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Assessment of landuse/landcover change analysis in the lower Kumaon region of the Uttarakhand Himalayas

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Abstract
This study investigates landuse and landcover changes in the lower Kumaon region which consists of Nainital, Champawat and Udham Singh Nagar district of the Kumaon Himalayas. Utilizing remote sensing and GIS techniques, the present work assesses the transformation of land patterns over a specified time frame of 2010 and 2020. By analyzing Landsat satellite imagery, the study aims to discern the extent and nature of land use alterations, identifying key drivers and implications for environmental management and sustainability. Through comprehensive spatial analysis and statistical methods, the research seeks to provide valuable insights into the dynamics of landuse change, facilitating planning and decision-making for regional development and conservation endeavors. The outcomes of the study contribute to a deeper understanding of the complex interactions between human activities and natural landscapes in the Himalayan region, offering valuable knowledge for policymakers, planners and environmental stakeholders striving to balance developmental needs with ecological preservation.

Keywords: Landuse, landcover, lower Kumaon region, Kumaon Himalayas, Uttarakhand

1. Introduction

Land utilization undergoes continuous change, its significance and arrangement shifting with time and differing across geographical regions, dependent on diverse efficiencies, capacities, priorities, and needs (Bisht & Tiwari, 1996) [2]. Due to recurrent natural phenomena and human interventions, the utilization and coverage of land represent a perpetually evolving aspect of the Earth's landscape. Throughout recent centuries, there have been significant alterations in Landuse and landcover (LULC) patterns (Ometto *et al*., 2016) [11]. The configuration of land utilization within a region closely reflects the extent of technological advancement, economic prosperity and societal sophistication among its inhabitants (Sharma, 2017) [14]. The predominant manner in which humans have impacted landuse is through the conversion and alteration of natural ecosystems for agricultural purposes (Ramankutty & Foley, 1999) [12]. Human activities' environmental repercussions have been longstanding; Marsh (1864) noted numerous instances of detrimental human actions altering the planet's landscape. In recent years, various beneficial concepts, strategies, tools and methods have emerged to mitigate the effects of LULC changes. Scientific landuse planning and management strategies, as suggested by Saxena *et al*., 2024 [13], may present a sustainable development option for regions facing pressure from growing populations and increasing demand for land resources. Monitoring changes in landuse/landcover necessitates the utilization of current and historical remotely sensed data, capable of capturing alterations induced by both natural processes and human interventions (Dhorde *et al*., 2012) [3]. Understanding the spatial distribution and temporal changes in landuse patterns is essential for formulating effective development plans (Tiwari *et al*., 2021) [16], with Remote Sensing and GIS emerging as indispensable tools for mapping and monitoring LULC (Singh *et al*., 2022, Kumar *et al*., 2022) [15, 6]. Multispectral and multi-temporal remote sensing data, coupled with GIS, facilitate accurate landuse classification and change detection, aiding in informed decision-making processes.

Numerous studies conducted in various regions, including the Himalayas, have utilized satellite data and aerial photo interpretation techniques for assessing LULC changes (Munsi *et al*., 2010; Batar & Kumar, 2017; Ullah *et al*., 2019; Kumar *et al*., 2019; Mishra & Rai, 2020; Negi & Irfan, 2022) [9, 1, 17, 4, 8, 10].

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Remote Sensing and GIS have consistently emerged as effective tools for such endeavors (Kumar *et al*., 2021; Kumar *et al*., 2022) [5, 6]. The lower Kumaon region, situated amidst the majestic Himalayas, boasts unparalleled natural beauty and cultural richness. However, beneath its scenic allure lies a complex interplay of human-environment interactions shaped by centuries of tradition, colonial legacy, and contemporary development pressures. The dynamics of LU/LC in this region exemplify the broader environmental challenges confronting mountainous areas, where the delicate balance between conservation and development is often precarious. In light of these challenges, this study aims to investigate the intricacies of landuse/landcover change in the lower Kumaon region, elucidating the driving forces, spatial patterns, and environmental implications of such transformations. Employing a multidisciplinary approach integrating remote sensing, GIS, and statistical analysis, this research endeavors to enhance understanding of the complex relationship between human activities and natural systems in the Himalayan context. Additionally, this study seeks to provide valuable insights for policymakers, planners and local communities grappling with the dual imperatives of conservation and development in the lower Kumaon region and beyond.

