Projection Modelling Based Geospatial Analysis of Land use Land Cover Change at Hasdeo River Watershed of Chhattisgarh, India

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Abstract

The land-use change in the Hasdeo River watershed has been observed with all its subwatersheds. The changing patterns may portend localized impairment to forest and agricultural watershed. In this study, Land-use land-cover (LULC) change was modeled using terrset modeling software. The Hasdeo river watershed (geographical extent of 10,396.373 km2) is a part of the Mahanadi River basin in Chhattisgarh, India. Hasdeo River originates from Sonhat (Koriya district, Chhattisgarh, India) and is submerged into the river Mahanadi. It flows in the stretch of 330 km from north to south direction. This river has eight subwatersheds with rich forest diversity and perennial water resources. IRS-1D & P6 LISS3 images from the years 2000 and 2013 were used to investigate the LULC pattern. This has been used for the prediction of LULC change patterns for the years 2035 and 2050 based on the Markov model. The result of the project LULC map for the year 2000-2035 and 2000-2050 shows that the dense forest area will decrease by 12.30% and 15.68% respectively. The settlement area will significantly increase by 20.13% (2035) and 34.90% (2050) and will be the dominant land-use type in the watershed. It shows that population pressure will directly affect forest vegetation and agriculture activities. This study will be helpful for the effective sustainability approach for maintaining the proper LULC pattern of LULC pattern of land-use change in the watershed. This changing pattern will also influence the farming pattern in the catchment area of the Hasdeo River watershed.

Keywords: Adaptive and integrated management, Deforestation and forest degradation, Landscape management, Monitoring and data collection, Sustainable forest management

Introduction

In the recent decade, a variety of land-use change models have been developed globally to meet the needs of land management and a better evaluation of the future role of LULC changes. Modelling of the LULC projection is a useful tool for alternate future paths, as well as for conducting experiments to test our understanding of essential processes and quantitatively defining the land use pattern (Karimi *et al.*, 2018; Veldkamp and Lambin, 2001). Satellite-based remote sensing is now widely employed to detect LULC changes in a reliable manner. Satellite data are useful, inexpensive, and widely used to create LULC datasets (Singh *et al.*, 2019, Lu et al., 2014). The rapid increase in population and extension of settlement and miming areas as a result of extensive ignorance on natural resource exploitation system has a significant impact on LULC patterns, as well as the conversion of fertile land and vegetation to land use for various purposes (An *et al.*, 2018). Satellite data is used in GIS technology to monitor LULC types by using spectral categorization and spatio-temporal reflectance to construct linear connections (Tan et al., 2009).

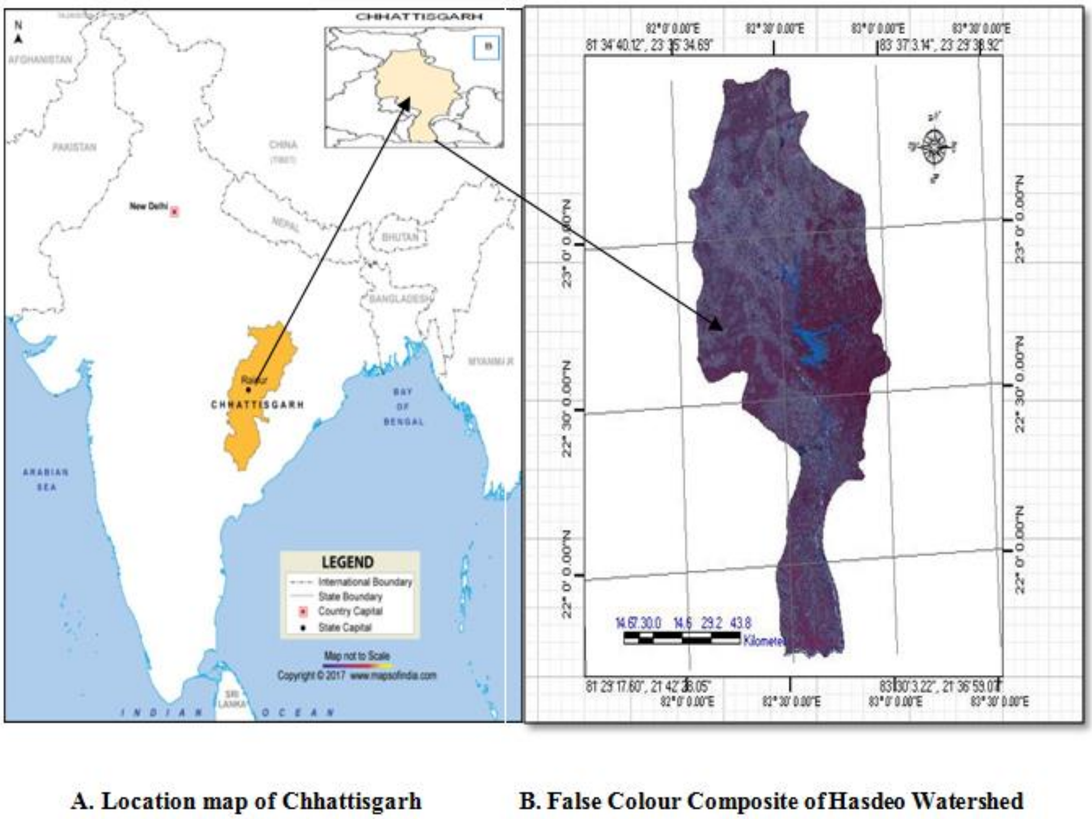
Land use and land cover analysis tracks change dynamics and uses land cover modelling to make a probabilistic prediction (Amsalu *et al.* 2007; Wubie *et al.*, 2016). LULC modelling aids in predicting future land use/cover for a given area (Pontius and Chen 2006; Stefanov *et al.*, 2001). In LULC change investigations, very few studies have attempted to combine satellite remote sensing and GIS to qualitative modelling methodologies. The Cellular Automata (CA) Markov chain is one of the most widely used land use and land cover modelling tools and approaches. It is a form of spatial transition-based model that may be used to forecast future land development using probabilistic predictions. Because RS and GIS data can be conveniently incorporated (Rozario *et al.*, 2017) and provide more precise information on a synoptic scale, the coupling of CA Markov Chain Model provides a robust approach in spatial and temporal dynamics modelling of LULCC (Schweitzer, 1968; Soe and Le, 2006). To assess the quantitative and qualitative character of the LULC change data and to priorities locations of impairment within a sub-watershed, Markov Chain models are used. It is a descriptive and interrogative technique for quantifying changes in land usage throughout a human-dominated landscape (Omar *et al.*, 2014; Muller and Middleton, 1994). This model examines how LULC affects interact with natural resource management practises (Piyathamrongchai *et al.*, 2016; Wehmann and Liu, 2015).

