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Land use land cover change analysis of Thoubal district, Manipur using remote sensing and GIS

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Abstract

The present study examined the extent of land use land cover changes through satellite images of Landsat TM 1991, 2006, and Landsat 8 TIRS/OLI 2021 for the same vegetation season using GIS and remote sensing technology of Thoubal district. The LULC are classified into 9 classes using maximum livelihood supervised classification and undergo an accuracy assessment for each classified image. Agricultural farming and aquaculture are important activities of the people of Thoubal district. Landscape shape index (LSI) and Patch Density techniques were profitably used to understand the complexity of the land-use feature and land fragmentation in each class respectively. CA Markov Modeling was used to forecast LULC for 2021 and 2036. The predicted LULC map of 2021 is validated with the observed value of 2021 through the chi-square test. The results showed area of agricultural land, wetland, and vegetated areas decreased while the expansion of settlement areas and dug-out ponds for aquaculture are the prominent changes seen in the selected region.

Keywords: *Land use/ land cover, Remote sensing, GIS, LSI, CA Markov Modeling, Thoubal district.*

Introduction

Land use/land cover (LULC) change is the outcome of how humans utilize the land over time and space. These changes play an essential role in the studies of regional, local, and global environmental change (Gupta & Munshi, 1985; as cited in Gupta and Singh, 2022). Change detection can be defined as the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh, 1989). Recently, issues related to LULC change have attracted scholarly attention from a wide range of researchers, from those who favor modeling spatiotemporal patterns of land conversion to those who try to understand the causes, impacts, and consequences (Verburg *et al.* 1999; Brown *et al.* 2000; Theobald, 2001). Thoubal District of Manipur in recent decades is experiencing a noticeable transformation in land use and land cover patterns. The district embraces important geographical features like a plain area having a gentle slope which is suitable for agriculture with a small hillock in between. The southwestern part is dominated by wetlands namely Ikop Pat and Kharung Pat. Besides, there are many small wetlands namely Waithou pat, Yaithibi, and Phulou pat which are rich in biodiversity and its surrounding area is suitable for aquaculture. These conditions have made it a suitable region for various economic activities and human settlements. However, these developments have come at a cost of rapid land use changes affecting the environment, biodiversity, water resources, and socio-economic conditions of the people of the district. Changes in LULC need not necessarily lead to the degradation of the land. However, due to a shift in land-use patterns, land cover changes affect biodiversity, water, and other processes that come together to affect climate and the biosphere (Riebsame *et al.*, 1994). Important factors that contributed to the LULC changes include urbanization, population growth and expansion of settlements, infrastructural development, encroachment of wetlands for agriculture and aquaculture, and other natural process.

The increasing population in Thoubal District too has led to expansion of the urban areas, encroachment on agricultural land, and the conversion of natural habitats into built-up environments. Besides alteration of the forest cover, wetlands and other natural habitats for agriculture and infrastructural development led to habitat loss, land fragmentation, and degradation. The rapid expansion of aquaculture and agricultural land from wetlands disturbs the existing ecosystem adversely affecting the biodiversity and threatening the survival of many plant and animal species. It also influences the hydrological cycle and water resources in the district like water availability, quality, and flood risk. The interchange of wetlands and water bodies for aquaculture is one of the distinct features seen in the area. The fertile land with a good drainage system endows the area with agricultural activities and aquaculture provides livelihood for a significant section of the population supporting the local economy but this conversion from agricultural land can potentially have a dwindling effect on agricultural productivity. The Manipur government passed the Manipur Conservation for Paddy Land and Wetland Act 2014 to conserve the paddy land and wetland which restricted the conversion of wetland and agricultural land to other land use at individual interest to protect the wetland and agricultural sector in Manipur. This act is imposed on the whole Manipur state where the Manipur Land Revenue and Land Reforms Act 1960 (No.33 of 1960) is enforced (Government of Manipur, Law and Legislative Affairs department, 2014). In spite of this act, aimed at conserving the existing paddy land and wetland, the area under cultivation has been decreasing in recent years. The rapid land use and land cover change in Thoubal district pose significant challenges to sustainable development and the environmental well-being of the region. Thus, understanding LULC changes is essential for decision-making in land, water, and environment management practices to maintain resources and their use in the district.

