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Detecting and Predicting Land Use/ Land Cover Change in Hisar District, Haryana, Through Geospatial Techniques

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Abstract

The rapid growth of the population is changing the surrounding landscapes in Haisar district in Haryana. This result in environmental degradation and influences the quality of life. The geospatial techniques can be of great use in understanding the dynamics of these changes and for better planning in the direction of sustainable land use. This study aims to identify land use and land cover (LULC) changes in Hisar district for 1997, 2009 and 2017 as reference time periods. The LULC changes in the district of Hisar are also predicted for the year 2037 on the basis of projections; using geospatial techniques. Multitemporal Landsat-TM (Thematic Mapper) and Landsat-OLI (Operational Land Imager) are used to estimate LULC patterns here. Multistage unsupervised classification is performed to classify the LULC. Markov model is used to predict the LULC for the year 2037. The study found that the agricultural and built-up area is increasing continuously while the area under water bodies, fallow land and forest is decreasing. The validation of LULC was performed for the year 2017, which shows more than 90 percent accuracy. This study will help land use planners and policy makers to make suitable decisions for sustainable land use by understanding the LULC change patterns.

Keywords: *Geospatial Technique, Image Classification, LULC, CA-Markov*

Introduction

The term landuse refers to the purpose served by land resource utilization and exploitation through various anthropogenic activities, while land cover describes presence of physical cover on the earth's surface, which includes water bodies, vegetation, forest, agricultural areas and urban landuse (Mishra and Rai 2016; Mariye et al, 2022). The phrase LULC thus signifies the categorization or classification of human activities and the natural elements on the landscape within a specific time frame based on established scientific and appropriate statistical methodologies (Lydia et al, 2018).

The increasing demand of growing population, rapid urbanization and exploitation of resources that are highly induced by human activities, have led to the modification and transformation of environmental settings and deterioration of health. Furthermore, it leads to the loss of biodiversity due to habitat fragmentation, deforestation and human enchrochment (Lia et al., 2021). Land is degrading rapildly due to grazing and the conversion of agricultural land into barren land as a result of intensive farming and overgrazing. Subsequently, these issues may lead to serious social, economic and political consequences because of the decline of natural resources and thus affect the food supply (Halmy et al., 2015; Regasa et al, 2021).

The significance of this issue has raised awareness about the need to anlayse and examine changing activities and their impact on land use and land cover (LULC). Detection of these long-term changes caused by human intervention is of great concern today. Understanding the current landcover and how it is being used, along with an accurate means of monitoring change over a period of time, is however crucial for proper land management and landuse planning. Quantifying, mapping and predicting of the current change in the use of land resources can be easily achieved by using cost-effective geospatial techinques. Remote Sensing (RS) and Geographical Information System (GIS) are effective tools for simulating LULC changes, which are useful for guiding planning and management (Sonametal,2021). Multiple researches with different approaches have been done to measure the change in landcover, yet well studied documentation is needs to analyse the present LULC pattern of Hisar district.

Taking into account the importance of studying LULC patterns, the present study chose the Hisar district of Haryana state becouse it is situated at the entry gate of the Thar desert. It is assumed that the district situated near the arid region receives very inadequate rain and experiences less human intervention and developmental activities. Satellite data from Landsat-TM (Thematic Mapper) and Landsat-OLI (Operational Land Imager) of February for the years 1997, 2009 and 2017 are used for the change detection here. IDRISI Terrasat has been used for prediction to generate a change detection matrix and change map within the study area.

Study Area

The Hisar district is situated in the West Central part of Haryana state with a total geographical area of 3983.00 km^2 (figure 1). It is confined between the latitude 28º 56' 00" N to 29º 38' 30" N and longitude 75º 21' 12" E to 76º 18'12" E. This district experiences subtropical climatic conditions, influenced by westerly winds rising temperature as high as 48ºC during summer, while north-westerly winds blow in winter providing a low temperature of about -1.70°C. Average annual rainfall received is about 85 percent during the short south western monsoon period (National Wetland Atlas Haryana, 2010). According to Census 2011, Hisar district occupies 2nd position in terms of size of population in the Haryana state.