The current study describes a method for analysing and forecasting LULC changes in the Hasdeo watershed, which is part of the Mahanadi river basin in Chhattisgarh, India, between 2000 and 2050, using satellite remote sensing, GIS, and Markov chain modelling.

Methodology

Study Area

The Hasdeo river is a tributary of Mahanadi river. It is located between 21^0 45’ North to 23^0 33’ North latitude and 82^0 00’ East to 83^0 04’ East longitude in Chhattisgarh, India. The total length of the river is 333 km. The geographical extent of the Hasdeo river watershed is 10,396.37 km^2. The watershed (fig. 1) is located in the northern topography of Chhattisgarh, India, and is one of the primary watersheds of the Mahanadi river basin. The watershed is geologically characterized by steep, rocky terrain, the presence of Gondwana rocks, and fertile soil, and it spans most of the area of the Koriya, Korba and Janjgir-Champa districts of Chhattisgarh state. The research area has a cool and warm sub-tropical climate with a good average rainfall of 1254 mm. The Hasdeo river (perennial) is the main stream of the Hasdeo watershed, with the Ahiran, Tan, Chornai, Bamhni etc as a tributary. The topographical conditions in the area is ideal for forest vegetation, irrigation and the production of high-yielding crops. The northern and central part of the watershed is full of tropical dry deciduous type of forest species. *Shorea robusta* is the primary forest tree species found in the area. The other subsidiary species found are *Tectona grandis, Terminalia arjuna, Terminalia tomentosa, Diospyrous melanoxylon, Anogeissus latifolia* etc.



