International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2022): 7.942

Spatio-Temporal Detection of Land Use Land Cover Changes in Jalpaiguri District; Geospatial Analysis

Mallick Manika[1], Krishnaiah, Y.V.[2]

[1]Research Scholar, Department of Geography and Disaster Management, Tripura University (A Central University), Suryamaninagar-799022, Tripura, India
Corresponding Author Email: *yvkrishna09[at]gmail.com; yvkrishna[at]tripurauniv.ac.in*

[2]Professor, Department of Geography and Disaster Management, Tripura University (A Central University), Suryamaninagar-799022, Tripura, India

Abstract: ***The incessant rise in population density has led to an escalating reliance on finite land resources, resulting in a transformation of land use and land cover patterns over the periods. For the sustainable development and management of land resources, continuous monitoring of land use and land cover has become a crucial aspect of research. Therefore, the objective of this study is to monitor changes in surface cover attributes in the sub-Himalayan district of Jalpaiguri from 2000 to 2020 using Remote Sensing and GIS. The analysis of LULC changes has used multi-spectral satellite data, including Landsat TM, Landsat ETM+, and Landsat OLI imagery for the years 2000, 2010, and 2020, to identify surface cover dynamics over the past two decades. Supervised and unsupervised classification of Landsat images was performed on 10-year time interval using maximum likelihood and K-Means method in the GIS platform. The generated classified layer demonstrates that between 2000 to 2020, a significant increasing trend has been observed in the classes of built-up area (140.39%) and tea plantation land (93.53%), while a sharp decline trend has been detected in water bodies (52.88%), sand deposition (53.46%), fallow land (32.76%) and agricultural land (18.57%) within the district. To validate the classified images, ground data and kappa coefficient analysis were employed, and the results showed overall accuracies of 0.85, 0.88, and 0.89 for the years 2000, 2010, and 2020, respectively. Finally, the satellite-based monitoring of land use and land cover changes with ground truth data, holds a significant importance for land use planning in this region to ensure sustainable land management in future.***

Keywords: Geospatial analysis, Land use land cover, Jalpaiguri district, Spatio-temporal

1. Introduction

Land use land cover (LULC) change is one of the major concerns in the current world [1,2]. The word LULC consist with two distinct concepts, which are frequently used interchangeably [3,4]. The term "land cover" refers to the natural or physical condition of the Earth's surface, which helps to identify the interaction of biodiversity with surrounding environment. It reflects the biophysical conditions of the environment, including features such as water bodies and vegetation cover, serving as fundamental parameters for ecosystem function. Conversely, land use refers to the continuous activities of human beings on the surface of the Earth. Land use land cover is inherently dynamic, providing a comprehensive understanding of the relationship and interaction between human activities and the natural environment [5]. The LULC pattern of a specific region offers insights into natural conditions, human influences, developmental processes, and the utilization of natural resources. Therefore, the determination of LULC patterns is essential for selecting land-use planning, managing, and putting into practice new plans, that will eventually meet the expanding needs of humankind.

The process of discerning alterations in any phenomena or object through the analysis of different time periods is referred to as change detection [6,7]. Land use land cover change encompasses modifications in surface cover at various levels, including global and regional scales [8]. The substantial growth in population, urbanization, and industrialization has led to land use land cover changes. Imparting significant impacts on the geo-environment and natural ecosystems, and recognized as a key driver of global environmental change [9,10,11]. The escalation of anthropogenic activities has resulted in the conversion of forest cover areas into alternative land use land cover types in the Himalayan region of India [12]. Historical data indicates that during the colonial period, the forest cover areas in the Himalayan foothill region of West Bengal decreased at a rate of 29.9 km^2 per year, while the tea plantation area increased by 8.5 km^2 per year, respectively [13]. Thus, accurate identification of Land Use Land Cover (LULC) changes across decades is critical for planning, environmental monitoring, and assessing the degradation of natural resources.

In recent times, the extensive utilization of multi-spectral and multi-temporal satellite data has been observed in the identification of various land features such as deforestation, built-up areas, agricultural land, vegetation cover, and urban expansion globally [14]. Remote sensing and Geographic Information System (GIS) have emerged as indispensable tools for mapping human utilization of landscapes and the transformation of the Earth's surface over time [15,16]. GIS offers numerous ways for mapping land use and land cover (LULC) aspects, among them, supervised and unsupervised image classification methods are widely utilized by researchers and scientists in various fields [17,18]. The Maximum Likelihood and K-Mean algorithms consistently maintain good accuracy in LULC classification[19,20,21, 22]. Conversely, numerous methods have been devised by various researchers for estimating Land Use Land Cover (LULC) change detection, encompassing techniques such as vegetation index differencing [23], post-classification methods [24,25], and multi-temporal composite image change detection [26,27]. The incorporation of these techniques provides a deeper insight into LULC patterns and facilitates change detection. Consequently, the current study aims to evaluate the land use land cover detection changes in Jalpaiguri district from 2000 to 2020 through the integrated application of remote sensing and GIS techniques.