Needless to mention, effective analysis and monitoring of land cover require a substantial amount of data about the earth's surface and the living habitats. The remote sensing data has become a major source for LULC change detection studies because of its high temporal frequency, a digital format suitable for computation, synoptic view, and a wider selection of spatial and spectral resolutions (Lunetta *et al*, 2004; Coops *et al*, 2006; as cited in Chen *et al*, 2012). In the present study, the temporal and spatial changes in LULC in Thoubal District have been analysed for three points of time- 1991, 2006, and 2021, by using LANDSAT

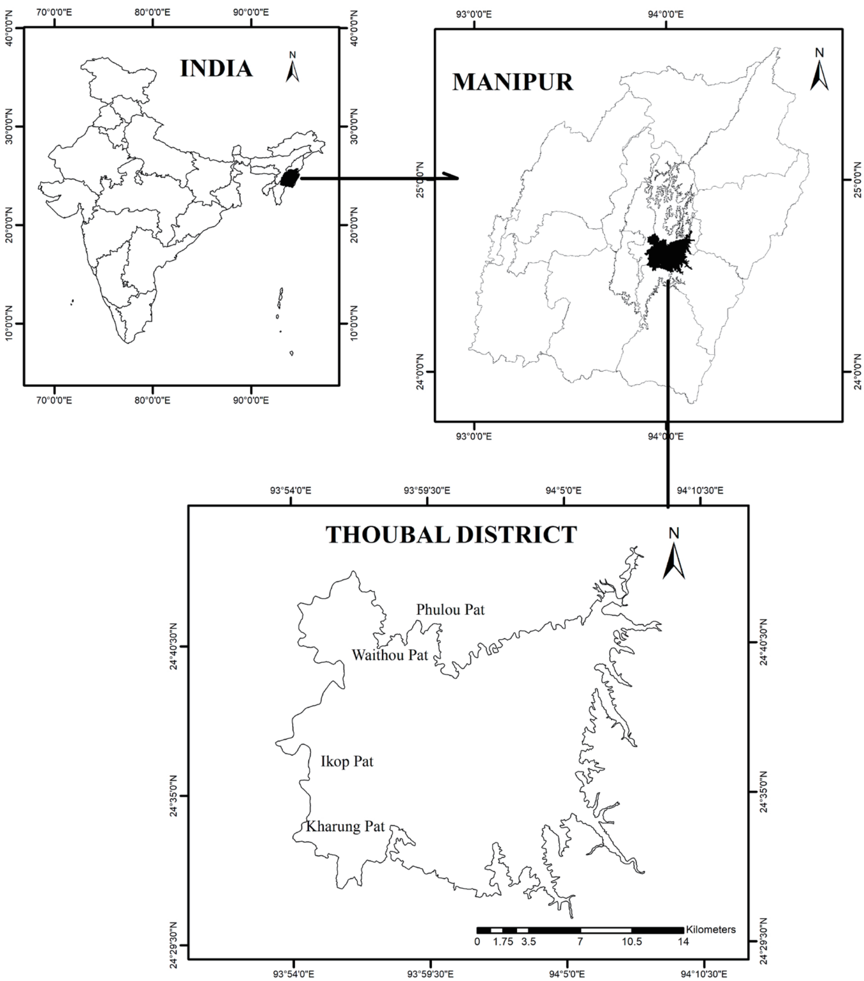

Fig. 1: Study area

imagery obtained from the United States Geological Survey (USGS) Earth Explorer (http://earthexplorer.usgs.gov) online portal. The CA-Markov model is the combination of Cellular Automata and transition probability matrix generated by the cross-tabulation of two different images. This combination of the CA-Markov model provides a robust approach to spatio-temporal dynamic modeling (Singh, *et al.* 2015). CA Markov modeling is used for LULC prediction for 2021 and 2036 and the predicted value for 2021 is cross-checked with the observed value of 2021. Landscape matrices such as landscape shape index (LSI) and patch density (PD) have been adopted to estimate the changes in the landscape pattern that help in measuring the complexity fragmentation of the landscape.