A. Location map of Chhattisgarh **B. False Colour Composite of Hasdeo Watershed**

Fig. 1. Location of Hasdeo watershed

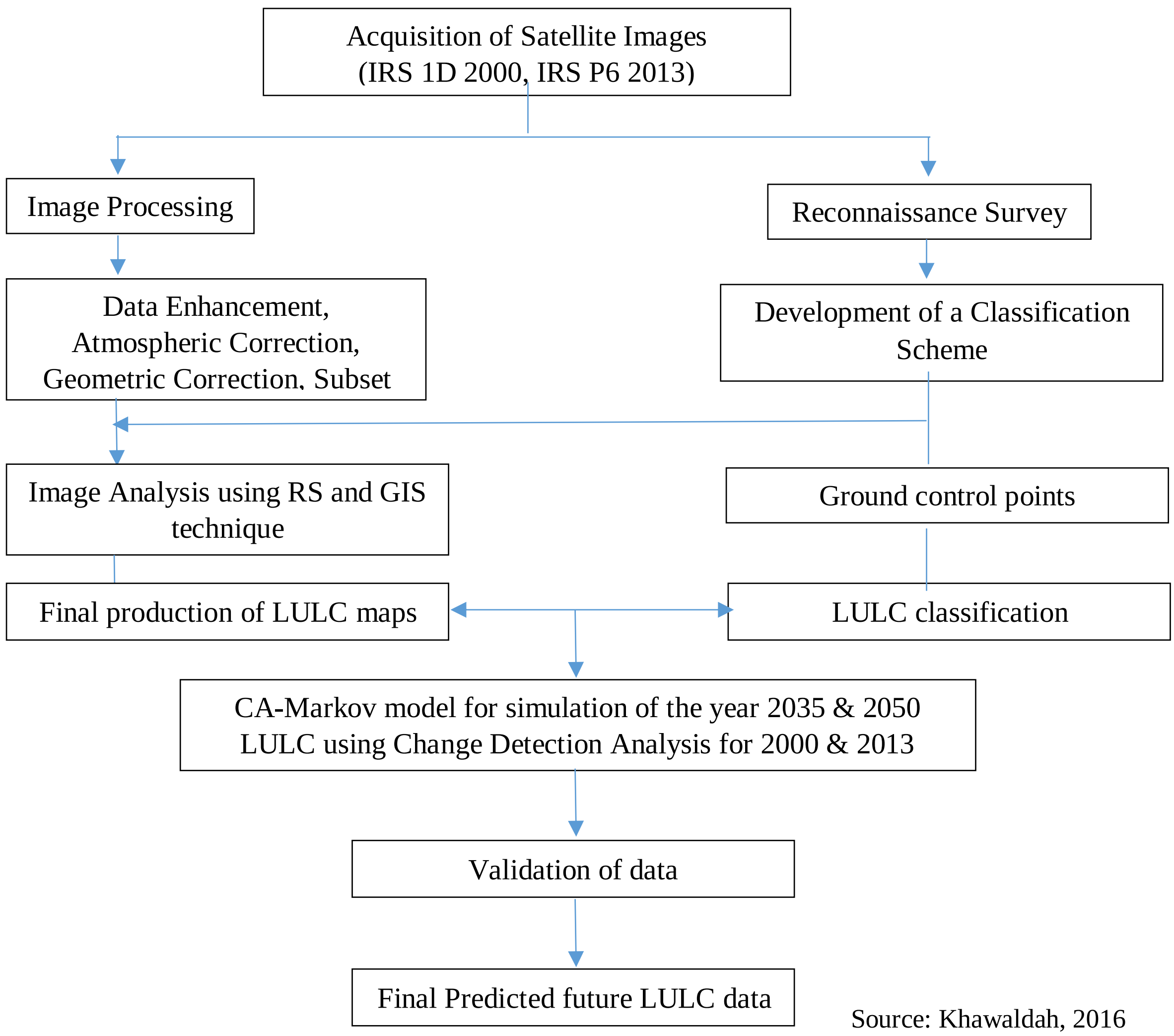
Materials and Methods

The image data products used in this investigation are from the IRS 1-D & P-6 LISS- III (Linear Imaging and Self Scanning) sensor (Indian Remote Sensing). The study employed satellite data from February 2000 and February 2013. The National Remote Sensing Centre (NRSC) in Hyderabad, India, provided the satellite data. Table 1 lists the specifications of the satellite data used for change analysis. The flowchart of the research field is shown in Fig. 2.

Table 1. Satellite images and bands were used for the Hasdeo watershed landscape analysis.

Satellite/Sensor	Year of acquisition	Spectral Band	Resolution
IRS 1D LISS 3	2000	B2: 0.52-0.59 µ B3: 0.62-0.68 µ B4: 0.77-0.86 µ B5: 1.55-1.70 µ	23.5 m
IRS P6 LISS 3	2013	B2: 0.52-0.59 µ B3: 0.62-0.68 µ B4: 0.77-0.86 µ B5: 1.55-1.70 µ	23.5 m

Source: National Remote Sensing Centre website (http:// nrsc.gov.in)



Source: Khawaldah, 2016

Fig. 2. Flowchart of the study methodology

Image Processing

Prior to the identification of change, satellite image pre-processing is critical, with the primary goal of building a more direct link between the gathered data and biophysical processes. Change detection requires data improvement and radiometric correction, which can lessen the disparities between images in changing atmospheric circumstances. The two images were taken in the same season for this. Using ground control points and the Global Positioning System, all of the scenarios were chosen to be radiometrically and geometrically corrected (GPS). IRS1D and P6 image raw data were delivered in DN format, which represented reflected radiance for each pixel at the top of the atmosphere. As a result, it was necessary to use remote sensing software to perform a radiometric correction on the photos in order to convert the DN to reflectance values. This was accomplished by measuring the reference spectral reflectance of the reference object in the image using absolute radiometric correction. To improve the quality of each image, image enhancing techniques such as histogram equalization were used. For the purpose of constructing a series of classed maps, the data of ground control points were altered for each classifier produced by its spectral signature.