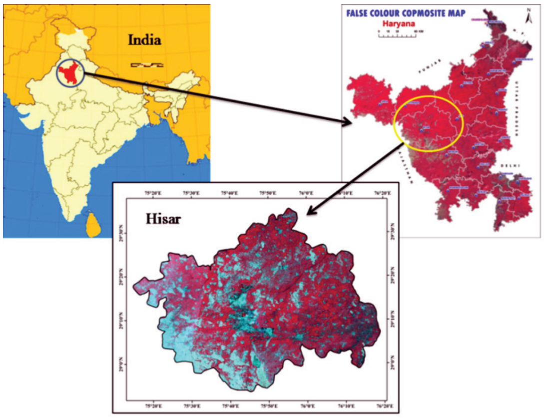

Fig 1: Location Map of Study Area (Hisar District)

Materials and Methodology

Quantitative and qualitative analyses were performed in which a combination of primary and secondary data was used to evaluate the land use and land cover (LULC) change and predict future scenarios for the Hisar district. First, a comparison approach using multistage unsupervised classification was adopted and then an accuracy assessment with post-classification was carried out to detect LULC changes for 1997 and 2017. Further, the future prediction and validation of LULC has been done for 2017 and 2037.

Data Sources

Satellite Images Used: Satellite images Landsat-TM (Thematic Mapper) and Landsat-OLI (Operational Land Imager) with Rows 147, 148 and Path 40 were used to acquire information for the month of February for three different years 1997, 2009 and 2017 from the earth explorer USGS of the United State Geological Survey (USGS) (website https://earthexplorer.usgs.gov). The data obtained from these sources have been processed to gain the reflectance value that involves DN, to Radiance conversion and Radiance to Reflectance conversion.

Method

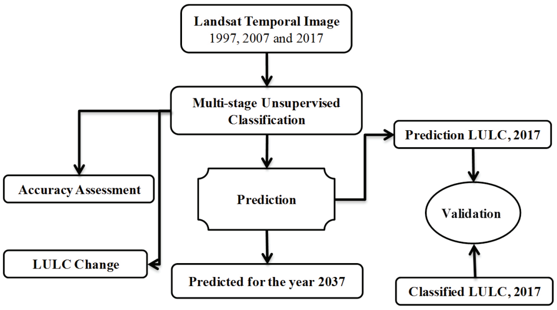

Fig. 2: Flow chart for the process method

Multistage Unsupervised Classification: A multistage unsupervised classification approach has been adopted here which includes hierarchical clustering and unsupervised classification. Unsupervised classification is a per-pixel classification technique, used to process the selected initializing (Principal Axis & Automatic) and Color Scheme Option (Approximate True Color) (Cheng et al, 2017). In the present study, the first fifty classes are categorized within the study area, which are later recoded into five classes (Water, Forest, Agriculture, Fallowland and Built-up). Each class obtained here was issued separately to make the satellite image (FCC). Further, the classification has been made for each class using unsupervised method. The final results obtained are then recoded into their original class. The remaining mixed pixels are then recoded into other classes. Similar processes are followed repeatedly on the classified image with the maximum value overlay rule until the mixing of classes is minimized at the optimum level. A final LULC classification map was generated for Hisar district with improved accuracy. After this, landuse change in Hisar district has been predicted for the year 2037 using Cellular Automata (CA) Markov model in Terrasat (IDIRISI) software (Trial version). A probability matrix was created based on 1997 and 2009 data to predict the LULC of year 2017 and then compared and validated the predicted image (2017) from the classified (actual image). Finally, based on the year 2017, a prediction of 2037 was made and an LULC change trend map was generated.

Markov Model

The CA Markov model is a statistical tool used to analyze the transition probability matrix based on neighborhood effects in a spatial influence algorithm that is widely used to model the current trends of land use dynamics (Nouri et al., 2014). It uses Markov chain model-based input for the change prediction. In the Markov chain model, the value X_t depends only on its value X_{t-1} at time t-1 (simple random walk). This depends on the sequence of values X_{t-2}, X_{t-3}, ……, X_0 (Singh et. al., 2013).