Study area

Thoubal District, located in Manipur, India, is known for its diverse landscapes, ranging

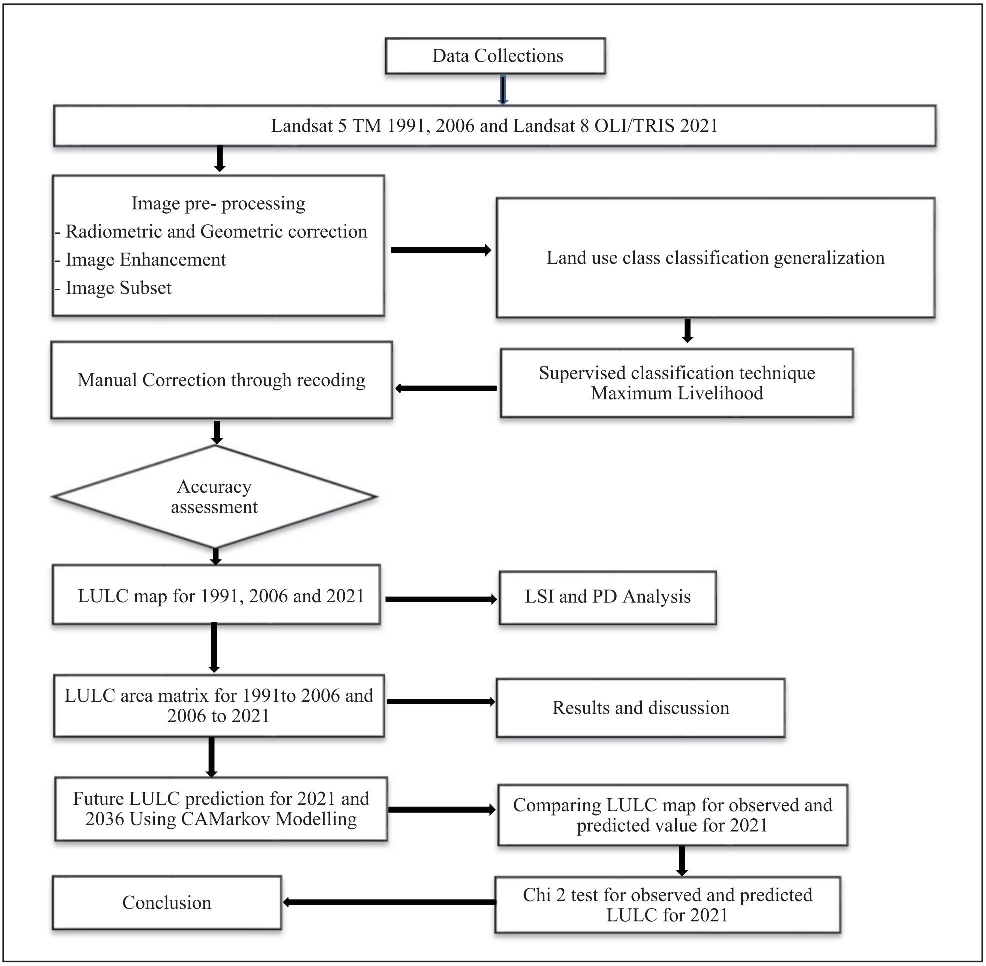

Fig. 2: Methodology

from fertile plains to hilly terrains. This study focuses on analyzing the Land Use and Land Cover patterns within the district. The district has an area of about 324 km^2 extending between latitude 24°30'13" N to 24°41'29" N and longitude 93°54'42" E to 94°7'50" E (Fig. 1). It is situated in the eastern part of the Manipur Valley with an elevation of 795 m above the mean sea level. The district is a crucial part of the Manipur Valley, known for its agricultural productivity. The topography of Thoubal District varies significantly, with the flat fertile plains ideal for agriculture in the west and undulating surface and hills in the east. The Imphal River and Thoubal River are the major rivers that flow in the district. Other important rivers include the Arong River, which flows through Charangpat and Khangabok and falls to Ikop Pat, and the Wangjing River, which flows through Heirok and Wangjing and falls to Kharung Pat.