Image analysis and LULC Classification:

The hybrid classification technique was used to classify IRS 1D and P6 pictures. Images from 2000 to 2013 were classified using the hybrid classification technique, which combined the findings of unsupervised and supervised classification to get the maximum possible accuracy. Using training areas, a supervised classification method was used. Finally, the unsupervised classification signature was combined with the supervised classification signature. We can assign each pixel in an image to a different land cover class using this method. Using IGIS software, a maximum likelihood technique was used to discover the LULC class types, and then GIS software was used to create the final map, as shown in Fig. 3. This study comprised eight LULC classes in its design. Dense Forest (DF), Open Forest (OF), Waterbody (WB), Riverbed (RB), Fallow Land (FL), Agriculture Land (AL), Settlement (ST) and Mines (M) are the LULC classes. Table 2 lists the descriptions of these classes.

Table 2. LULC classification classes and description.

Class	**Description**
Dense forest (DF)	Trees growing very closely together or closed canopy.
Open forest (OF)	Trees growing in gaps or open canopy
Waterbody (WB)	River, open water, lakes, ponds, and reservoirs
Riverbed (RB)	Channel occupied by a river

Mines (M)	Land representing coal mines
Fallow land (FL)	Land areas of exposed soil and barren area
Agriculture land (AL)	Land devoted to agriculture
Settlement (ST)	Residential, commercial, industrial, transportation, roads, mixed urban

CA-Markov Model

In GIS, a raster data model is used to describe continuous data over space and to create a specific layer that the TerrSet land change modeller of Clark Labs, USA was used. The technique used to analyse expected LULC based on early and later maps of LULC that have enabled us to obtain probability matrix records, which is a probability of each land cover category changing to another category.

Using two LULC in 2000 and 2013 derived from satellite images, the CA-Markov model was used to predict the change for each class in the years 2035 and 2050, and to apply this model, which is based on the number of a random process, X(t), if the Markov process for any moment of time, t1, t2......tn tn +1, thus, the random process will satisfy the equation:

$Fx(X(t_{n+1}) \leq x_{n+1}/X(t_n)=x_n, X(t_{n-1})=x_{n-1}, X(t_1) = Fx(X(t_{n+1}) \leq x_{n+1}) / X(t_n) = x_n)$

When tn is the current time, tn+1 represents some future points, and t1, t2, tn1 represents various points in the past . The future is independent of the past based on current data. To put it another way, the future of a random process is not determined by where it is now or where it was previously (Memarian *et al.*, 2012; Thomas and Laurence, 2006). The probability of transitioning from state I to state j in one time instant is; if the Markov chain is expressed by X[k], and the states are x1, x2, x3, then the probability of transitioning from state I to state j in one time instant is; $P_{i,j}$ Pr (X[k+1] = j / X [k] = i)

Results and Discussion

The correctness of the produced classes must be tested, hence accuracy assessment was tested. A total of 20346 pixels were chosen for the IRS-1D LISS3-2000 LULC map, which were validated at 1:50,000 topographic maps. The overall accuracy of the results is 98.02 percent. The Kappa coefficient index was calculated 99.10 percent. This indicates that the classification method correctly classified 99.10% of the data.

A total of 33450 pixels were chosen for the IRS-P6-2013 LULC map and validated on 1:50,000 topographic maps. The overall accuracy of the results is 99.23 percent. The Kappa co-efficient index was 99.56 percent. The value indicates that the method was successful in avoiding 99.23% of the errors.

Finally, the overall accuracy of more than 90% for the two maps (2000 and 2013) demonstrates that the image processing approach used in this work has proven to be effective in providing compatible LULC data throughout time.

Detection of LULC

In the current study the classification of LULC was done using the USGS Land Cover System classification scheme. The land cover classes were separated into two tiers under the USGS method given in Table 3. To incorporate the LULC classes concentrating on watershed health for the two-time series and build a thematic map to investigate dynamics of distinct LULC classes in the Hasdeo watershed, GIS and remote sensing were employed (Fig. 2). The data showed that between 2000 and 2013, the settlement area and waterbody rose by 1527.39 km2 and 81.81 km^2, respectively, indicating that the number of people has increased and this has an influence on agricultural land, dense forest, and fallow land. During the period, the fallow land showed the loss, accounting for 1.04 percent of the total area. Fellow and agricultural land encroachment was evident in the south-western half of the watershed, continuing toward Pali area. Agricultural land, open forest, and dense forest areas, on the other hand, have dropped by 173.43 km2 (1.67 percent), 533.68 km2 (5.13 percent), and 739.81 km2 (7.12 percent) respectively over the same time period.