It is expressed as:

$$P\{X_t = a_j \mid X_0 = a_0, X_1 = a_1, \ldots\ldots, X_{t-1} = a_i\}$$
$$= P\{X_t = a_j \mid X_{t-1} = a_i\}$$

This is convenient in the context of change processes in discrete time (t= 0, 1, 2, 3……..)

Transition probabilities were calculated from base maps (1997→2009) using the Markov module to produce the transition matrix P_Δt for Δt = 12 years. Annual transition probabilities P_1 were derived by P_1 = exp((1/Δt) * log(P_Δt)) and then raised to the required power to obtain P_ΔT for the projection interval. Spatial allocation of transitions was performed using a Cellular Automata (Moore 3×3 neighborhood, neighborhood radius = 1, contiguity weight = 0.5) combined with conditional transition potential maps where available. Predicted maps (2017 for validation and 2037 final projection) were generated and validated by comparison with the classified 2017 map using confusion matrix, overall accuracy and Kappa. All transition matrices, CA parameters and validation points are provided in Supplementary material.

Results and Discussion

LULC change has been studied using Landsat Thematic Mapper and OLI data for the years

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1997, 2009 and 2017. Broad classes such as forest, agriculture, built-up, water and fallow land and other have been identified and mapped with sufficient accuracy. The CA Markov model is used to predict LULC for the year 2017 and 2037.

Land Use Land Cover (LULC) 1997: Here, Table 1 depicts the percentage of land use and land cover for the year 1997. In 1997, there was a dominance of agricultural land use (68.50%) followed by fallowland (27.07%) over the study region. The forest area coverage was only 1.15%. The built-up area (2.59%) was identified to be high at the central part while patches of urban and rural setup of small size were well distributed. The area covered by water bodies is 0.7% of the total area of the district and its distribution was mainly concentrated near the built-up area only (figure 3).

Table 1: LULC area along with percentage coverage for 1997

LULC Classes	Area (ha) 1997	Area (%)
Water	2770.49	0.70
Forest	4573.93	1.15
Agriculture	272844.25	68.50
Fallowland and other	107812.26	27.07
Built-Up	10333.07	2.59

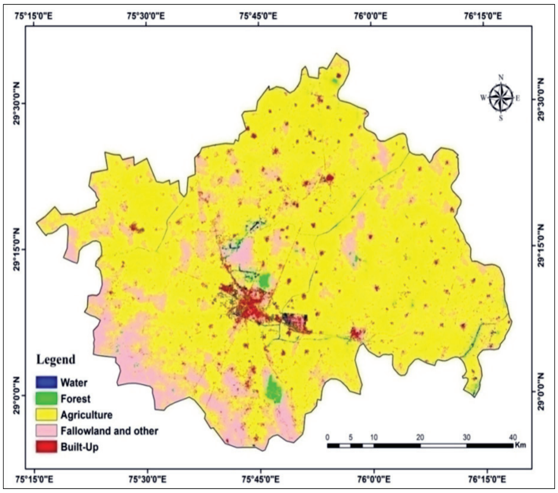

Fig. 3: LULC of the year 1997

Table 2 represents the LULC of 2009, where agricultural land use is still a dominant category covering an area of 77.76% of the total geographical area of the district and showing a significant increase. Fallow land is identified to be 16.39%, followed by built-up 4.41%, forest cover 1.02% and water body 0.42% of area coverage (figure 4).

Table 2: LULC area along with percentage coverage for 2009

LULC Classes	Area (ha) 2009	Area (%)
Water	1669.31	0.42
Forest	4055.55	1.02
Agriculture	308961.47	77.76
Fallowland and other	65127.85	16.39
Built-Up	17519.81	4.41

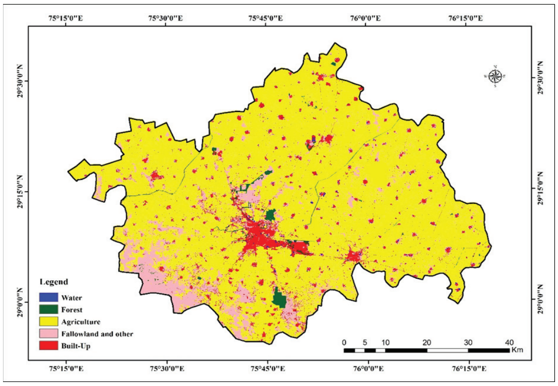

Fig. 4: LULC of the year 2009

Land Use land Cover- 2017: Table 3 represents the LULC of 2017, where agricultural land use is still a dominant category covering an area of 77.75% of the total geographical area of the district and again showing a significant increase. Fallow land is identified at 15.54%, followed by built-up at 5.31%, forest cover at 0.99% and water bodies at 0.41% of area coverage (figure:5).