2. Data and Methods

In the present study, Landsat Multispectral satellite imagery of 2010 and 2020 attained from the USGS Porta, forms the foundation of analysis. This imagery boasts a spatial resolution of 30 meters, providing a detailed view of the study area. To ensure accuracy, the imagery underwent radiometric correction using ERDAS Imagine 2014 software and was geometrically rectified via ground control points (GCP), subsequently projected to the UTM projection with the WGS 84 datum. Then, the creation of a False Colour composition (FCC) was achieved by blending blue, green, red and infrared bands through layer stacking and mosaicking tools within the ERDAS Imagine software (Figure 1). This process not only facilitated Ortho-rectification of the satellite images but also enhanced their visual clarity for analysis purposes. The detailed methodological framework employed for the preparation of landuse/landcover within the study area is depicted in Figure 1, providing a clear roadmap for the analysis undertaken. Landuse/landcover classification for the study area has been done by supervised image classification method through training sites in GIS software. Thereafter, the Global Positioning System (GPS) and Google Earth Pro were also taken into account for ground truthing and verification.

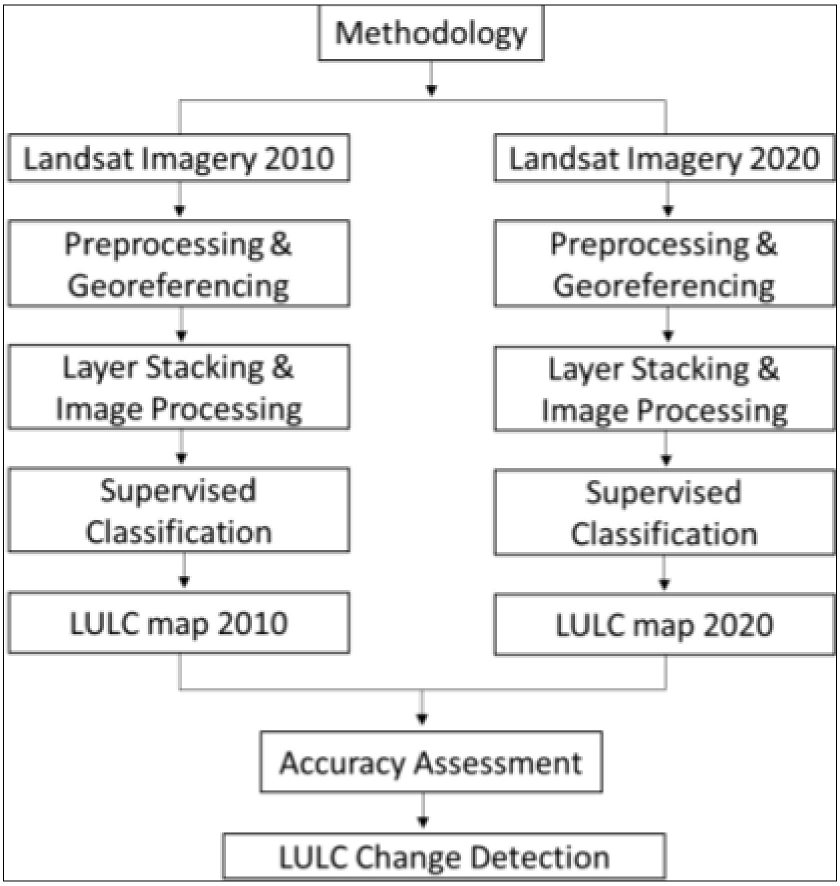

Fig 1: Methodological framework and process of data preparation for landuse/landcover (2010 & 2020)

3. Study Area

The study area lies between 28º30' N and 29º30' N latitudes to 79º10' E and 80º20' E longitudes and encompasses an area of 10211.5 Km^2 (Figure 2). It nestled within the awe-inspiring expanse of the Himalayas, is a land of profound natural beauty and cultural heritage. Located in the northern part of India, the lower Kumaon region comprises a mosaic of landscapes, from verdant valleys to snow-capped peaks, making it a haven for biodiversity and a sanctuary for spiritual seekers and adventurers alike.