2. Methodology

2.1. Study area

The current research focuses on the Jalpaiguri district, located in the foothill region of the Himalayas in West Bengal. It encompasses an area of 3380 km², with coordinates ranging from 26°15'47" to 26°59'34" N latitude and 88°23'2" to 89°7'30" E longitude [28]. The district is demarcated by the international border with Bangladesh to the south, Bhutan to the north, Alipurduar district to the east, Cooch Behar to the southeast, Kalimpong to the north, and Darjeeling to the west and northwest. Administratively, the region comprises two subdivisions, seven community development blocks, 80 Gram Panchayats, and 391 inhabited villages. Geographically, Jalpaiguri district is characterized by the physiographic divisions of northern hilly terrain, a central tract with a moderate alluvial fan, and a gently sloping floodplain region in the south (Figure 1). Numerous river systems, such as the Mahananda, Teesta, Torsa, and Jaldhaka, intricately crisscross the topography and give rise to a number of narrow land formations in the northern region [29]. The defining climatic characteristic of the district is the south-easterly monsoon [13]. The month of May stands on the hottest month, with an average temperature of 32°C, while January is the coldest, with a mean temperature of 11°C. The average annual rainfall is 3440 mm, with the maximum occurring in June and the minimum in January. The average annual relative humidity is approximately 85%.

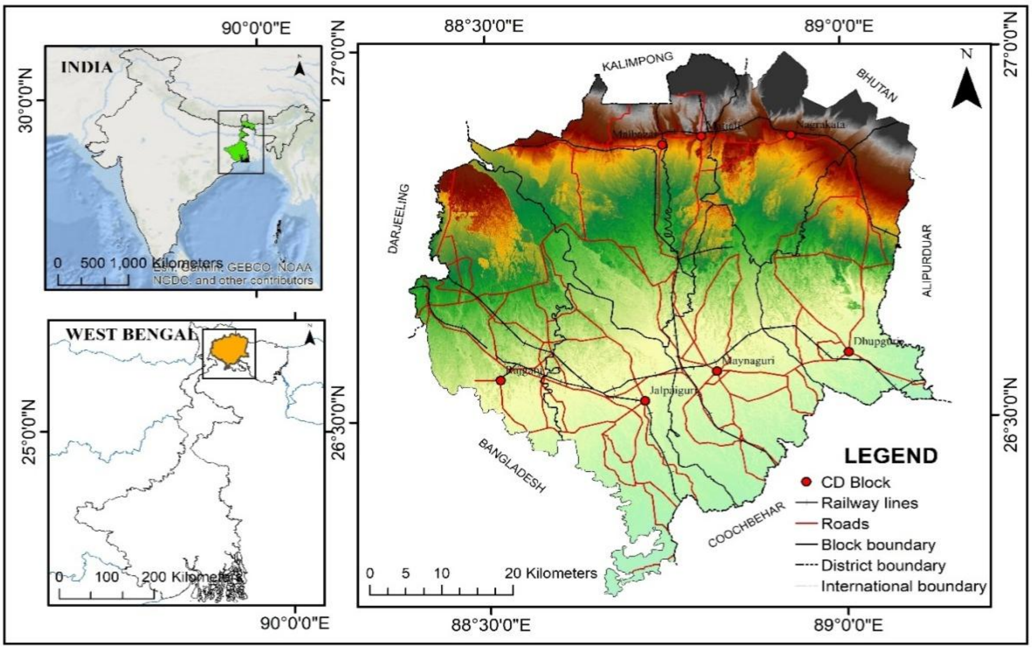

Figure 1: Location map

2.2. Data collection

In order to analyse changes in surface cover within a specific time period, a collection of various Landsat datasets was collected for the North Bengal region in India. The spectral reflectance data, including Landsat Thematic Mapper (TM) for 2010, Enhanced Thematic Mapper Plus (ETM+) for 2000, and Operational Land Imageries (OLI) for 2020, were acquired from the Earth Observation Data Centre of the United States Geological Survey (USGS). For the validation, high-resolution images from Google Earth Pro were acquired in order to correlate the final classified image with ground-truth information. Additionally, 120 GPS points were systematically collected from distinct Land Use and Land Cover (LULC) features within the chosen study area to augment accuracy and minimize potential errors in the current classified image (Figure 2 & Table 1).