Table 3: LULC area along with percentage coverage for 2017

LULC Classes	Area (ha) 2017	Area (%)
Water	1631.84	0.41
Forest	3939.47	0.99

LULC Classes	Area (ha) 2017	Area (%)
Agriculture	309718.00	77.75
Fallowland and other	61886.89	15.54
Built-Up	21157.79	5.31

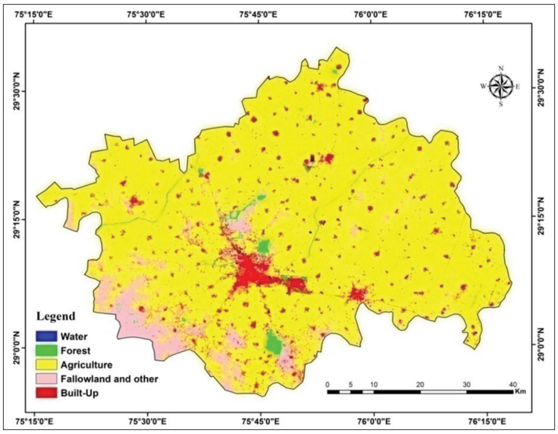

Fig. 5: LULC of the year 2017

Accuracy Assessment: In assessing the LULC classification accuracy, Tables 4 and 5 represent different parameters of accuracy such as producer's accuracy (PA), user's accuracy (UA), over all accuracy and kappa coefficient. The overall accuracy of the classified image for February 2017 was 92.80% with kappa coefficient of 0.86. Both the producer's and user's accuracies of individual classes are found to be extremely high. The producer's accuracy for different categories is found as 94.74% in water, 94.30% in agriculture, 91.55% in fallowland and other, 88.24% in built-up areas and 80.00% in forest cover. The user's accuracies were 98.51%, 90.91%, 90.00%, 79.27% and 75.00% in the agriculture, water, forest, fallowland and other and built-up categories respectively. The accuracies of the classes calculated are better than the expected level. The lower UA for the built-up area class is due to its mixing with Fallowland having a similar signature. Points from Google Earth and ground truth (GCP) information covering different LULC classes have made it possible to access the classification results reliably with a good accuracy level.

Table 4: Confusion matrix for the accuracy assessment of LULC in 2017.

Classified Data	Water	Forest	Agriculture	Fallowland and other	Built-Up Areas	Row Total
Water	18	1	1	0	0	**20**
Forest	0	20	0	0	2	**22**
Agriculture	0	3	331	2	0	**336**
Fallowland and other	0	0	15	65	2	**82**
Built-Up Areas	1	1	4	4	30	**40**
Column Total	**19**	**25**	**351**	**71**	**34**	**500**

Table 5: Producer's Accuracy and User's Accuracy of classified image of the year 2017

Class Name	Reference	Classified	Number Correct	PA	UA
Water	19	20	18	94.74%	90.00%
Forest	25	22	20	80.00%	90.91%
Agriculture	351	336	331	94.30%	98.51%
Fallowland and other	71	82	65	91.55%	79.27%
Built-Up Areas	34	40	30	88.24%	75.00%
Overall Accuracy = 92.80%			**Kappa Coefficient = 0.86**		

LULC Change Analysis: In the analysis of LULC, Table 6 illustrates the change in LULC between 1997 and 2017. Here a remarked change has been noticed in this time span of two decades. The classified temporal images of 1997 and 2017 were analysed to examine the changes based on interconversion of each class into other classes and a change map was obtained and is represented here in Figure 5. It is observed that agriculture and built-up areas have increased and water, forest and fallowland and other classes have decreased. Table 5 shows that the area covered under water bodies was 2770.49 ha (0.70%) in 1997, which decrease to 1631.84 ha (0.41%) in 2017. This shows a total 1138.65 ha (0.29%) decrease in surface water area. Most of the area of the water class is converted into agriculture, fallowland and built-up areas.