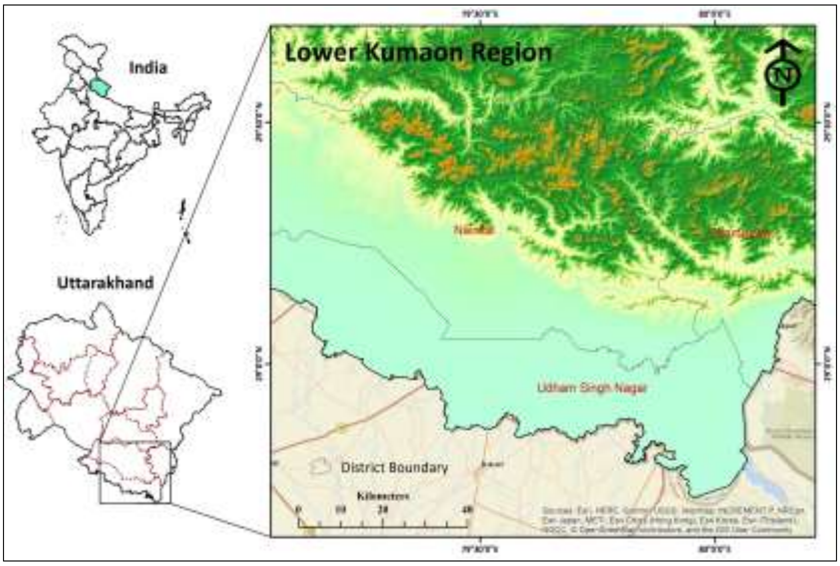

Fig 2: Showcases the location of the study area

4. Results and Discussion

4.1 Landuse/Landcover Classification

Landuse/landcover (LULC) classification is a vital tool for understanding the distribution and utilization of land resources within a given area. Based on the supervised classification, the area of interest (AOI) is classified into six major LULC categories namely forest land, agricultural/cropland, waterbodies, built-up land, scrubland and wasteland (Figure 3). In 2010, the agricultural land accounted for 38.28% (3923.36 km^2) of the total area, indicating significant utilization for farming and cultivation purposes. Forest land, comprising 47.61% (4878.82 km^2) of the area, represents substantial forest cover, highlighting the importance of preserving natural ecosystems. Other categories such as Built-up land, Scrubland, Waterbodies and wasteland contribute 6.76% (693.01km^2), 4.15% (425.62 km^2), 1.79% (183.29 km^2) and 1.41% (144.20 km^2) to the overall landscape diversity and play crucial roles in ecological processes and human activities (Table 1).

In 2020, the area covered by different LULC types exhibited distinct proportions. Agricultural land occupied 28.68% (2939.55 km^2) of the total area, emphasizing the significance of agriculture in the region's economy. wasteland, comprising 3.84% (393.43 km^2), represents areas devoid of vegetation and human settlement. Buildup land, constituting 9.16% (939.05 km^2), denotes urban and built-up areas, indicating human habitation and infrastructure development. Forest land, covering a significant 51.74% (5302.09 km^2), underscores the importance of preserving natural ecosystems and biodiversity. Scrub land, comprising 4.76% (488.31 km^2), typically indicates areas with sparse, low-lying vegetation and waterbodies, encompassing 1.81% (185.87 km^2), highlighting the presence of lakes, rivers and other aquatic environments.