Results and discussion

Table 1 shows the error matrices of the classified images which include the producer's accuracy, user's accuracy, overall

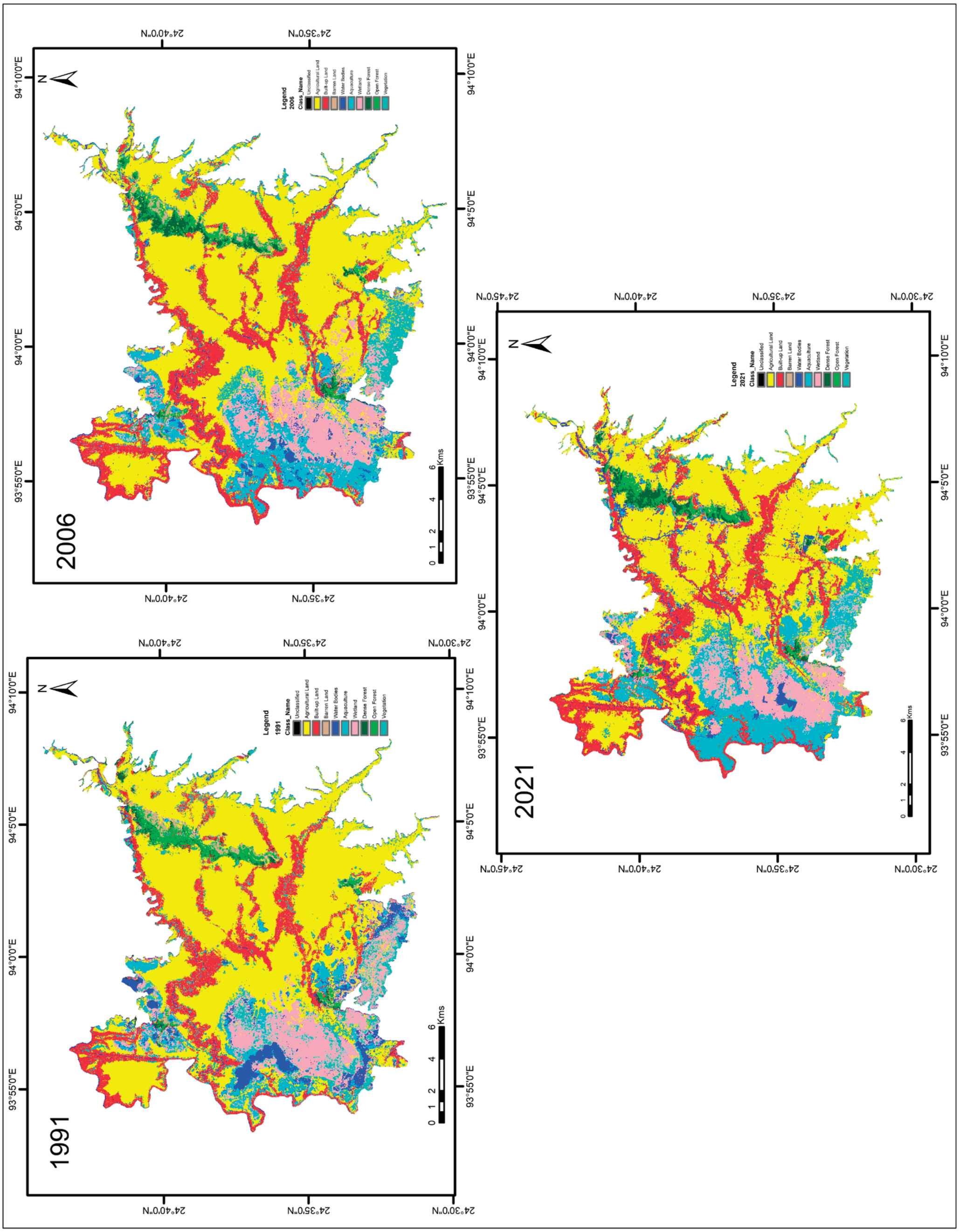

Fig. 3: LULC maps of Thoubal District for 1991, 2006, and 2021.