Table 6: Change matrix showing change between 1997 to 2017

Change Matrix	Water	Forest	Agriculture	Fallowland and other	Built-up Areas	Total (1997)
Water	636.43	487.10	713.59	459.51	473.86	2770.49
Forest	82.83	1723.01	1043.36	843.85	880.88	4573.93
Agriculture	208.71	549.91	252134.29	16335.55	3615.80	272844.25
Fallowland and other	544.06	951.51	54216.05	42096.48	10004.16	107812.26
Built-up Areas	159.82	227.95	1610.71	2151.51	6183.09	10333.07
Total (2017)	1631.84	3939.47	309718.00	61886.89	21157.79	398334.00

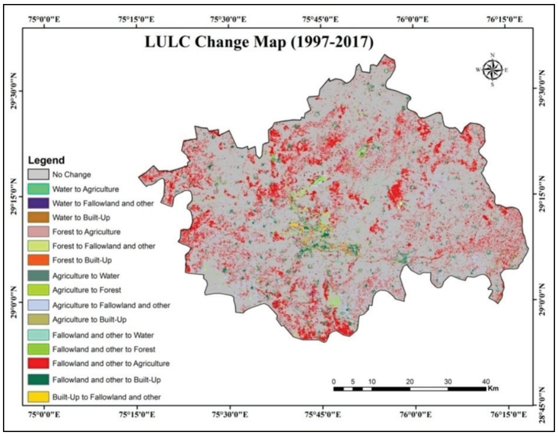

Fig. 6: LULC Change Map between 1997- 2017

The forest area of 4573.93 ha (1.15%) in 1997 declined to 3939.47 ha (0.99%) in 2017 i.e., the total forest area of 634.45 ha (0.16%) decreased in these twenty-year periods. The agriculture class has shown a drastic change in the percentage coverage of the total geographical area of the district Hisar from 1997 to 2017 with an increase of approximately 10% i.e. from 68.50 % to 77.75%. In terms of area, it has increased from 272844.25 ha to 309718.00 ha. The increase in area under cultivation may be due to conversion of wasteland to agricultural land to meet the current food demand of the growing population. The study indicates that the major portion of fallowland 54216.05 ha (13.61%) has been converted into agricultural land. Furthermore, a second major part of fallowland 10004.16 ha (2.51%) has been identified to be transformed into built-up areas. In 1997, Built-up areas covering the total geographical area of the Hisar district was 10333.07 ha (2.59%) which changed to 21157.79 ha (5.31%) in 2017. This shows an increase in built-up area of 10824.72 ha (2.72%) in the last two decades (Figure 6).

Prediction and Validation of LULC for the year 2017: LULC change simulation using predictive models is essential to assess future changes, so that proper planning can be suggested for resource management. The LULC of 1997 and 2009 was used to predict the LULC for 2017. The original classified map of 2017 was used for the validation of the simulated LULC. The results have shown that the CA-Markov model is efficient in simulating future LULC. Furthermore, the LULC for 2037 is simulated using the LULC of 1997 and 2017 as base year data. The results from the prediction and validation are described below:

Transition Probability Matrix: The transition probability matrix shows the probability of a class to change into other classes. The transition probabilities of different LULC classes are depicted in Table 7. The diagonal of the matrix shows the probabilities of the classes to be remaining in the same class during a given time period i.e. from 1997 to 2009. The water body has shown a transition probability of 0.3154 in the diagonal which means that the water has a 32% chance of remaining in water until 2009. The off-diagonal element shows probability of a class being changed into another class. Thus water has a probability of 0.2022 to change into forest, 0.1809 into agriculture, 0.151 into fallowland and 0.1506 into built-up areas. Forestland has a transition probability of 0.4849 to last in the forest class only, 0.0192 to change into water bodies, 0.1498 into agriculture, 0.1722 into fallowland and other and 0.174 into built-up areas.