According to the study, population pressure and settlement probability are constantly exerting pressure on agricultural land, open forest, and dense forest areas. Another decline occurred in the riverbed class, which decreased by 1.93 km2 (0.02 percent) during the same period, contrasted to the waterbody class, which gained an additional 81.81 km2 (0.79 percent) due to the good monsoon of 2013. Furthermore, because urban spread generally occurs in a radial fashion around the city centre or in a linear route along highways, a rapid urban sprawl occurred around the Baikunthpur, Korba and Surajpur mining landscape. As a result, Potter *et al.*, (2009) found that the presence of transportation routes inside the research region supported urban sprawl, with city transportation as socially polarised as the city structure itself. The expansion of watershed settlement areas, particularly in metropolitan regions, had a severe impact on the local environment (Sudhira *et al.*, 2004). The abundance of water bodies attracts people to stay in the watershed, but water resources are beginning to run out in some mining areas. Farming is the most common activity in the area, with about 80% of the inhabitants involved in some way. Paddy is the main crop, with some legumes and vegetable kinds added in for variety. Forest areas in the watershed's southwestern corner are in direct contact with the local people. They harvest key forest timber species (especially *Shorea robusta*) for personal or social gain.

Non-wood forest products such as tendu leaves, sal seed, mahua flower, wild medicinal herbs, and so on are not collected informally. The grazing habits of domestic animals have a direct impact on the ability of plants in the forest to regenerate, resulting in a significant loss of forest in the area over time. As a result, the study employed the markov model to forecast LULC for the years 2035 and 2050, as well as the future of watershed LULC health and direction, allowing for improved planning in the area.

Table 3. Area estimation and the overall amount of change in LULC for the study area

Level 1		**Level 2**	**LULC-2000**		**LULC-2013**	
Code	Class name	Class name	Area		Area	
			Km2	%	Km2	%
1	OF	Deciduous forest land, Mixed forest land	2768.45	26.63%	2234.77	21.50%
2	WB	River, Pond, Lake, Streams, Well	73.81	0.71%	155.62	1.50%
3	DF	Deciduous forest land, Mixed forest land	2313.11	22.25%	1573.3	15.13%
4	RB	Channels of river	156.97	1.51%	155.04	1.49%
5	FL	Exposed soil and barren area	287.96	2.77%	179.89	1.73%
6	AL	Farmlands	3556.47	34.21%	3383.04	32.54%
7	ST	Residential, commercial, industrial, transportation, roads, mixed urban	1063.51	10.23%	2590.9	24.92%
8	M	Strip mines, Gravel pits	176.09	1.69%	123.81	1.19%

