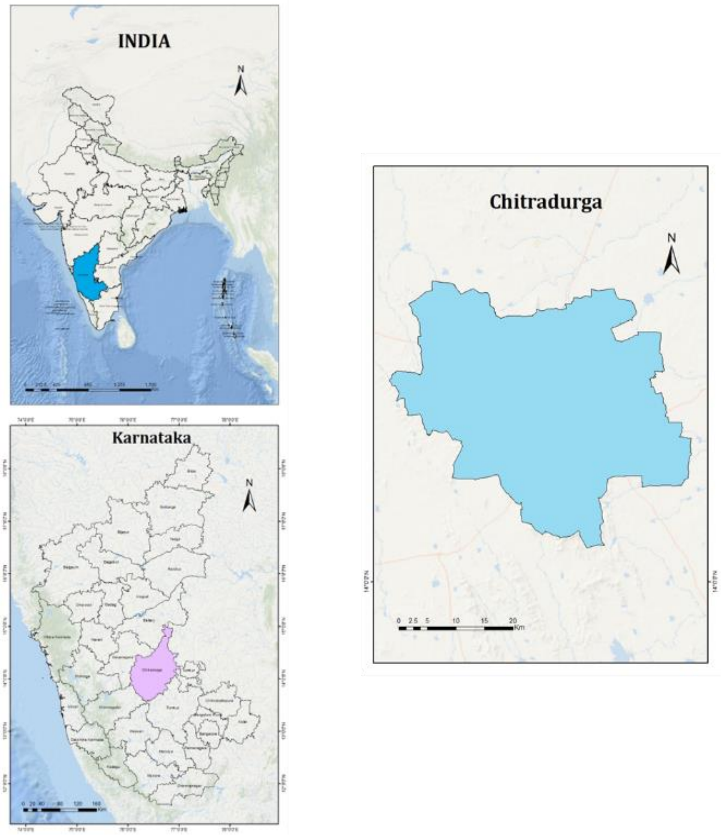

Figure 1. Location of the study area: Chitradurga taluk within Karnataka and India.

2.2 Data and pre-processing

Two cloud-free Landsat 8 OLI scenes, one per epoch (2013 and 2021), were obtained from the USGS EarthExplorer portal at 30 m spatial resolution (Table 1). Scenes were selected from the same dry-season window to minimise phenological and atmospheric differences between epochs. Standard pre-processing—layer stacking, radiometric and atmospheric correction, and sub-setting to the taluk boundary—was performed prior to classification.

Table 1. Satellite data used in the study.

Sensor	Acquisition year	Spatial resolution	Source
Landsat 8 OLI	2013	30 m	USGS EarthExplorer
Landsat 8 OLI	2021	30 m	USGS EarthExplorer

2.3 Image classification

Image classification assigns each pixel to a land-cover category by grouping pixels with similar spectral response. Both unsupervised and supervised approaches were applied (Figure 2). For the unsupervised step, ISODATA and K-means clustering were used to identify natural spectral groupings in the multi-date imagery and to inform class definition. For the supervised step, training signatures were collected for each target class in ERDAS Imagine, using high-resolution Google Earth imagery as ancillary reference, and a maximum-likelihood classifier was applied. Seven classes were mapped: agriculture, barren land, built-up, fallow land, vegetation, water bodies and wetland.

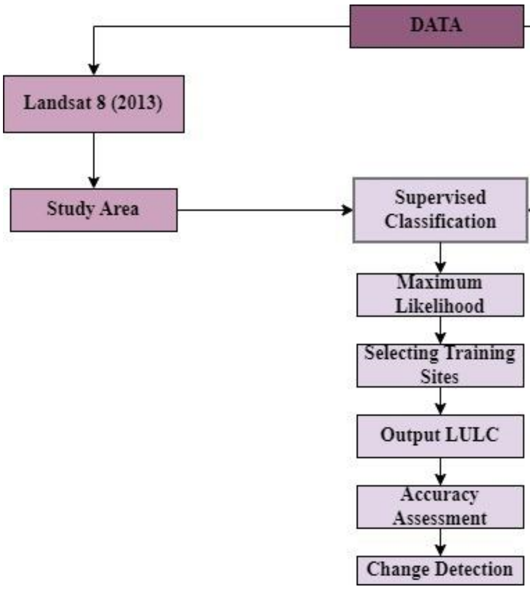

Figure 2. Methodological workflow for LULC classification and change detection

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2.4 Accuracy assessment

Accuracy assessment is a universal requirement in thematic mapping because it quantifies how closely a classification reproduces ground conditions and allows objective comparison among methods and analysts (Congalton, 1991). For each epoch, the classified map was compared against reference points using an error (confusion) matrix, from which overall accuracy, user's accuracy (commission error) and producer's accuracy (omission error) were derived. Overall agreement beyond chance was summarised with Cohen's kappa coefficient (Cohen, 1960).