Similarly, the agricultural land transition probability is 0.9423 remaining agricultural land, 0.0005 for changing into water bodies, 0.0014 for forest, 0.0483 for fallowland and others and 0.0075 for built-up area category. Fallowland has a transition probability of 0.4802 to remain fallowland and other but 0.0049, 0.0077, 0.4216 and 0.0856 to be changed into water body, forest, agriculture and built-up area classes respectively. The built-up area category has a transition probability of 0.6885 to be in the same built-up category, but this value changed to 0.0155 in water bodies, 0.0191 in forest, 0.0819 in agriculture and 0.1949 in fallowland and other classes.

Table 7: Transition Probabilities of LULC for the year 2017 based on LULC of 1997 and 2009

LULC classes	Water	Forest	Agriculture	Fallowland	Built-Up Areas
Water	0.3154	0.2022	0.1809	0.1510	0.1506
Forest	0.0192	0.4849	0.1498	0.1722	0.174
Agriculture	0.0005	0.0014	0.9423	0.0483	0.0075
Fallowland and other	0.0049	0.0077	0.4216	0.4802	0.0856
Built-Up Areas	0.0155	0.0191	0.0819	0.1949	0.6885

Predicted LULC of 2017: The predicted LULC map for the year 2017 is obtained on the basis of the processed LULC maps of 1997 and 2009. From Table 8, it has been identified that the water body has covered an area of 1377 ha (0.35%), forest 5037.82 ha (1.27%), agriculture 310616.33 ha (77.98%), fallowland and other 60901.16 ha (15.29%) and built-up area 20365.69 ha (5.11%). The projected map of LULC for 2017 showed an increase in water, agriculture and built-up area classes and a decrease in forest and fallowland and other classes. The similar results are obtained from the classified map of 2017 using unsupervised classification (Table 7).

Table 8: Land Use/Land Cover Area, Predicted 2017

LULC Classes	Prediction 2017	Area (%)
Water	1377.00	0.35
Forest	5073.82	1.27
Agriculture	310616.33	77.98
Fallowland and other	60901.16	15.29
Built-Up Areas	20365.69	5.11

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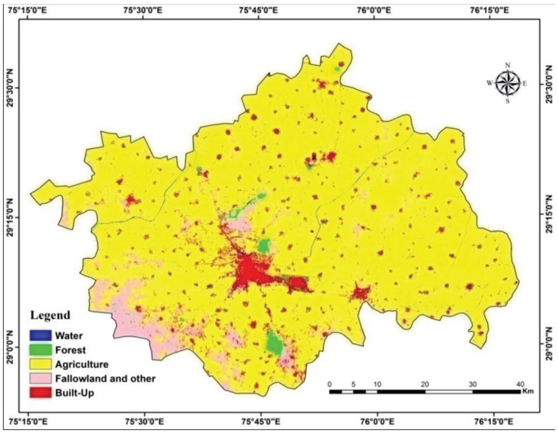

Fig. 7: LULC predicted map of the year 2017

Validation of predicted LULC for 2017: Validation of the predicted LULC was performed based on the change matrix (predicted and classified image). Here, Table 7 signifies the analysis of inter-conversion statistics of various LULC classes along with the change map in the spatial domain. The major part of the map shows that the classified categories have no change which means the predicted LULC is very accurate. Furthermore, Table 7 illustrates the comparison of the LULC area of both the classified and predicted images for 2017 for the Hisar district. The water is found to cover 1639.61 ha under the classified image while it is 1661.16 ha in the predicted image, thus the change obtained for the particular class is 21.55 ha (0.01%), which is very less. The area covered by forest is 3967.41 ha in the classified image and 3893.34 ha in the predicted image and change obtained is 74.07 ha (0.02%), which is again much less than the total geographical coverage of the forest in the study area. The area covered by agriculture is 309962.05 ha in the classified image and 315549.34 ha in the predicted image, which represents a change of 5587.29 ha (1.35%).