Table 1: Description of satellite imageries

Satellite	Sensor	Path/Row	Acquisition Date	Band used	Spatial resolution	Processing
Landsat 5	Thematic Mapper (TM)	138/42	23.12.2010	B1, B2, B3, B4, B5, B7	30	L1/C2
		139/41	14.12.2010			
		139/42	14.12.2010			
Landsat 7	Enhance Thematic Mapper Plus (ETM+)	138/42	30.09.2000	B1, B2, B3, B4, B5, B7	30	L2/C2
		139/41	26.12.2000			
		139/42	10.12.2000			
Landsat 8	Operational Land Imageries (OLI)	139/41	23.11.2020	B1, B2, B3, B4, B5, B6, B7	30	L2/C2
		139/42	23.11.2020			

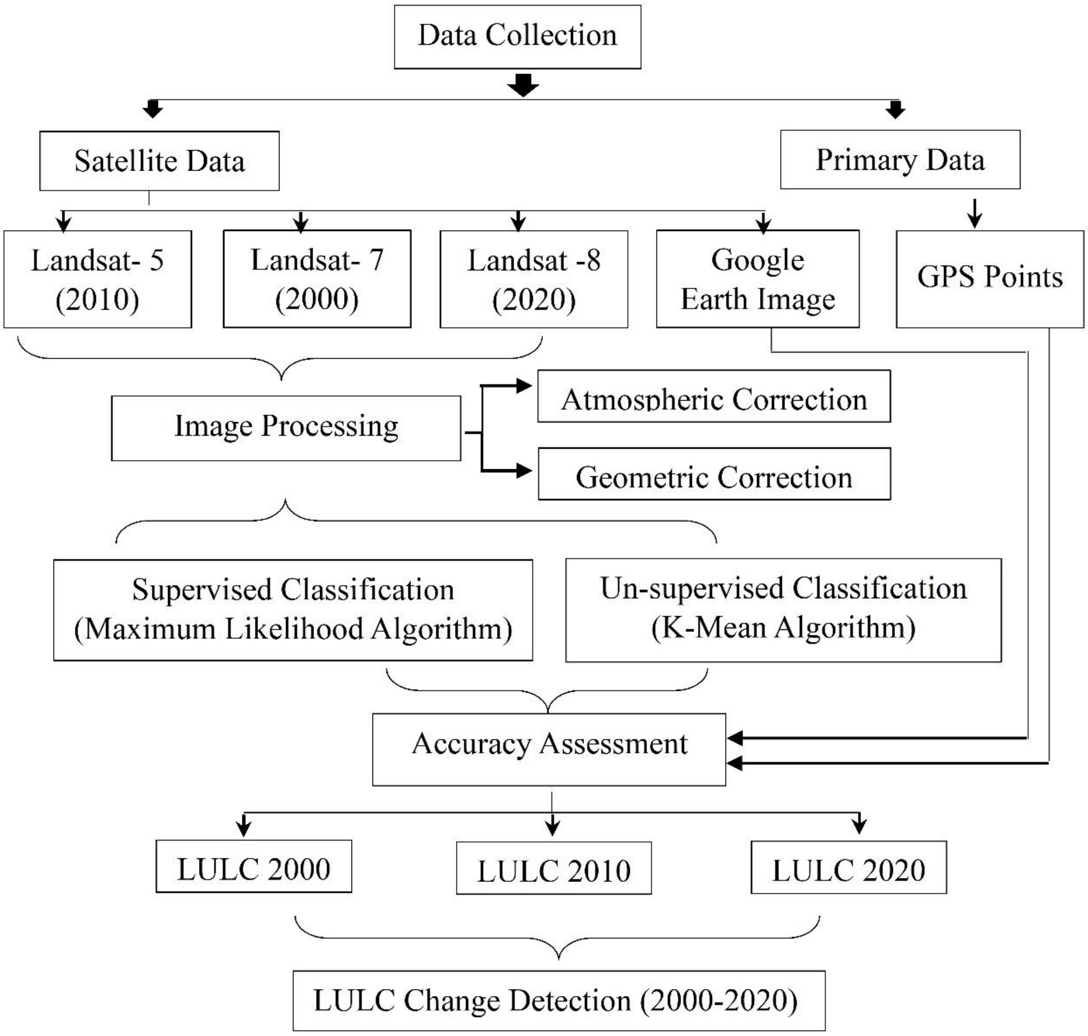

Figure 2: Flow chart of research design

2.3. Image pre-processing and classification:

As the area is comes under the sub-tropical climatic zone, the surface reflectance images must be associated with some weather interferences with other noises and disturbances. Image pre-processing includes image enhancement to extract some useful information from it. As the images were collected from the level I and level II data sets, it needs to processed the operation of atmospheric and geometric correction. Atmospheric correction of collected datasets were performed in QGIS software using the atmospheric correction tool. Radiometric rectification is performed through the registration process of each band. Additionally, the systematic striping lines were removed from the collected Landsat imageries in ArcGIS and ERDAS Imagin software. After that, pre-processing pixel based supervised and unsupervised image classification technique was used to classified the final LULC map of the selected study region. A total 270 training samples were taken into consideration for segregating one features to another in ArcGIS 10.8 software.