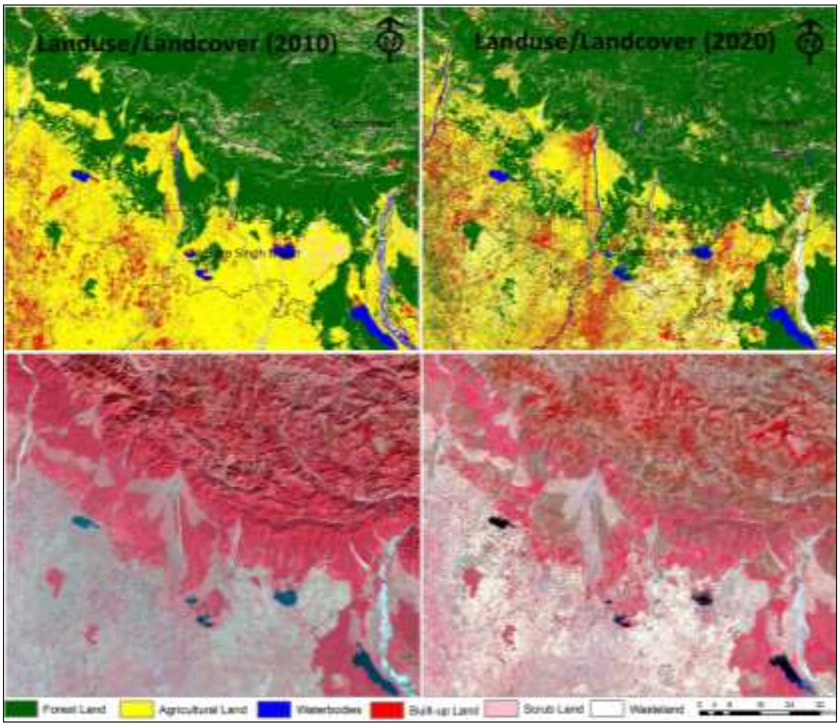

Fig 3: Illustrating the landuse/landcover in the lower Kumaon region of the Uttarakhand Himalayas over a period of one decade from 2010 to 2020

Table 1: Illustrating the landuse/landcover dynamics using a supervised classification technique and LULC change over a decade from 2010 to 2020

S. No.	LULC Type	2010		2020		Change (km^2)
		Area	%	Area	%	
1.	Agricultural Land	3923.36	38.28	2939.55	28.68	983.81^-
2.	Wasteland Land	144.20	1.41	393.43	3.84	249.23^+
3.	Buildup-Land	693.01	6.76	939.05	9.16	246.04^+
4.	Forest Land	4878.82	47.61	5302.09	51.74	423.27^+
5.	Scrub Land	425.62	4.15	488.31	4.76	62.69^+
6.	Waterbodies	183.29	1.79	185.87	1.81	2.58^+
	Total	10248.30		10248.30		

Note: (-): negative change & (+): positive change

4.2 Landuse/landcover Change

The results of the LULC) dynamics using a supervised classification technique reveal significant changes between 2010 and 2020 across various categories. In 2010, agricultural land dominated the landscape, covering 38.28% of the total area, amounting to 3923.36 km^2. However, over the decade, this area decreased substantially by 983.81 km^2 (-), representing a shift towards other landuse categories. Conversely, barren land witnessed a notable increase (+) from 1.41% in 2010 to 3.84% in 2020, with a change of 249.23 km^2 (Figure 4). The buildup land category also experienced a substantial rise (+) from 6.76% to 9.16%, equating to a positive change of 246.04 km^2. Forest land, despite being the dominant category in both years, exhibited a modest increase (+) from 47.61% to 51.74%, with a change of 423.27 km^2. Scrubland and water bodies also experienced slight increments (+), with changes of 62.69 km^2 and 2.58 km^2, respectively (Figure 4). These changes illustrate a complex interplay of urbanization, agricultural practices and environmental dynamics over the past decade, indicating shifts in landuse patterns and highlighting the need for sustainable land management policies to address emerging challenges.