Similarly, fallowland covers 61567.33 ha in the classified image and 55984.54 ha in the predicted image. The total change obtained is 5582.79 ha (1.35%) between the predicted and classified images. The model is identified to overpredict the agriculture class and underpredict the fallowland class. The built-up area is predicted perfectly by the model with less than 0.01% change. The areas of the built-up class ware 21197.60 ha and 21245.62 ha in the classified and predicted images respectively, which showed a change of 48.03 ha. Therefore, the total accuracy of the predicted image with respect to the classified image is 97.26% and the overall error obtained is 2.74%. Hence, this model is found to be efficient for the simulation of LULC for future predictions.

Table 9: Change analysis between predicted and classified images in 2017

LULC Class	Water	Forest	Agriculture	Fallowland and other	Built-Up Areas
Predict	1661.16	3893.34	315549.34	55984.54	21245.62
Classified	1639.61	3967.41	309962.05	61567.33	21197.60
Change	21.55	-74.07	5587.29	-5582.79	48.03
Change (%)	0.01	-0.02	1.35	-1.35	0.01

Prediction of LULC for 2037

The same model was used to predict LULC for the year 2037 by incorporating the LULC of 1997 and 2017 as base year data for the analysis. The difference of 20 years is taken into consideration to make symmetry between the time gap for the base of LULC and the simulation time frame. The results from the prediction analysis are interpreted under the following head.

Transition Probability Matrix: Here, Table 10 depicts the transition probabilities of different classes to change into another class for the prediction of LULC in 2037. The water body has shown a transition probability of 0.2297 to remain in the water body class only, where 0.176 to change into forest, 0.2575 into agriculture, 0.1658 into fallowland and other and 0.1711 into built-up area classes. Forest cover showed a transition probability of 0.3771 to remain in forest class, while 0.0181, 0.2276, 0.1658, and 0.1927 transition values changed into water body, agriculture, fallowland and other and built-up area categories respectively. Agricultural land showed a transition probability of 0.9241 to remain as agricultural land and 0.0008, 0.002, 0.0599 and 0.0133 to change into water bodies, forests, fallowlands and other and built-up areas respectively. Correspondingly, fallowland showed a probability of transition of 0.3903 to remain in the same class i.e. fallowland and other categories, 0.0051, 0.0088, 0.5029 and 0.0929 to change into water body, forest, agriculture and built-up area classes respectively. The built-up area class showed a transition probability of 0.5985 to remain in the built-up area category only, and 0.0155 to change into water bodies, 0.0221 to forest, 0.1558 to agriculture and 0.2082 to fallowland and other categories.

Table 10: Transition Probability Matrix to 2037 based on LULC map 1997 and 2017

LULC classes	Water	Forest	Agriculture	Fallow	Built-Up Areas
Water	0.2297	0.176	0.2575	0.1658	0.1711
Forest	0.0181	0.3771	0.2276	0.1845	0.1927
Agriculture	0.0008	0.002	0.9241	0.0599	0.0133
Fallow land and other	0.0051	0.0088	0.5029	0.3903	0.0929
Built-Up Areas	0.0155	0.0221	0.1558	0.2082	0.5985

LULC statistics for the year 2037: The predicted LULC map of 2037 is obtained based on processed LULC maps of 1997 and 2017 (Figure 7). Table 11 represents the predicted area of different classes for the year 2037. The water body covered the area of 1374.37 ha (0.35%), 3427.58 ha (0.86%) of forest, 321933.37 ha (80.82%) of agriculture, fallowland and other class 48060.19 ha (12.07%) and 23538.48 ha (5.91%) of built-up areas (Figure 8). Increases in agriculture and built-up areas have been observed here. Both the forest and fallowland classes showed significant decreases in terms of their area covered. Minor changes are also observed for water bodies.