2.4. Change detection and accuracy assessment:

The change detection analysis of classified images was made to quantify the change rate, direction, and pattern of classified LULC features. To examine the primary transformation, the present classified images were subtracted with the previous classified image in ArcGIS 10.8 platform. The magnitude of change detection was calculated using the following formula-

$$Mi = li - ki$$

The percentage of change detection in each LULC category was estimated using the following equation-

$$Pi = \frac{li - ki}{ki} \times 100$$

Where, i = Total number of classes in an image
Mi = Magnitude of change in class ‘i’
Pi = Percentage of change in class ‘i’
li = Base image
ki = Latest image

To assess the congruence between the classified satellite imagery and the actual ground conditions, an accuracy assessment of the Land Use/Land Cover (LULC) imageries was conducted. The evaluation of classified accuracy involved the computation of overall accuracy and Kappa Coefficient through the utilization of a confusion matrix within Geographic Information System (GIS) software, as defined by the following equation. A total of 120 randomly selected ground control points were obtained from the actual land cover, enabling the estimation of producer and user accuracy for each of the specified years, 2000, 2010, and 2020.

Paper ID: SR231227231047 DOI: https://dx.doi.org/10.21275/SR231227231047

$$\text{Producer accuracy (\%)} = \frac{P_{RC}}{P_{+R}} \times 100$$

$$\text{User accuracy (\%)} = \frac{P_{RC}}{P_{+R}} \times 100$$

$$\text{Overall accuracy (\%)} = \frac{1}{N}\sum_{k=1}^{r} n_1 \times 100$$

$$\text{Kappa Coefficient (K)} = \frac{N\sum_{k=1}^{r} \cdot P_{RC} - \sum_{k=1}^{r}(P_{+C} \cdot P_{+R})}{N^2 - \sum_{k=1}^{r}(P_{+C} \cdot P_{+R})}$$

Where, N = Total number of pixels
r = The number of classes of each classified image
P_{RC}= Total number of correctly classified pixel in each category
P_{+R} = Total number of reference pixel in that category (Row total)
P_{+C} = Total number of reference pixel in that category (column total)

3. Result and Discussion

Land use and land cover (LULC) are manifestations of the socio-economic activities carried out by individuals within a specific geographic region. Satellite-based image classification serves as a valuable tool for obtaining both high-quality and extensive information regarding LULC practices and their temporal changes. In the context of Jalpaiguri district, seven primary LULC features have been identified, encompassing tea plantations, vegetation cover, waterbodies, sand deposition, agricultural fields, fallow land, and built-up areas. The classification map of LULC spanning the last two decades has been generated using the Maximum Likelihood and K-Mean method for supervised and un-supervised image classification, employing a visual interpretation technique-

3.1. Spatio-temporal variation of LULC changes of Jalpaiguri district (2000, 2010, &2020)

For the year 2000, Land Use/Land Cover (LULC) map for the study area, derived from the Landsat ETM+ dataset, is depicted in figure 2. The geographical representation reveals that among the seven LULC classes, agricultural land, tea plantations, and natural vegetation covered the maximum areas which are 47.28%, 15.66% and 14.93%, respectively. In contrast, the smallest areas were occupied by sand deposition, built-up areas, and waterbodies constituting of 6.07%, 3.01% and 2.01%of the total study area (Figure 3a& Table 2).

For the year 2010, the classification of Landsat image shows that 47.09% (1594.90 km^2) of total geographical distribution occupied by cultivation land. The tea plantation land occupies an area of 613.55 km^2 (18.12%), and vegetation cover 469.23 km^2 (13.86%). Whereas minimum percentage of area bounded by the feature of water-bodied (1.37%), sand deposition (4.56%) and built-up areas (4.8%) respectively. The spatial distribution map reveals that the southern part situated within the lower elevated plain physiographic division, is predominantly characterized by agricultural activities, while the northern part is largely occupied by tea cultivation. Waterbodies and sand deposition features are covering a smaller geographical area, it has extended from north to south along the central part of the district (Figure 3b& Table 2).

For the year 2020, the present status of Land Use Land Cover (LULC) dynamics in the sub-Himalayan Jalpaiguri district was assessed using the Landsat 8 OLI dataset. The most extensive land cover category for the year 2020 is agricultural land has encompassing 38.50%, it has distributed predominantly in the southern and central parts of the district. The second most extensive LULC feature is tea plantations (30.30%), it extends in the northern part in an integrated manner and in southern part in scattered manner. The vegetation covers an area is 12.8%, remain fallow land and built-up land. The entire study region is intersected by the numerous river system, covering an area with sand deposition(Figure 3c& Table 2).