2.5 Change detection

After accuracy assessment, the two classified maps were compared cell-by-cell using post-classification change detection. This produced a "from–to" transition matrix recording the area converted between every pair of classes, together with per-class area statistics for each epoch, enabling the magnitude and direction of change to be quantified.

3. Results

3.1 Classification accuracy

The 2013 classification achieved an overall accuracy of 80% and a kappa coefficient of 0.76 (Table 2); the 2021 classification achieved an overall accuracy of 84% and a kappa coefficient of 0.61 (Table 3). Water bodies, barren land and wetland were classified with the highest reliability in both epochs, whereas the agriculture–fallow–built-up group showed greater confusion, reflecting their spectral similarity in a semi-arid landscape. These accuracy levels are consistent with the operational standard expected of Landsat-based LULC mapping and support the change analysis that follows.

Table 2. Confusion matrix for the 2013 classification (overall accuracy 80%; kappa 0.76).

	WB	**Veg**	**Agr**	**FL**	**BU**	**BL**	**WL**	**Total**	**UA (%)**	**PA (%)**
Waterbody	2	0	0	0	0	0	0	2	100	100
Vegetation	0	4	1	1	0	0	0	6	66.7	80
Agriculture	0	0	3	0	0	0	0	3	100	60
Fallow land	0	1	0	4	0	0	0	5	80	66.7

	WB	Veg	Agr	FL	BU	BL	WL	Total	UA (%)	PA (%)
Built-up	0	0	1	1	3	0	0	5	60	100
Barren land	0	0	0	0	0	3	0	3	100	100
Wetland	0	0	0	0	0	0	1	1	100	100
Total	2	5	5	6	3	3	1	25		

Table 3. Confusion matrix for the 2021 classification (overall accuracy 84%; kappa 0.61).

	WB	Veg	Agr	FL	BU	BL	WL	Total	UA (%)	PA (%)
Waterbody	4	0	0	0	0	0	0	4	100	100
Vegetation	0	5	1	0	0	0	0	6	83.3	100
Agriculture	0	0	1	0	1	0	0	2	50	50
Fallow land	0	0	0	3	0	0	0	3	66.7	60
Built-up	0	0	0	2	4	0	0	6	66.7	80
Barren land	0	0	0	0	0	2	0	2	100	100
Wetland	0	0	0	0	0	0	2	2	100	100
Total	4	5	2	5	5	2	2	25		

3.2 LULC distribution in 2013 and 2021

The classified maps for the two epochs are shown in Figures 3 and 4, and the corresponding area statistics in Table 4. In 2013 the landscape was dominated by fallow land (702.72 km²; 50.82%), followed by vegetation (413.44 km²; 29.90%) and built-up land (117.66 km²; 8.51%). By 2021 the dominant class was vegetation (494.13 km²; 35.74%), followed closely by built-up land (390.76 km²; 28.26%) and fallow land (380.95 km²; 27.55%). Water bodies and wetland occupied less than 0.5% of the taluk in both epochs.

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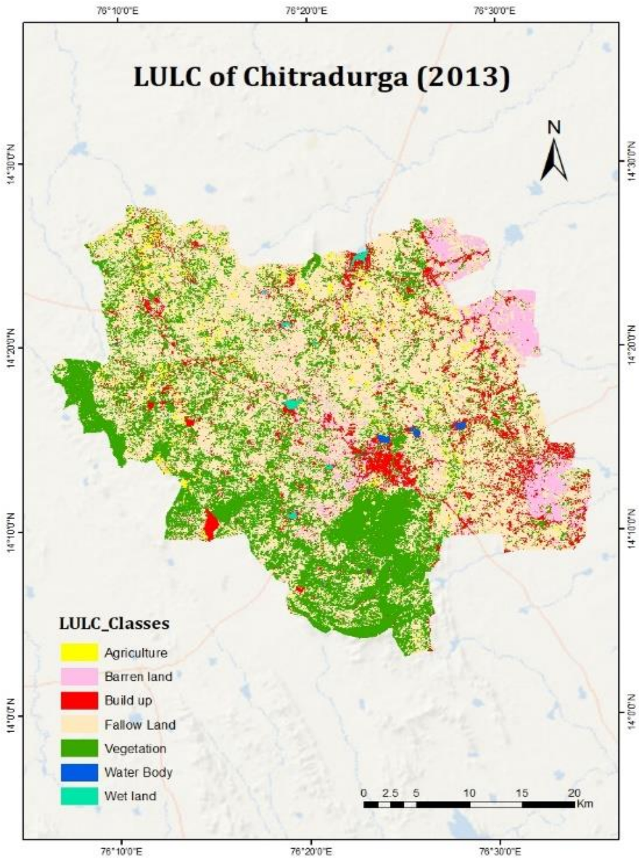

Figure 3. LULC map of Chitradurga taluk, 2013.