Table 11: Area of predicted LULC for the year 2037

LULC Classes	Prediction 2037	Area (%)
Water	1374.37	0.35
Forest	3427.58	0.86
Agriculture	321933.37	80.82
Fallowland and other	48060.19	12.07
Built-Up Areas	23538.48	5.91

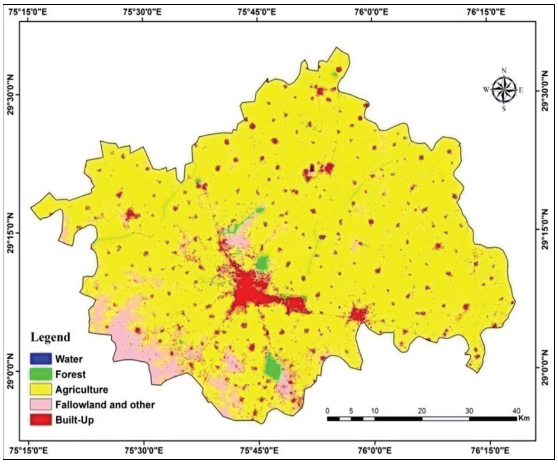

Fig. 8: LULC predicted map of the year 2037

Comparison of LULC area for 1997, 2009, 2017 and 2037

The graph represented in Figure 8 and Table 12 shows the area (in ha) of LULC classes during 1997, 2009, 2017 (predicted), 2017 (classified) and 2037 (predicted). Water body area, forest area and fallowland classes are continuously decreasing while agriculture and built-up areas are increasing. The increase and decrease in the area of various classes from 1997 to 2037 is independent in nature and will not differ much if any major natural or anthropogenic changes occur. However, it is expected that the changes in LULC inside the study region will definitely vary because of anthropogenic activities.

Table 12: Area of LULC for 1997, 2009, 2017 and 2037

LULC Classes	1997	2009	2017 (Pr)	2017 (Cl)	2037
Water	2770.49	1635.11	1631.84	1377.00	1374.37
Forest	4573.93	3956.48	3939.47	5073.82	3427.58
Agriculture	272844.25	310616.33	309718	310616.33	321933.37
Fallowland and other	107812.26	61365.14	61886.89	60901.16	48060.19
Built-Up Areas	10333.07	20760.93	21157.79	20365.69	23538.48

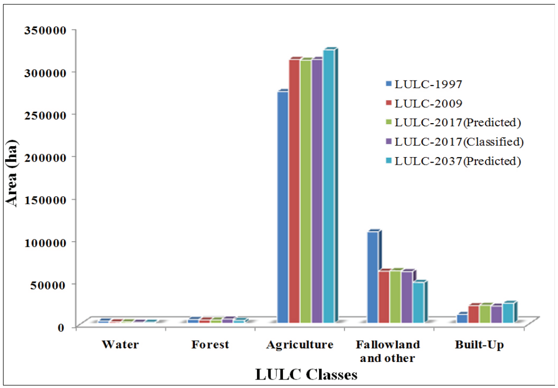

Fig. 9: Comparison of LULC area

Findings

Analysis of Land Use/Land Cover (LULC) dynamics in Hisar District (1997-2017) revealed that while agriculture remained the dominant land use, its share slightly declined due to a marked increase in built-up areas, reflecting rapid urban expansion. The study's multistage unsupervised classification was highly reliable, achieving an overall accuracy exceeding 92% and a Kappa coefficient of 0.86 for the 2017 map. Furthermore, the CA-Markov model was validated with high agreement (97.26%) in predicting the 2017 LULC, effectively reproducing the observed conversion of agricultural land to built-up areas. The model projects this trend to continue through 2037, with further urban growth concentrated around existing settlements and transport corridors at the expense of agricultural and fallow categories, while forest and water body classes are expected to remain stable.

Conclusion

This study demonstrates the effectiveness of geospatial techniques, particularly CA-Markov modeling, in detecting and predicting land use/land cover (LULC) dynamics over the semi-arid Hisar district of Haryana. The novelty lies in integrating multi-temporal Landsat data with predictive modeling to assess long-term changes (1997-2017) and forecast future scenarios (2037) with high accuracy. The findings highlight a continuous expansion of agriculture and built-up areas at the expense of forests, water bodies, and fallow lands, underscoring the pressures of population growth and resource exploitation. These insights are highly valuable for policymakers, urban planners, and agricultural managers in designing sustainable land use strategies that balance food security, ecological conservation, and urban expansion. The study further opens pathways for future research by integrating climate change variables, socio-economic drivers, and higher-resolution datasets to refine predictive capabilities and support adaptive land management in vulnerable semi-arid regions.

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