Table 2: Temporal variation of LULC changes in Jalpaiguri district (2000, 2010 & 2020)

LULC Classes	2000		2010		2020	
	Area (km^2)	% of area	Area (km^2)	% of area	Area (km^2)	% of area
Tea Plantation	530.28	15.66	613.55	18.12	1026.27	30.30
Vegetation Cover	505.72	14.93	469.23	13.86	432.80	12.78
Waterbodies	67.94	2.01	46.44	1.37	32.01	0.95
Sand Deposition	205.49	6.07	154.58	4.56	95.63	2.82
Agriculture Land	1601.37	47.28	1594.90	47.09	1303.87	38.50
Fallow Land	373.97	11.04	366.44	10.82	251.44	7.42
Built-up Area	101.91	3.01	141.52	4.18	244.98	7.23

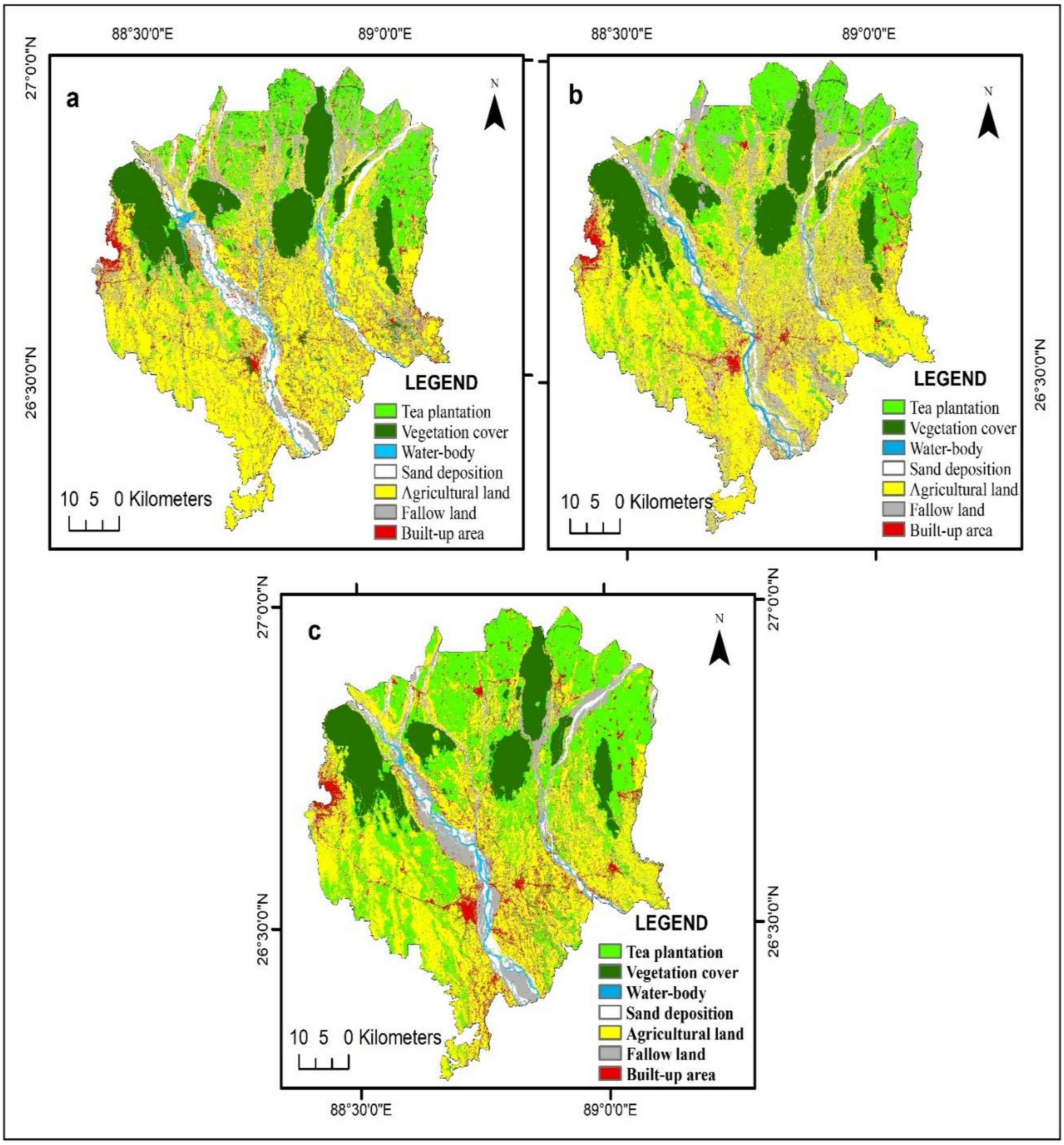

Figure 3: Spatial LULC map of Jalpaiguri district, 3a. 2000, 3b. 2010, 3c. 2020

3.2. Decade wise detection of LULC changes in Jalpaiguri district (2000-10, &2010-20)

From 2000-2010, decade wise change detection analysis plays a crucial role in the study are using geospatial technology, allowing for the quantification of alterations between images at different time intervals. In this study, the classified images for the years 2000 and 2010 were utilized to discern the patterns and magnitudes of Land Use/Land Cover (LULC) changes occurring in the study region. The data reveals those significant transformations in built-up areas, water bodies, and sand deposition areas between 2000 to 2010. Built-up area has increased by 38.87%, water bodies has decreased by 31.64%, and sand deposition has reduced by 24.77% respectively (Table 3).