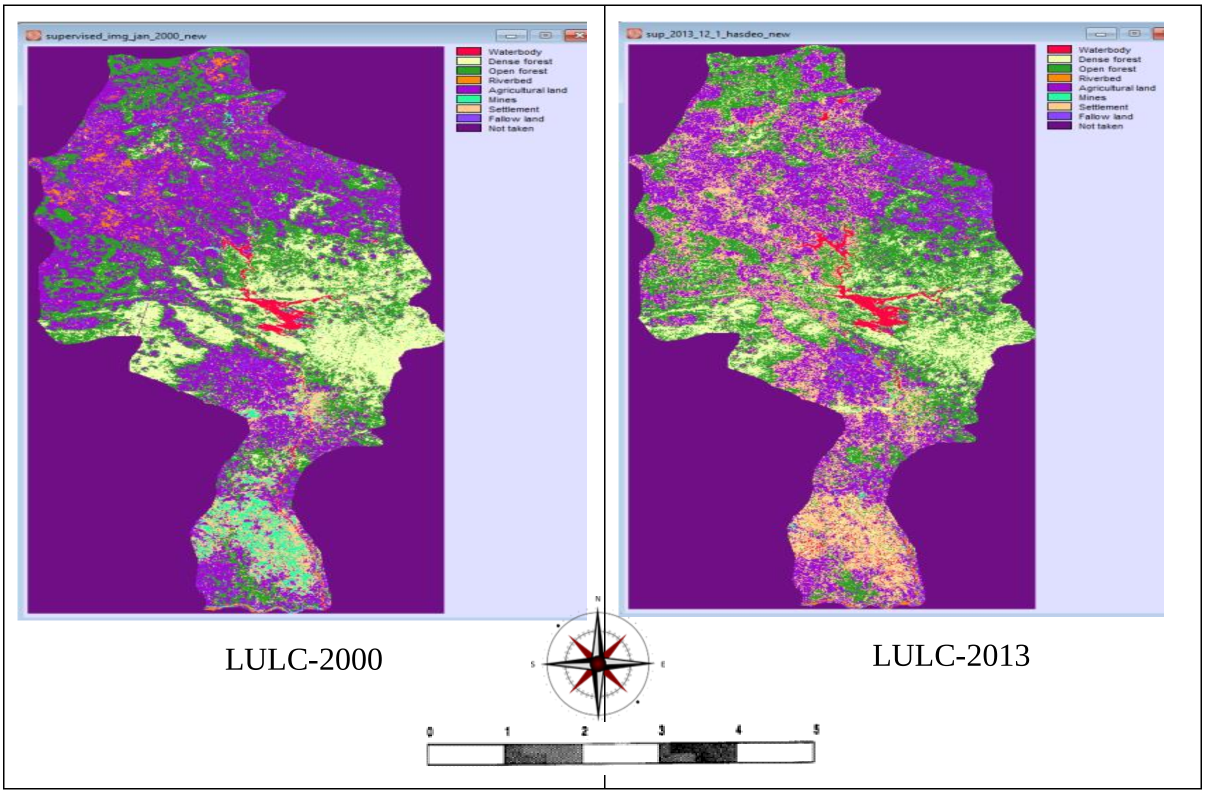
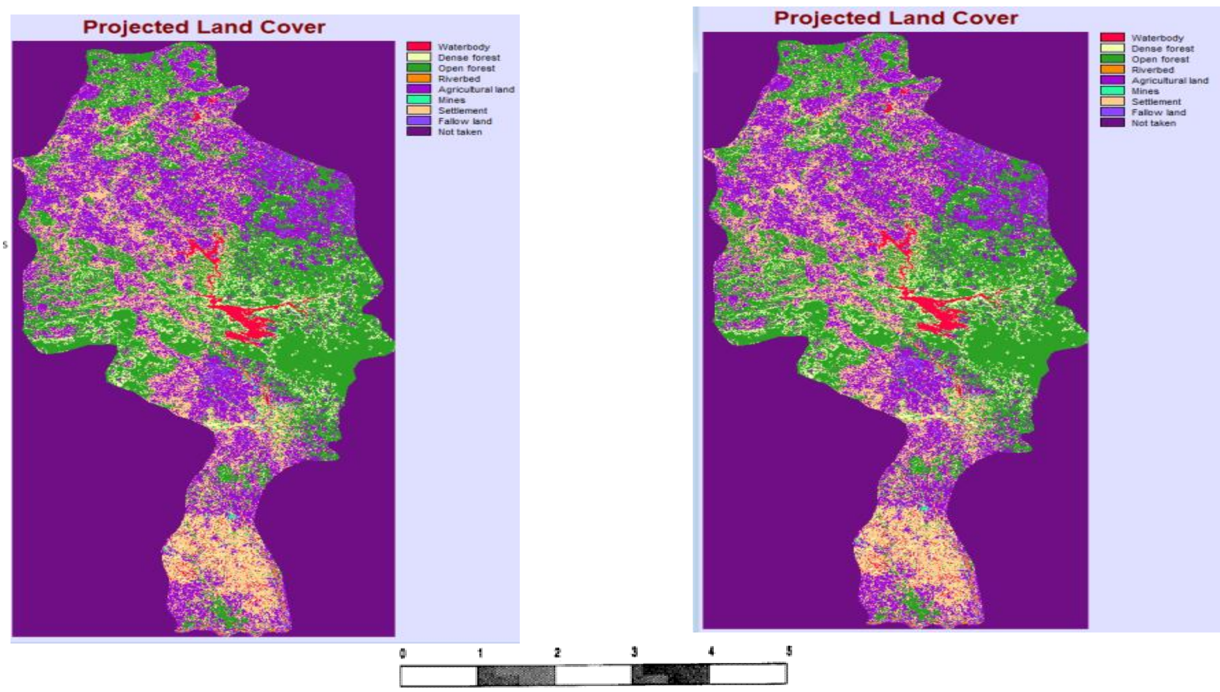


Fig. 2. LULC changes during (2000-2013) in Hasdeo watershed

Predicting 2035 and 2050 LULC using CA-Markov Model

The CA-Markov model was used to forecast the 2035 and 2050 LULC based on probability matrix records derived from the observed 2000 and 2013 LULC. As illustrated in figure 3, agricultural land increase is forecast in the south-central part of the existing open forest region in 2035, rather than in the east of the Hasdeo swatershed. Another 565.33 km2 is expected to be added to the settlement area (to be 30.36 percent of the study area compared to 24.92 percent in 2013). Dense forest and Fallow areas are expected to account for 9.95 percent and 3.05 percent of the study area in 2035, respectively, compared to 15.13 percent and 1.73 percent in 2013.

Agriculture land is expected to decrease in the west-central part of the watershed in (2000-2035) and (2000-2050), with 6.08 percent and 9.09 percent, respectively. The dense forest is expected to shrink 12.30 percent in 2000-2035 and 15.68 percent in 2000-2050. The southwestern part of the watershed had the most projected forest decline. However, compared to 25.16 percent (2035), the open forest area is expected to shrink 24.69 percent (2050) (Table 4).