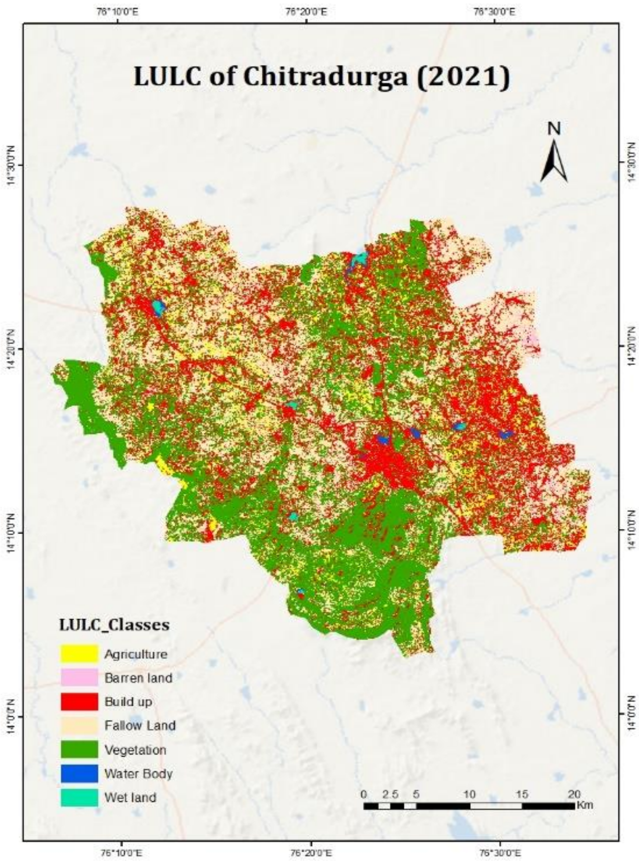

Figure 4. LULC map of Chitradurga taluk, 2021.

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Table 4. LULC area statistics for 2013 and 2021.

LULC class	2013 area (km²)	2013 (%)	2021 area (km²)	2021 (%)
Agriculture	46.12	3.34	99.77	7.22
Barren land	96.06	6.95	8.72	0.63
Built-up	117.66	8.51	390.76	28.26
Fallow land	702.72	50.82	380.95	27.55
Vegetation	413.44	29.90	494.13	35.74
Water body	2.30	0.17	4.17	0.30
Wetland	4.35	0.31	4.14	0.30
Total	1382.65	100.00	1382.65	100.00

3.3 Change detection, 2013–2021

Post-classification comparison reveals substantial landscape reorganisation over the nine-year period (Figure 5; Table 5). Built-up land was the most dynamic class, expanding by roughly 273 km² to occupy more than a quarter of the taluk by 2021. This expansion was supplied principally by fallow land (about 200 km² converted to built-up) and vegetation (about 81 km²), with smaller contributions from barren and agricultural land. Concurrently, barren land was largely reclaimed, with about 57 km² transitioning to fallow land and 24 km² to built-up. Table 5 reports the area of each class-to-class transition; the diagonal entries (persistence) and the largest off-diagonal flows together summarise the dominant pathways of change.

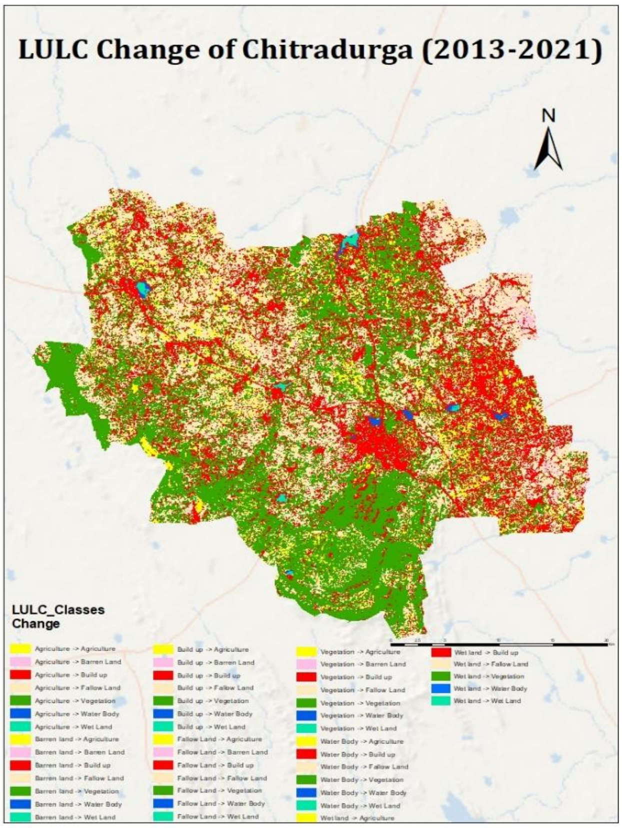

Figure 5. Spatial distribution of LULC transitions in Chitradurga taluk, 2013–2021.