The conversion matrix provides detailed information about the transitions between different LULC categories. It is observed from the table 4 that the expansion of built-up areas primarily occurred through the conversion of agricultural land, followed by fallow land. Over the course of the decade, an estimated 31.35 km^2 of agricultural land and 9.81 km^2 of fallow land experienced transformation. Conversely, the decreases in water bodies and sand deposition were calculated as a result of the alteration of water bodies into sand deposition (27.15 km^2) and sand deposition into fallow land (73.78 km^2) (Table 4).

From 2010-2020, the analysis of recent changes in land use and land cover (LULC) involved the utilization of Landsat 5 TM and Landsat 8 OLI images. The overall percentage changes in each LULC class within the study area are presented in table 3. The obtained values indicate a significant transformation during this period, notably in tea plantations and built-up areas, which increased substantially from 613.55 km^2 to 1026.26 km^2 and 141 km^2 to 244 km^2, resulting in overall growth rates of 67.27% and 73.11%, respectively. Conversely, a marked decline was observed in the categories of sand deposition (38.14%), water bodies (31.07%), and agricultural land (18.25%), resulting in reduced areas of 58.95 km^2, 14.43 km^2, and 91.0 km^2, respectively(Table 3).

As evident from the table, there has been as appreciable increasing in the area of built-up area and tea plantation land, primarily resulting from the conversion of agricultural fields. It has been estimated that during the period of 2010-2020, 57.55 km^2, and 324.7 km^2 of agricultural field was converted into settlement area and plantation area respectively. Furthermore, a concomitant shrinkage in the area was observed in sand deposition, fallow land and agricultural field. Detailed analysis revels that from 2010 to 2020, 55 .88 km^2 of sand deposited area transformed into fallow land, 107.04 km^2 of fallow land and 324.72 km^2 of agricultural land converted into plantation land (Table 5).

Table 3: Decade wise detection of LULC changes in Jalpaiguri district

LULC Classes	2000-2010		2010-2020		2000-2020	
	Area (km^2)	% of area	Area (km^2)	% of area	Area (km^2)	% of area
Tea Plantation	83.27	15.70	412.72	67.27	495.99	93.53
Vegetation Cover	-36.49	-7.22	-36.43	-7.76	-72.92	-14.42
Waterbodies	-21.49	-31.64	-14.43	-31.07	-35.93	-52.88
Sand Deposition	-50.90	-24.77	-58.95	-38.14	-109.85	-53.46
Agriculture Land	-6.47	-0.40	-291.03	-18.25	-297.50	-18.58
Fallow Land	-7.53	-2.01	-115.00	-31.38	-122.53	-32.76
Built-up Area	39.61	38.87	103.46	73.11	143.07	140.39

Table 4: LULC Conversion matrix of Jalpaiguri district between 2000 - 2010

Classes	Tea Plantation	Vegetation Cover	Water-bodies	Sand Deposition	Agriculture Land	Fallow Land	Built-up Area	Total (2000)
Tea Plantation	364.58	34.74	0.19	1.07	69.55	55.79	4.36	530.28
Vegetation Cover	45.54	411.29	0.36	1.41	24.80	15.91	6.42	505.73
Water-bodies	0.64	0.67	9.57	27.15	13.57	15.24	1.11	67.94
Sand Deposition	1.03	0.02	23.19	87.80	18.67	73.78	1.00	205.48
Agriculture Land	129.27	19.10	4.46	16.11	1319.33	82.37	31.35	1601.98
Fallow Land	71.05	2.79	6.28	16.30	147.22	120.52	9.81	373.97
Built-up Area	1.44	0.62	3.02	4.76	1.75	2.84	87.49	101.91
Total (2010)	613.55	469.23	47.06	154.59	1594.89	366.44	141.52	3387.29

Table 5: LULC Conversion matrix of Jalpaiguri district between 2010 - 2020

Classes	Tea Plantation	Vegetation Cover	Water-bodies	Sand Deposition	Agriculture Land	Fallow Land	Built-up Area	Total (2010)
Tea Plantation	532.40	15.92	0.31	0.76	42.74	6.67	14.76	613.55
Vegetation Cover	54.59	400.40	0.03	0.29	4.66	3.51	5.54	469.03
Water-bodies	1.84	0.02	4.95	10.56	2.55	24.70	2.42	47.04
Sand Deposition	4.12	0.54	9.50	52.92	29.54	55.88	2.09	154.59
Agriculture Land	324.72	7.67	5.54	15.21	1126.33	57.88	57.55	1594.90
Fallow Land	107.04	6.12	11.50	15.56	94.65	94.60	36.96	366.44
Built-up Area	1.55	2.12	0.26	0.33	3.41	8.20	125.65	141.52
Total (2020)	1026.26	432.80	32.08	95.63	1303.88	251.44	244.98	3387.07