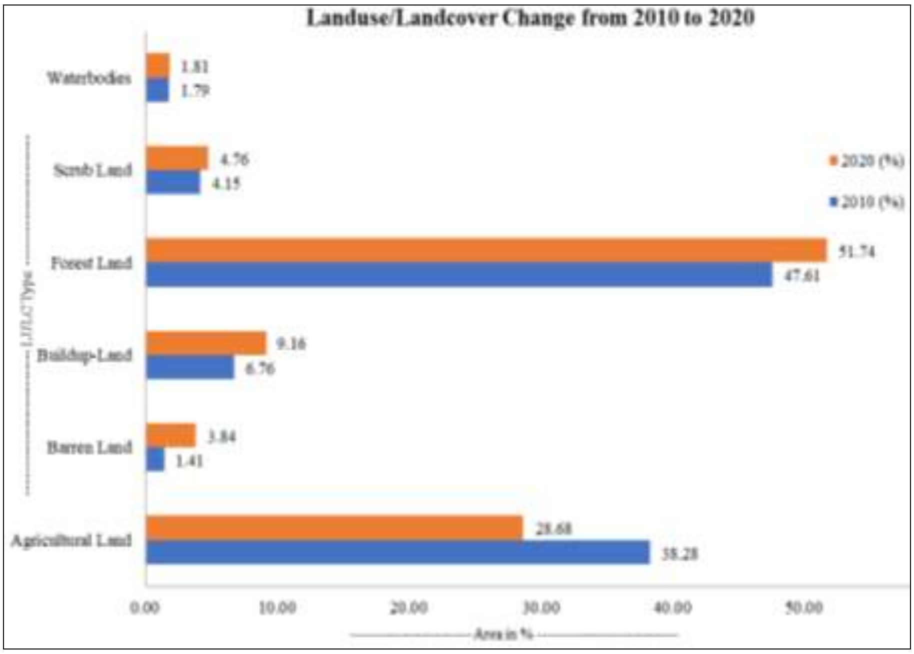

Fig 4: Landuse/landcover change analysis using Landsat 8 data of 2010 and 2020

4.2 Accuracy assessment of classified landuse/landcover

The evaluation of the precision of classified LULC is a crucial stage in assessing the reliability of LULC data and remotely sensed datasets. This process involves comparing the outcomes of classification with reference data obtained from field surveys or other dependable sources, offering quantitative evaluations of classification accuracy and facilitating result interpretation. Geographical Information System (GIS) software presents a variety of tools and workflows for conducting accuracy assessments of LULC classifications, including the Confusion Matrix tool and the Classification Evaluation tool. These resources streamline the accuracy assessment process, delivering more precise evaluations of LULC trends and alterations over time.

The accuracy assessment of LULC within the designated study area was carried out using ArcGIS 10.8, involving several sequential steps. Firstly, reference data were gathered, representing samples of the LULC classes under scrutiny, acquired through field surveys or from existing sources such as satellite imagery and Google Earth Pro. Subsequently, a confusion matrix was generated in ArcGIS by juxtaposing the reference data against the classified map. This matrix depicted true positives (Accurately classified pixels), false positives, false negatives and the overall accuracy (OA) of the classified imagery. Following this, various accuracy statistics were computed based on the confusion matrix, encompassing overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA) and kappa coefficient. The PA gauges the classifier's ability to correctly identify a specific land use/land cover class, whereas the UA measures the precision of the classification system in identifying target classes. Overall accuracy (OA) denotes the frequency with which the LULC classification model accurately classified different LULC types within the region, while the kappa coefficient quantifies the agreement between observed and expected class. Refinement of the classification may be necessary to rectify inaccuracies, achieved through adjustments to classification parameters or the acquisition of additional reference data. Finally, the validation of results is essential, either through comparison with additional reference data or through statistical analyses of accuracy measures, ensuring the reliability and robustness of the accuracy assessment process.