Table 1: Accuracy Assessment in percentage

Feature Class	1991		2006		2021	
	Producers accuracy	Users accuracy	Producers accuracy	Users accuracy	Producers accuracy	Users accuracy
Agricultural land	98.04	94.34	96.15	96.15	100.00	96.00
Built up land	90.91	83.33	89.47	94.44	95.00	95.00
Barren Land	33.33	100.00	50.00	50.00	0	0
Water	33.33	100.00	100.00	100.00	60.00	100.00
Aquaculture	100.00	77.78	100.00	83.33	100.00	84.62
wetland	84.62	84.62	75.00	75.00	80.00	80.00
Open Forest	50.00	50.00	100.00	50.00	50.00	100.00
Dense Forest	100.00	100.00	66.67	100.00	100.00	33.33
vegetation	66.67	75.00	71.43	71043	50.00	75.00

1991 - Overall classification accuracy=89.00 overall kappa statistics= 0.8248
2006 - Overall classification accuracy=90.00 overall kappa statistics= 0.8527
2021 - Overall classification accuracy=91.00 overall kappa statistics= 0.8711

**Calculated at Erdas Imagine 2014 Software.*

Table 2: LULC Area of the classes

Class Name	Area in % 1991(O)	Area in % 2006(O)	Change in Area% 2006	Area in % 2021(O)	Change in Area % 2021	Area in % 2036(P)	Change in Area% 2036(P)
Agricultural Land	52.87	49.56	-3.31	45.94	-3.62	36.65	-9.29
Built- up land	12.80	15.62	2.82	18.84	3.22	19.94	1.10
Barren Land	1.25	1.01	-0.24	0.60	-0.41	4.18	3.58
Water Bodies	5.24	3.53	-1.71	3.16	-0.37	6.92	3.76
Aquaculture	4.74	8.20	3.46	13.04	4.84	11.06	-1.98
Wetland	11.76	11.29	-0.47	8.79	-2.50	11.94	3.15
Dense Forest	1.20	1.82	0.62	1.91	0.09	2.11	0.20
Open Forest	2.14	1.64	-0.50	1.93	0.29	3.47	1.54
Vegetation	8.00	7.33	-0.67	5.79	-1.54	3.72	-2.07

accuracy, and overall kappa statistics. The overall accuracies of 1991, 2006, and 2021 LULC classifications are satisfactory at 89, 90, and 91 percent respectively (Anderson *et al.*,1976 cited in Manandhar, *et al.*, 2009). The area of LULC class features is calculated in hectares and percentages for each year and then compared with each other. Table 2 shows the proportion of area under nine categories of LULC features and the changes therein. At least two base years are required for CA Markov modeling to generate a probable future LULC map. Using the Software Idrisi 17 Selva Probable LULC maps for 2021 and 2036 are predicted using 1991 and 2006 LULC values and 2006 and 2021 LULC values respectively (Fig. 3). The predicted values are also shown in the same table.

Figure 2 is a better visual understanding of the data in Table 2.

It is clear from Table 2 and Fig. 4 that agricultural land, including fallow and cropland, occupies the largest area though experiencing a gradual decrease from 52.87 percent in 1991 to 45.94 percent in 2021 and is expected to decrease further to 36.65 percent in the year 2036. A significant change noticeable in land use change is the transformation of agricultural land in the vicinity of the built-up areas due to the expansion of the settlement area and area under aquaculture resulting in a significant increase of built-up area from 12.80 percent in 1991 to 18.84 percent in 2021 which is expected to increase up to 19.94 percent by the year 2036. The built-up areas are mostly concentrated around the Thoubal, Wangjing, and Arong rivers in linear patterns of settlements. The northwestern and western boundaries of the district are demarcated by the Imphal River and the settlements around the river form the same linear pattern. Barren land with degraded and bare soil is mostly confined to the hilly areas largely due to deforestation, abandoned shifting cultivated fields, and land excavation. The area under this land feature however has experienced some decline from 1.25 percent in 1991 to 0.60 percent in 2021. But in predicted LULC values of 2036, the area under barren land shows a huge increase of up to 4.18 percent. In the hills, barren lands are being converted to forests through afforestation efforts both by the government and the people. Ban on deforestation in reserved and protected forests has also helped to retain existing forest cover. As a result, dense forests and open forests have been increasing as seen from the spectral reflectance of the image. The two forests seem to interchange in some areas as trees are being cut down from the dense area and the open area remains untouched which led to the increase in tree density in around 15 years.