3.3. Spatio-temporal detection of LULC changes in Jalpaiguri district (2000 to 2020)

The spatiotemporal changes of quantified data for two decades shows that subsequent increasing trend was observed in tea plantation and built-up areas, with the growth rate 93.53% and 140.39%. On the other hand, remaining classes of Jalpaiguri district experienced negative growth from 2000 to 2020, i.e., sand deposition (53.46%), waterbodies (52.88%), fallow land (37.76%, agricultural land (18.58%) and vegetation cover (14.42%) respectively (Figure 4 &Table 3).

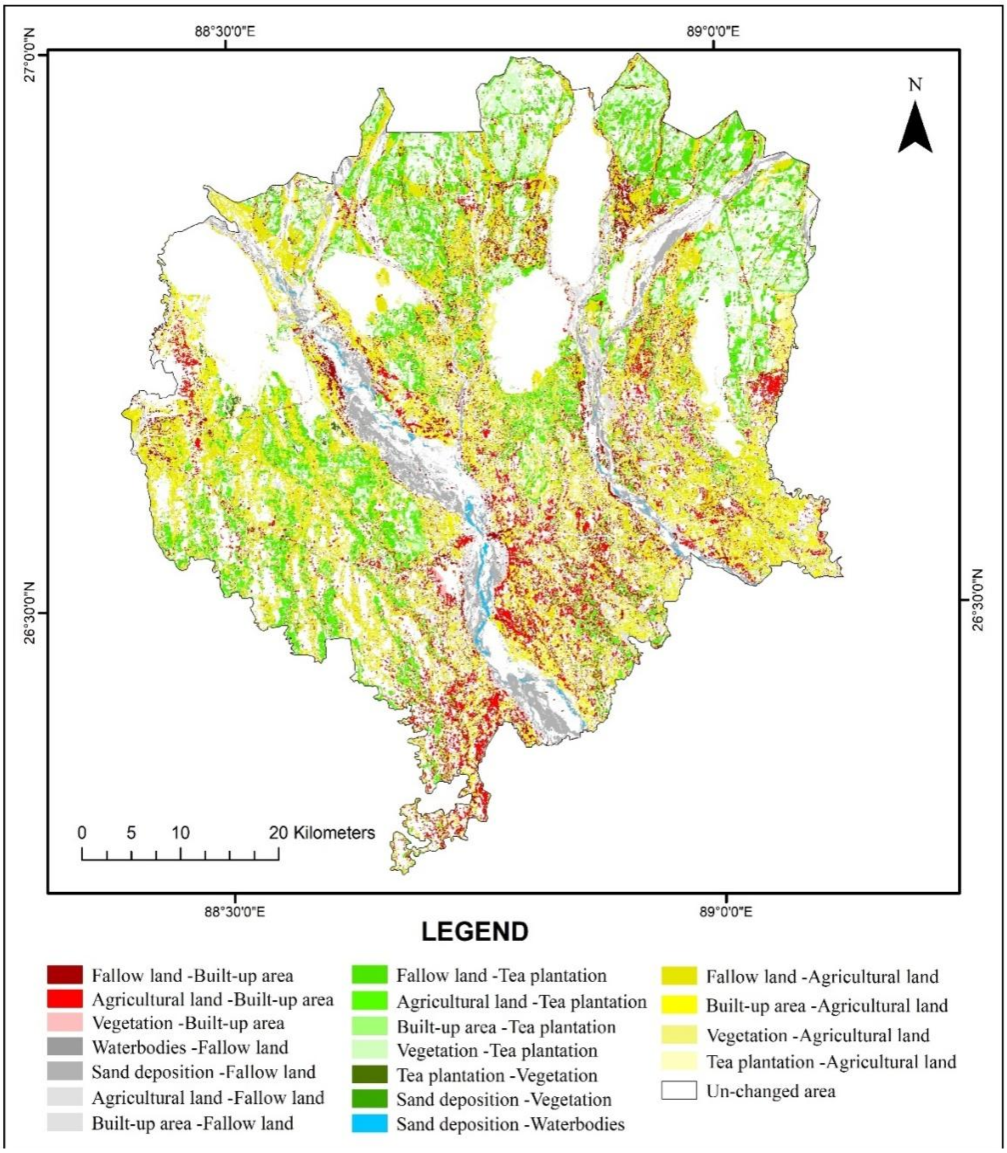

Figure 4: Spatial changes of LULC from 2000 to 2020

The conversion matrix shows that during 2000-2020, maximum area conversion has been occurred from agricultural land into plantation land i.e., 375.38 km2, and from agricultural land into built-up area (91.95 km^2), which is the main responsible factor for drastic growth in tea plantation and built-up area and sharp declination in the agricultural field(Table 6)