$$UA = \frac{\text{No. of accurately classified pixels in each class}}{\text{Total no. of classified pixels in that class (Row total)}} * 100$$

$$PA = \frac{\text{No. of correctly classified pixels in each class}}{\text{Total no. of classified pixels in that class (Column total)}} * 100$$

$$\text{Overall Accuracy (OA)} = \frac{\text{Total no. of correctly classified pixels (Diagonals)}}{\text{Total no. of reference pixels}} * 100$$

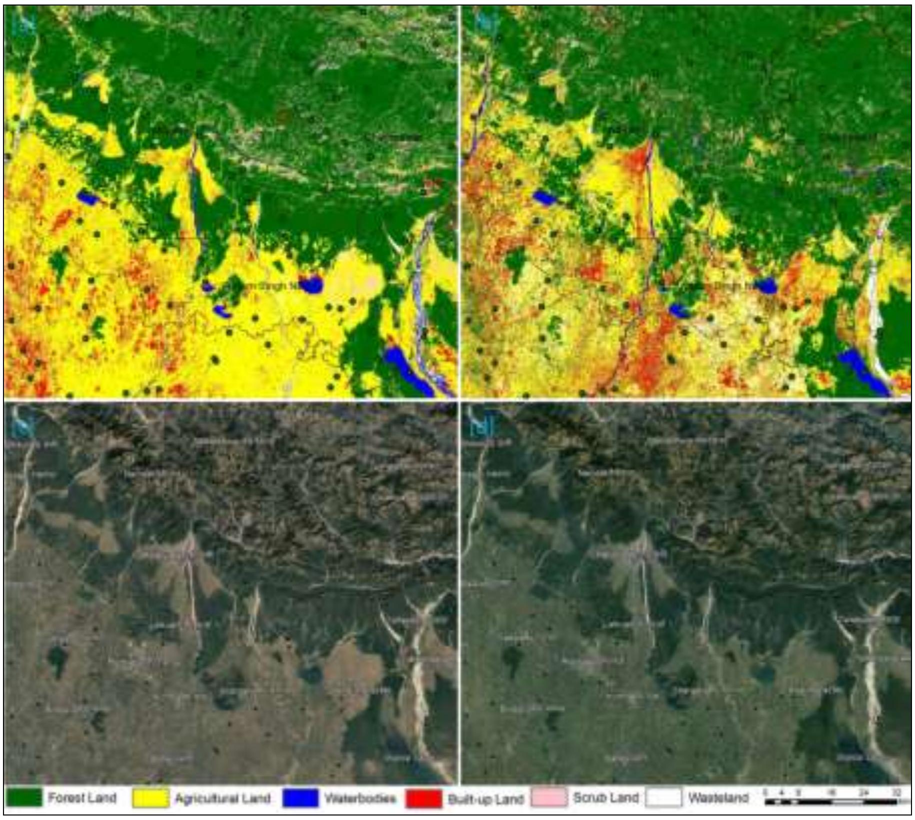

Fig 5: Accuracy assessment random sampling points [a] 2010 [b] 2020, [c] & [d] google earth image of 2010 and 2020

For accuracy assessment, 100 random samples have been taken from classified landuse/landcover of 2010 & 2020 to check the level of accuracy using GPS and Google Earth Pro (Figure 5). The confusion matrices for the 2010 & 2020 LULC classification are presented in Tables 2 &3. Within these matrices, the columns signify the classes to which the pixels in the validation set (Ground truthing) are attributed, while the rows indicate the classes assigned to the pixels within the image. The diagonal of the matrix represents accurately classified pixels, while those outside the diagonal denote misclassifications, indicating uncertainty in the classification process. Furthermore, the off-diagonal elements in the rows of the confusion matrix, normalized by the total number of pixels assigned to the corresponding Landsat image class, denote commission errors. These errors illustrate confusion between the specified image class and other LULC categories, representing the likelihood that a pixel assigned to one class actually belongs to another. The error matrices presented in Tables 2 & 3 show an overall accuracy (OA) of 80% and 81% respectively. However, in the 2010 classified map, the accuracies for map producers ranged from 68.42% (wasteland) to 94.44% (Waterbodies), and user accuracies varied from 62.50% (scrubland) to 100% (Waterbodies). In the 2020 classified image, PA ranged from 66.67% (wasteland) to 94.44% (Waterbodies), while UA varied from 68.75% (Built-up) to 100% (Waterbodies) (Table 2& 3).