The southwestern part is Ikop and Kharung pat, mostly comprising of wetland and water bodies with less built-up area. In this area, both wetland and agricultural areas are gradually decreasing due to the expansion of pisciculture increasingly adopted as a livelihood option by the local inhabitants increasing from 4.74 percent in 1991 to 13.04 percent in 2021. However, it is likely to decline in the coming years and is estimated at 11.06 percent in 2036. Smaller wetlands namely Phulou pat, Yaithibi, and Waithoulake are also diminishing and there is an alteration of wetlands to agricultural fields and fish farms. Fishing activities in the area are the main occupation of the people. Snail oysters are found in these wetlands which are of considerable economic value. The areas covered with vegetation found outside of the hills are different in quality and can rarely be classified as forests. Even these areas are decreasing due to the expansion of agricultural land and built-up areas. If there is rain in that particular season the open land often gives out the spectral response of vegetation as small plants and grass start growing. Besides some agricultural land areas are under this category as winter crops give out the same spectral response. The vegetated area decreased from 8 percent in 1991 to 5.97 percent in 2021 and is expected to decrease to 3.72 percent in 2036. The district as a whole has better agricultural potential with fertile land and a good drainage system. Besides, the government has made legal provisions to regulate land use change so as to conserve the

Table 3: Land use transfer matrix 1991 and 2006

Feature class	Agricultural Land	Aquaculture	Barren Land	Built-up Land	Dense Forest	Open Forest	Vegetation	Water Bodies	Wetland	Grand Total 1991
Agricultural Land	14906.43	285.91	72.58	692.27	21.16	64.05	946.92	120.15	186.99	17296.46
Aquaculture	84.73	1097.07	4.7	93.03	0.72	0.66	64.32	105.74	100.65	1551.62
Barren Land	62.36	2.37	145.6	13.21	25.37	137.48	15.45	2.67	5.62	410.13
Built-up Land	98.71	10.52	9.16	3998.51	8.92	8.38	26.18	8.03	18.25	4186.66
Dense Forest	37.55	4.17	6.9	32.02	232.06	75.99	3.98	0.44	0.42	393.53
Open Forest	76.33	5.1	74.1	19.12	279.28	220.76	23.57	0.79	0.08	699.13
Vegetation	668	201.3	9.53	173.53	28.41	23.39	794.52	78.8	640.76	2618.24
Water Bodies	136.96	473.88	4.2	9.45	4.83	5.72	140.3	577.97	359.59	1712.9
Wetland	154.01	589.92	7.71	79.23	3.59	4.93	471.94	144.56	2391.36	3847.25
Grand Total 2006	16225.08	2670.24	334.48	5110.37	604.34	541.36	2487.18	1039.15	3703.72	32715.92