Year 2035 Year 2050

Fig. 3. Predicted LULC change from CA-Markov modeling for the years 2035 and 2050

Table 4. Predicted areas of LULC for 2035 and 2050 in the study area

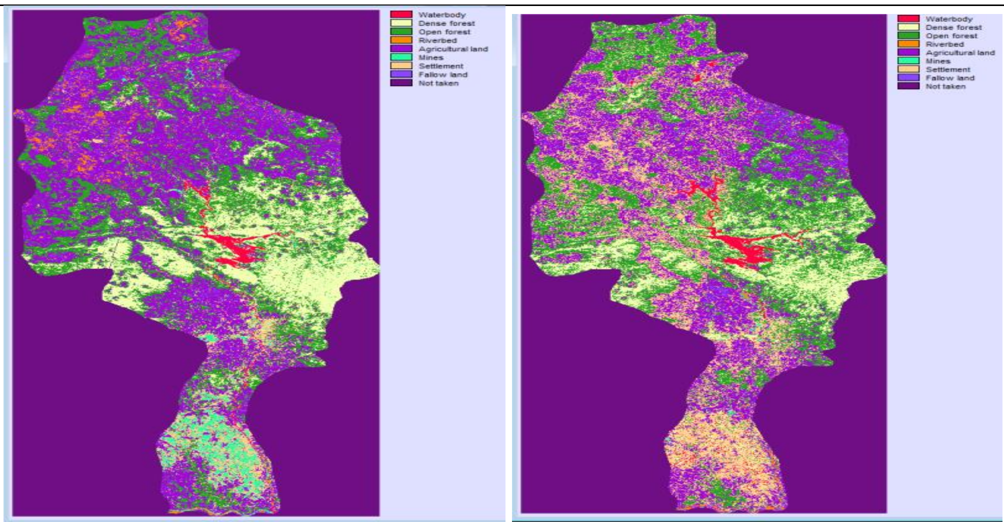
Year	LULC classes	OF	WB	DF	RB	FL	AL	ST	M
2035	Area in km^2	2615.74	214.16	1034.61	24.43	317.49	2924.39	3156.23	109.32
	Area in percentage	25.16%	2.06%	9.95%	0.23%	3.05%	28.13%	30.36%	1.05%
2050	Area in km2	2566.77	231.83	683.02	28	581.14	2611.06	3628.1	66.45
	Area in percentage	24.69%	2.23%	6.57%	0.27%	5.59%	25.11%	34.90%	0.64%

Validation of CA-Markov Model Results

The validation of the model's performance is a critical step in determining the model's capacity to replicate the known data set. In the literature, many goodness-of-fit statistics have been utilised in spatial modelling (O'Sullivan, 2001; Knudsen and Fotheringham,1986). The performance of the Markov model will be evaluated and its predictions will be validated against a real data set using one main statistical test of goodness-of-fit. R2 (Birkin et al. 2015) is a regularly used statistic that is formulated as follows:

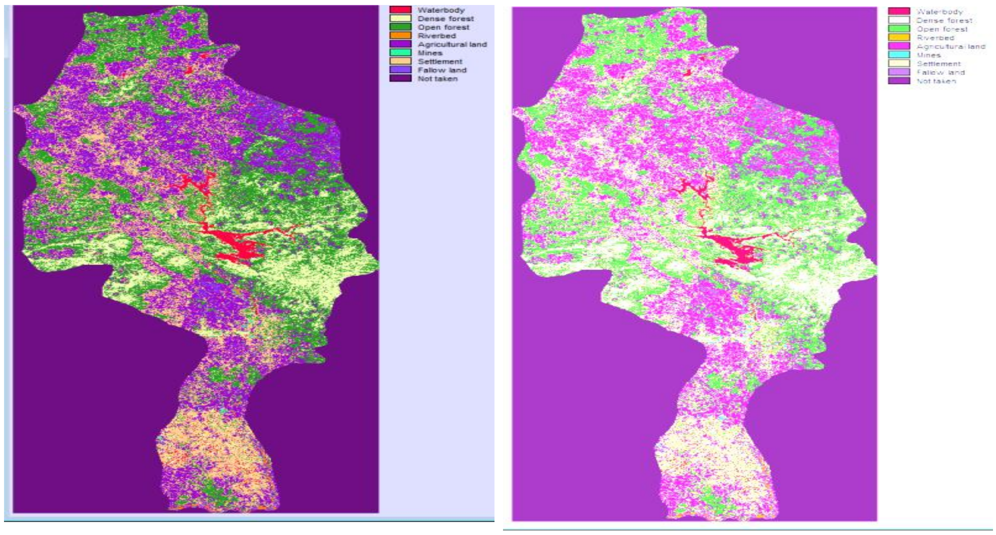
$$R^2 = \left[\frac{\sum_i \sum_j (s_{ij} - \bar{s}_o)(\hat{s}_{ij} - \bar{s}_c)}{\left[\sum_i \sum_j (s_{ij} - \bar{s}_o)^2 * \sum_i \sum_j (\hat{s}_{ij} - \bar{s}_c)^2 \right]^{1/2}} \right]^2$$

Here, S_o represents the mean of the S_{ij}'s (observed values) and S_c represents the mean of the $\hat{S}_{ij}$'s (predicted values). R^2 values range between zero and one.