The Kappa (k) statistic quantifies the discrepancy between the observed agreement of reference data and an automated classifier against the expected agreement by chance with a random classifier. This statistic, known as the Kappa Coefficient, indicates the proportion of correct classifications in an error matrix that can be attributed to true agreement rather than random chance. The Kappa coefficient ranges from -1 to +1, where +1 signifies perfect agreement, 0 indicates agreement purely due to chance, and negative values suggest disagreement worse than chance. A Kappa coefficient of 0.6 or higher is generally considered a strong level of agreement. These metrics are instrumental in assessing the accuracy of LULC classification. The computation of the kappa statistic involves.

$$\hat{k} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+}\cdot x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+}\cdot x_{+i})}$$

Where, r represent the number of rows, Xii denote the count of observations in both row 'i' and column 'i' (along the main diagonal), Xi+ signify the sum of observations in row 'i' (indicated as the marginal total to the right of the matrix), X+i represent the sum of observations in column 'i' (shown as the marginal total at the bottom of the matrix), and N2 denote the total number of observations encompassed within the matrix.

Table 2: Theoretical error matrix (confusion) for Accuracy Assessment of Landuse/Landcover 2010 of the study area resulting in classifying test pixels

S. No.	Classification Data (2010)	Reference Data								
		FL	AL	WB	BL	SL	WL	Row Total	PA	UA
1.	Forest Land	15	1	0	0	2	0	18	71.43	83.33
2.	Agricultural Land	1	13	0	1	0	1	16	81.25	81.25
3.	Waterbodies	0	0	17	0	0	0	17	94.44	100
4.	Built-up Land	1	1	0	12	0	2	16	85.71	75.00
5.	Scrub Land	3	0	0	0	10	3	16	83.33	62.50
6.	Wasteland	1	1	1	1	0	13	17	68.42	76.47
	Column Total	21	16	18	14	12	19	100		
Overall Accuracy = (15+13+17+12+10+13)/100*100 = 80%										

Note* FL= Forest land, AL: Agricultural land, WB: Waterbodies, BL: Built-up Land, SL: Scrubland WL: Wasteland, PA: Producer accuracy, UA: User accuracy.

$$N\sum_{i=1}^{r} X_{ii} = 100 * (15 + 13 + 17 + 12 + 10 + 13) = 8000$$

$$\sum_{i=1}^{r} X_{i+} * X_{+i} = (21*18) + (16*16) + (18*17) + (14*16) + (12*16) + (19*17) = 1679$$

$$\text{Kappa Coefficient (k)} = \frac{8000 - 1679}{(100)^2 - 1679} = 0.76$$

Table 3: Theoretical error matrix (confusion) for accuracy assessment of landuse/landcover 2020 of the study area resulting in classifying test pixels

S. No.	Classification Data (2020)	Reference Data								
		FL	AL	WB	BL	SL	WL	Row Total	PA	UA
1.	Forest Land	16	1	0	0	1	0	18	76.19	88.89
2.	Agricultural Land	1	13	0	1	0	1	16	81.25	81.25
3.	Waterbodies	0	0	17	0	0	0	17	94.44	100
4.	Built-up Land	1	1	0	12	0	2	16	80.00	75.00
5.	Scrub Land	2	0	0	0	11	3	16	91.67	68.75
6.	Wasteland	1	1	1	2	0	12	17	66.67	70.59
	Column Total	21	16	18	15	12	18	100		
Overall Accuracy = (16+13+17+12+11+12)/100*100 = 81%										