**Area in hectares*

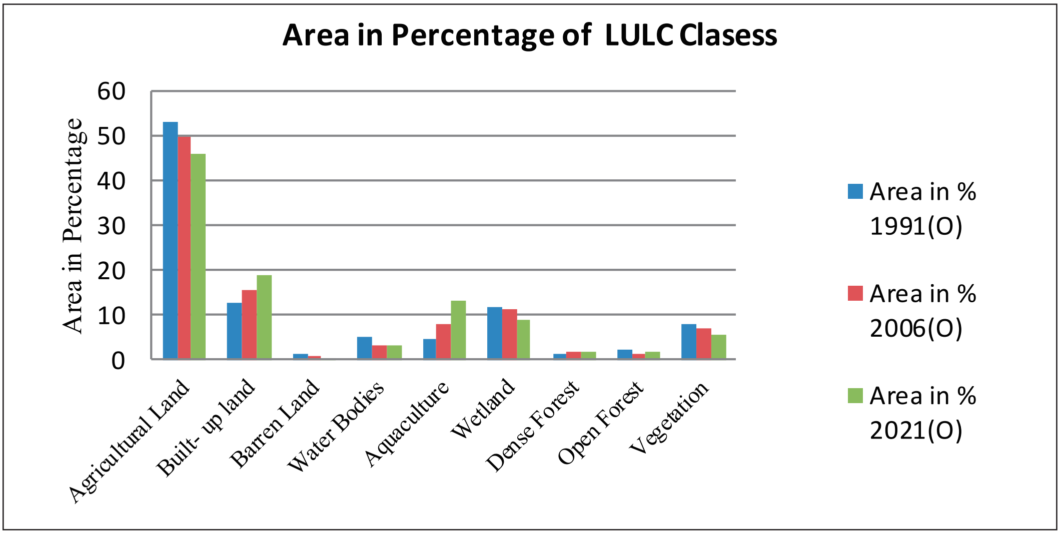

Fig. 4: Chart of the area in percentage for each class for different years.

existing paddy land and wetlands as the area under cultivation has been reducing in recent years.

The LULC transformation matrix shows the land use categories transferred to and from other land use categories. Table 3 and Table 4 show the area matrix of different classes of LULC change for 1991-2006 and 2006-2021.

LULC changes are a complicated process and the Markov-based cellular automata for prediction offers a wide understanding of the complexity of the components of the spatial system (Hamad *et al.*, 2018). The CA Markov trend is based on past land-use changes and it requires two base years. So, using the land-use changes value of 1991 and 2006, LULC for 2021 is predicted; is compared with the observed value of the LULC map of 2021 and is used to determine whether they are significant on the chi-square test. The calculation and its values are shown in table 5. This test is based on the comparison of the difference between the observed results and the theoretical results (Singh *et al*, 2008). The null hypothesis proposed is: that the observed area and the predicted area are the same.

From the given table the calculated Chi-square value of 5.58 is less than 15.507, and the tabulated values for 8 degrees of freedom

Table 4: Land use transfer matrix 2006 and 2021

Feature class	Agricultural Land	Aquaculture	Barren Land	Built-up Land	Dense Forest	Open Forest	Vegetation	Water Bodies	Wetland	Grand Total2006
Agricultural Land	13487.72	516.67	41.81	700.45	19.64	56.15	762.53	420.92	207.27	16213.16
Aquaculture	83.25	2406.38	6.09	14.48	0.68	0.71	39.02	9.5	122.74	2682.85
Barren Land	73.71	9.64	54.03	15.01	16.06	142.7	8.94	1.82	7.51	329.42
Built-up Land	85.71	16.35	10.19	4801.12	4.67	21.22	143.96	8.22	20.11	5111.55
Dense Forest	11.89	3.4	12.08	21.58	430.1	104.92	10.62	0.77	0.07	595.43
Open Forest	51.94	4.01	51.08	27.93	131.78	250.62	17.7	0.93	0.23	536.22
Vegetation	782.43	195.93	10.98	322.55	13.43	24.93	677.8	101.95	267.79	2397.79
Water Bodies	173.26	295.92	4.05	151.28	4.75	6.62	34.51	293.64	191.59	1155.62
Wetland	279.76	818.53	5.69	108.22	4.66	22.32	199.09	196.65	2058.59	3693.51
Grand Total 2021	15029.67	4266.83	196	6162.62	625.77	630.19	1894.17	1034.4	2875.9	32715.55

**Area in hectares*

Table 5: CA Markov model validation through chi-square test

Class Name	Observed area in% 2021(O)	Expected area in% 2021(E)	O-E	$(O-E)^2$	$(O-E)^2/E$
Agricultural Land	45.94	44.31	1.63	2.65	0.059
Built-up land	18.84	16.17	2.67	7.12	0.44
Barren Land	0.6	2.31	-1.71	-2.92	-1.26
Water Bodies	3.16	5.78	-2.62	-6.86	-1.18
Aquaculture	13.04	5.63	7.41	54.90	9.75
Wetland	8.79	11.36	-2.57	-6.60	-0.58
Dense Forest	1.91	2.77	-0.86	-0.73	-0.26
Open Forest	1.93	3.49	-1.56	-2.43	-0.69
Vegetation	5.79	8.14	-2.35	-5.52	-0.67
Total	100	100			5.58