2000 2013

Calibration



2013 observed Validate

2013 predicted

Fig. 4. Observed LULC change in 2013 versus the predicted for the same year in Hasdeo watershed

Two maps of LULC in the study region for the years 2000 and 2013 were used to calibrate the Markov model in order to construct the 2013 LULC map in the study area using the Markov model (Fig. 4). The Markov-created LULC for 2013 was compared to the observed 2013 LULC of the research area for validation. The model validates the LULC areas as per received data by the user. The comparison of different classes was also based on conversion difficulties.

Conclusion

Not only is it vital to have information about how LULC patterns vary over time for sub-watershed planning, but it is also necessary for better land resource management. This study has demonstrated the value of using RS and GIS techniques to produce accurate LULC maps and change statistics for one of the largest sub-watersheds of the Hasdeo watershed in Northern Chhattisgarh, which is useful for effectively monitoring settlement, forest area, and agriculture land expansion over time.

The study area's dense forest covered 2313.11 km^2 in 2000 and 1573.30 km^2 in 2013, or 22.25 percent and 15.13 percent of the study area, respectively, according to the results of LULC change detection. However, it is expected to shrink by 1034.61 km^2 (9.95%) in the next 22 years, 683.02 km^2 (6.57%) in the next 37 years. Agricultural land change detection analysis, on the other hand, shows that agriculture land was 3556.47 km^2 (34.21 percent) in 2000, but was reduced to 3383.04 km^2 (32.54 percent) in 2013. However, it will be 2924.39 km^2 (28.13

percent) and 2611.06 km^2 (25.12 percent) in the next 22 and 37 years, respectively. However, according to the LULC, the settlement area in the study area was 1063.51 km^2 (10.23 percent) in 2000, 2590.90 km^2 (24.92 percent) in 2013, and expected to be 3156.23 km^2 (30.36 percent) in 2035, and 3628.10 km^2 (34.90 percent) in 2050. The statistics show a net decrease in thick forest area in the watershed's western, eastern and northern parts. It also suggests that due to the abundant water supply and well-connected highways, the settlement area will be primarily concentrated in the eastern and southern parts.

In the next 37 years (2050), the settlement will also display an increasing pattern, indicating that the population in the area will be high. Because of the abundant work opportunities in the mining and industrial areas, the majority of migratory individuals from the state and other parts of the country will settle in the area. Riverbed, fallow land, and mines areas were converted to habitation and rich water availability between 2000 and 2013.

The paper's second section looks at how to use a GIS-based Markov model to forecast future LULC change in the study area in 2035 and 2050. In 2013, the model was calibrated using satellite pictures from 2000 and 2013 of the research area to anticipate the LULC. The anticipated LULC map in 2013 was then compared to the observed LULC map in 2013. The results of calculating the predicted and observed LULC map of the study region in 2013 revealed that the model performed well in simulating future LULC change within the study area. However, due to the rapid population growth noted above, real LULC class changes in the study area were larger than the expected expansion by the Markov model.

Study Implications and Future Research

The current study's implications can be stated in three areas. First, the findings suggested that dense forest, open forest, and agricultural land declination will occur in several places within the study area in 2035 and 2050, respectively, with an expansion in water body and settlement. In terms of road networks, infrastructure, pond creation, canal formation, agriculture land distribution, and allocating some locations for future watershed management activities, it should be taken into account by forest, agriculture, and water resource planners in their future plans for the Hasdeo watershed. Second, the analysis revealed that settlement and farm land displaced the majority of the forest(dense and open), which may be averted through future regulations or initiatives. Finally, for efficient monitoring of watershed planning and management trends, watershed planners and decision makers should use remote sensing and GIS approaches. As a result, their expectations and predictions of future settlement development and location, forest distribution patterns, and agriculture land utilisation techniques would improve for more sustainable land management.

Acknowledgement

The authors (SSS) wishes to express gratitude to the Ministry of Environment, Forest and Climate Change, New Delhi, India for funding the project. He also express gratitude to the National Remote Sensing Centre in Hyderabad, India, for providing satellite imagery used in the project, as well as the State Forest Department of Chhattisgarh for assistance during field research.

User rights and responsibilities:

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