Table 6: LULC Conversion matrix of Jalpaiguri district (2000 to 2020)

Classes	Tea Plantation	Vegetation Cover	Water-bodies	Sand Deposition	Agriculture Land	Fallow Land	Built-up Area	Total (2000)
Tea Plantation	443.31	18.28	0.12	0.82	35.04	18.73	13.97	530.27
Vegetation Cover	61.14	401.16	0.15	0.89	22.78	14.31	5.29	505.73
Water-bodies	5.41	0.74	6.38	24.30	9.18	12.57	9.36	67.94
Sand Deposition	2.98	0.31	16.02	49.57	54.50	78.26	3.84	205.48
Agriculture Land	375.38	6.23	2.13	7.61	1042.09	76.40	91.95	1601.80
Fallow Land	136.66	4.11	5.69	10.31	138.40	47.86	30.94	373.97
Built-up Area	1.37	1.97	1.61	2.12	1.88	3.31	89.65	101.91
Total (2020)	1026.26	432.80	32.10	95.63	1303.88	251.44	244.99	3387.10

4. Accuracy Assessment

The accuracy assessment was conducted for the land use land cover (LULC) images of 2000, 2010, and 2020 using randomly collected reference data, comprising a total of 120 random points sampled from various LULC classes. The overall classification accuracies for the respective years were 87.40%, 89.62%, and 90.74%, while the Kappa coefficient values were 0.85, 0.88, and 0.89. The Kappa statistic as poor when its value is < 0.4, good when it falls within the range of 0.4-0.7, and excellent when the value exceeds 0.7 (REF)[30]. According to this criterion, the coefficients for all the images in the study indicate an excellent level of agreement. The classification image is considered sufficient if the overall accuracy is 85% or higher [31,32,33]. In this study, both the Kappa statistic and overall accuracy demonstrate a robust agreement for all classified images, meeting the general acceptable range for subsequent land use land cover change detection analyses (Table 7).

Table 7: Accuracy assessment of LULC classification for 2000, 2010, &2020

LULC Class	2000		2010		2020	
	UA	PA	UA	PA	UA	PA
Tea plantation	93.88	92	95.99	94	96	96
Vegetation cover	96	87.27	96	90.57	96	96
Water-bodies	83.33	92.59	86.67	89.66	93.33	84.85
Sand deposition	84	79.25	88	88	88	81.48
Agricultural land	92	93.88	94	95.92	94	94
Fallow land	70	77.78	75	88.24	80	72.73
Built-up area	75	83.33	75	93.75	70	87.5
Overall Accuracy in %	87.4		89.62		90.74	
Kappa Coefficient (T)	0.85		0.88		0.89	

UA = User accuracy, PA = Producer accuracy

5. Conclusion

The research endeavors aimed to quantify and understand the alterations of the Land Use/Land Cover (LULC) changes within Jalpaiguri district, utilizing a combination of multi-spectral Landsat data and field observation data spanning the period from 2000 to 2020. The obtained values reveal significant LULC changes in the study area over the past two decades. Notably, there has been a marked positive change in built-up and tea plantation area. Conversely, a declining trend is evident in the remaining LULC classes, including water bodies, sand deposition, fallow land, agricultural fields, and vegetation cover.

In 2020, the built-up area has increase by 140.39% and tea plantation area has growth by 93.53% compared to the preceding decade2000. In contrast, crucial LULC units in Jalpaiguri district such as water bodies (52.88%), agricultural land (18.57%), and vegetation cover (14.41%) have decreased from the year 2000 to 2020. The primary driver behind these notable changes in the LULC pattern of the study region is the burgeoning population and their unbridled demand for natural resources. Historical data indicates that the emergence of tea plantation was a pivotal factor contributing to a drastic reduction in vegetation cover in the sub-Himalayan region. Currently, the trend has shifted towards agricultural land, driven by individuals seeking immediate financial gains, leading to the transformation of cultivated land into plantation. Since that each type of land has its unique potential to support specific crops, alterations in their patterns may result in diverse environmental impacts, including biodiversity loss, low productivity, soil erosion, and land degradation. Additionally, there is a looming possibility of a decline in the extent of cultivated land in the near future. The research findings emphasize the imperative need for extensive work on the evaluations of resources, human activities, and environmental sustainability. Sustainable land-use planning emerges as a paramount measure for government officials and land-use planners to manage the dynamic changes in LULC and land resources in this region in a sustainable manner.

Acknowledgement:
Authors would like thanks the USGS Earth explorer, Food and Agricultural Organization (FAO), and Tea Research Organization (TRA) of Jalpaiguri district West Bengal, India for providing various types of data and information in their websites. Authors are also grateful to the editors and reviewers for their valuable suggestion and comments.

COI: The authors declared that they have no competing interests.

Authors' contribution: Both authors contribute equally

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