Table 6: LSI and PD for 1991, 2006 and 2021

Class Name	LSI			PD		
	1991	2006	2021	1991	2006	2021
Agricultural Land	43.9943	43.4365	50.9165	9.2532	8.6656	9.3659
Built-up land	62.9453	54.3869	63.2868	5.3224	4.6129	7.9622
Barren Land	28.4044	28.0960	26.7917	1.7812	1.7660	1.6564
Water Bodies	56.6607	68.5422	73.3992	8.0505	10.4803	12.2433
Aquaculture	44.8971	43.2435	39.1788	5.2797	4.8596	4.5033
Wetland	58.2211	50.4754	38.3322	6.5494	7.5847	4.3572
Dense Forest	32.1395	21.1963	18.4634	1.8269	0.9317	0.7582
Open Forest	34.0171	35.6154	32.6527	2.0431	2.2928	2.3263
Vegetation	85.1795	73.3647	73.1779	15.3216	13.9849	13.7383

**Calculated at FRAGSTAT v4.2 Software.*

at a 0.5 level of significance. It shows that the null hypothesis is accepted and CA Markov modeling values are true for this case of future LULC prediction. Thus, the probable predicted values of LULC 2036 will account for true.

FRAGSTATS offers a comprehensive choice of landscape metrics and was designed to be as versatile as possible. The programme is almost completely automated and thus requires little technical training (Mcgarigal *et al.*, 1995). Landscape metrics have been increasingly applied in understanding landscape dynamics with adequate explanations of the underlying processes (Aithal, *et al.*, 2012). Landscape matrices like the LSI and PD are adopted to estimate the changes in the landscape pattern. It represents the landscape heterogeneity due to landscape processes. LSI measures the complexity of the landscape while PD measures the fragmentation of the landscape. Class with high patch density indicates a higher number of patches identified and is thus considered to be fragmented i.e. more distributed across the study area.

The class feature which has a higher LSI has a higher complexity landscape. The LSI value of water bodies, agricultural land, and built-up land increased from 1991 to 2021 revealing the unplanned increase and irregular edges of the land feature which shows the complex nature of the landscape. Among these, water bodies which increased from 56.6607 in 1991 to 73.3992 have the highest value. In other classes, the LSI values are decreased among these dense forests lowest in 2021. The decrease in LSI shows that the class feature is more aggregated. The classes that have a higher value of LSI mean a greater impact on human activities and have a more complex shape.

The Patch Density of vegetation, water bodies, agricultural land, and wetlands are high as compared to other classes for each year (Table 6). It means that these LULC classes are more fragmented as compared to other classes. The PD of built-up land and water bodies has increased abruptly from 5.3224 in 1991 to 7.9622 in 2021 and from 8.0505 in 1991 to 12.2433 in 2021 respectively showing the expansion and more fragmentation of the class. It is because built-up land and water bodies are unconnected to numerous pieces, and the built-up area is growing while new settlements have come up. The same goes with water bodies too as people dug out new ponds and the large natural water bodies are fragmented by changing some portion of it like the swallow area for aquaculture. Thus, the increase in PD shows greater human intervention. The classes which have a weakening trend in PD show their concentrated nature of the land use feature.

Conclusion

The study explored the nature of LULC changes, landscape patterns, and the future predicted value of LULC. It shows that the existing land use pattern is changing both on account of natural and human activities. Agricultural land which occupies the largest area has been decreasing due to population increase and changes in the economic activities of the people. Due to human intervention the wetland area, natural water bodies, and some agricultural areas adjacent to these regions are converted into aquacultural land. High values in LSI and PD show a high level of unplanned expansion of the land features and the complexity level. It shows the human intervention in the LULC feature. The controlled value of LSI and PD in some classes indicates that it becomes less fragmented. The observed land use and land cover changes in Thoubal district have important implications for the environment, economy, and society. The findings of this study contribute to the understanding of land use and land cover changes in the district and provide insights for decision-makers, policymakers, and stakeholders for adopting sustainable land management practices, conserving ecosystems, and integrating environmental considerations into development plans.

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