Table 5. LULC transition matrix, 2013–2021 (area in km²). Rows = 2013 class; columns = 2021 class.

2013 \ 2021	Agr	Barren	Built-up	Fallow	Veg	Water	Wetland
Agriculture	9.91	0.12	11.84	14.37	9.80	0.05	0.03
Barren land	2.67	6.40	24.26	56.78	5.79	0.08	0.02
Built-up	6.97	0.34	72.05	15.06	20.47	1.78	0.96
Fallow land	59.03	1.69	199.52	249.74	191.68	0.33	0.49
Vegetation	20.91	0.18	81.00	44.82	266.22	0.10	0.12
Water body	0.17	0.00	0.24	0.01	0.02	1.56	0.31
Wetland	0.09	0.00	1.76	0.01	0.01	0.26	2.22

4. Discussion

The results show that Chitradurga taluk underwent rapid and directional land transformation between 2013 and 2021, dominated by built-up expansion at the expense of fallow and open land. Each class trajectory carries a distinct interpretation, summarised below.

Agriculture. Cultivated land—supporting rice, jowar, ragi, groundnut, Bengal gram, horticulture and plantation crops—more than doubled, from 46.12 km² in 2013 to 99.77 km² in 2021. At the same time about 14 km² of land mapped as agriculture in 2013 reverted to fallow, indicating that cropping in this semi-arid setting remains sensitive to water availability and is spatially mobile rather than fixed.

Barren and fallow land. Barren land contracted sharply, from 96.06 km² to 8.72 km², as roughly 57 km² was converted to fallow and 24 km² to built-up. Fallow land, the dominant class in 2013, also declined—from 702.72 km² to 380.95 km²—as large areas were absorbed into built-up and vegetated cover. Together these shifts indicate that previously idle land is being actively brought into settlement and productive use.

Built-up land. The most consequential change was the more-than-threefold growth of built-up area, from 117.66 km² to 390.76 km². This pattern is consistent with population growth, expanding road networks, urbanisation and employment opportunities that draw residents from villages toward the taluk's urban core, and it represents a permanent, low-reversibility conversion of land.

Vegetation, water and wetland. Vegetation increased from 413.44 km² to 494.13 km², while water bodies rose modestly from 2.30 km² to 4.17 km², plausibly reflecting improved water-harvesting and irrigation infrastructure. Wetland area was effectively stable (4.35 km² to 4.14 km²). Because wetlands and tanks are critical habitat—particularly for migratory birds—their persistence is encouraging, but their small extent leaves them vulnerable to the built-up expansion documented here.

Comparison and implications. The accuracy and kappa values obtained here fall within the range reported for recent Landsat-based district studies in comparable settings (Hishe et al., 2024; Hassan et al., 2016), supporting the reliability of the trajectory. The dominant signal—extensive conversion of fallow and barren land to built-up cover—mirrors urbanisation trends documented across semi-arid South Asia and underscores a tightening competition between settlement growth and the land and water base of agriculture. For district planners, the priority implication is the protection of remaining wetlands and the strategic siting of new settlement to limit further loss of cultivable and recharge land.

Limitations. The 30 m resolution of Landsat 8 limits the separation of spectrally similar classes, most notably the agriculture–fallow–built-up group, which explains the residual confusion in the error matrices and the lower 2021 kappa. Single-date imagery per epoch cannot capture intra-annual cropping cycles, and the reference sample for accuracy assessment was modest. Future work should incorporate multi-season composites, higher-resolution or fused sensors (e.g., Sentinel-2), machine-learning classifiers such as random forest, and a larger probabilistically drawn validation sample to strengthen both classification accuracy and the change estimate.

5. Conclusion

This study quantified LULC change in the semi-arid Chitradurga taluk of Karnataka between 2013 and 2021 using Landsat 8 imagery, complementary unsupervised and supervised classification, and post-classification change detection. The classifications were reliable (overall accuracy 80% and 84%; kappa 0.76 and 0.61), and revealed substantial nine-year transformation: built-up area expanded more than threefold while barren and fallow land contracted, and vegetation, agriculture and water bodies increased moderately. The transition matrix shows that built-up growth was supplied chiefly by fallow and vegetated land, signalling intensifying land-resource pressure. The resulting baseline provides district administrators and watershed managers with the quantitative evidence needed to safeguard cultivable land, protect scarce wetlands and guide sustainable land-use planning. Extending the analysis with multi-temporal, higher-resolution data and predictive (e.g., CA–Markov) modelling would enable anticipation of future change and proactive intervention.

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