Note* FL= Forest land, AL: Agricultural land, WB: Waterbodies, BL: Built-up Land, SL: Scrubland WL: Wasteland, PA: Producer accuracy, UA: User accuracy

$$N\sum_{i=1}^{r} X_{ii} = 100 * (16 + 13 + 17 + 12 + 11 + 12) = 8100$$

$$\sum_{i=1}^{r} X_{i+} * X_{+i} = (21*18) + (16*16) + (18*17) + (15*16) + (12*16) + (18*17) = 1678$$

$$\text{Kappa Coefficient (k)} = \frac{8100 - 1678}{(100)^2 - 1678} = 0.77$$

The k values derived from the calculations for the classified images of 2010 and 2020 (0.76 and 0.77) are slightly lower than the previously computed overall accuracies (0.80 and 0.81). Such disparities between these metrics are to be anticipated, as they each capture distinct types of information. While overall accuracy focuses solely on the data along the main diagonal, disregarding errors of omission and commission, the kappa coefficient takes into account the non-diagonal elements of the error matrix, factoring in both row and column margins. The wide range of accuracy values suggests a significant confusion between wasteland and build-up land with other LULC categories.

5. Discussion

The landuse/land cover (LULC) classification of the Lower Kumaon region of Uttarakhand, utilizing Landsat imagery and supervised classification techniques in a Geographic Information System (GIS) platform, provides invaluable insights into the dynamic changes occurring in the region over the past decade. The presented data from 2010 to 2020 offers a comprehensive snapshot of how various land use categories have evolved, highlighting both positive and negative changes in their respective areas.

Agricultural land, constituting a significant portion of the region, has witnessed a notable decline from 38.28% in 2010 to 28.68% in 2020, indicating a substantial shift in land use practices. This decline may be attributed to factors such as urbanization, land degradation, or changes in agricultural policies. Conversely, barren land has exhibited a considerable increase, indicating potential land degradation or abandonment of previously cultivated areas. The expansion of built-up land signifies rapid urbanization and infrastructure development within the region. The substantial increase of 246.04 km^2 in build-up areas underscores the growing urban footprint and the associated socio-economic transformations. However, this expansion raises concerns about land fragmentation, loss of natural habitats, and environmental sustainability. Forest land, a crucial component of the region's ecosystem, has experienced a moderate increase, suggesting efforts towards forest conservation and regeneration. This positive trend reflects the importance of forest ecosystems in mitigating climate change, preserving biodiversity, and supporting local livelihoods. Scrub land and water bodies have also shown modest increases, indicating relatively stable environmental conditions. The observed changes underscore the complex interactions between natural processes, human activities, and policy interventions shaping the landscape of the Lower Kumaon region. Understanding these dynamics is essential for decision-making, planning, sustainable land management and conservation of land. It is imperative to integrate remote sensing techniques, GIS analysis, and field observations to monitor and assess land use changes accurately. The findings emphasize the need for adaptive landuse planning, conservation strategies and community engagement to ensure the long-term ecological resilience and socio-economic well-being of the region. Collaborative efforts involving government agencies, research institutions, local communities, and other stakeholders are essential for addressing emerging challenges and promoting sustainable development in the Lower Kumaon region.

6. Conclusion

The landuse/landcover classification of the Lower Kumaon region of Uttarakhand using Landsat imagery and supervised classification techniques in the GIS platform provide valuable insights into the evolving landscape dynamics over the decade from 2010 to 2020. The analysis reveals notable changes in various LULC types. Agricultural land witnessed a significant decrease, indicating potential shifts in agricultural practices or landuse policies. Conversely, barren land, built-up areas, forest land, scrubland, and water bodies experienced positive changes, suggesting dynamic transformations in urbanization, afforestation efforts and water resource management. This comprehensive assessment underscores the importance of employing remote sensing and GIS technology for monitoring and managing landuse changes, thereby aiding in sustainable development and conservation efforts in the region.

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