Watershed Management & Its Impact on Land Use Patter: A Geographical Study of Dholpur District

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ABSTRACT

The current research area is a micro watershed in a semi-arid region of Dholpur, Rajasthan. Over the last 10 years, governments and nonprofit organisations have prioritised land reclamation in this area. This paper's major goal is to investigate how multitemporal remote sensing data and Geographic Information Systems (GIS) might be used to enhance land use, land cover change (LULC) in agricultural, wasteland, and degraded forest regions. To assess the change detection between 2015 and 2023, it comprises LULC classification and post classification approaches. Population growth during the previous few decades boosted land cultivation, which sped up the shift in land use and land cover. Agriculture growth, climatic changes, and government regulations are only a few of the numerous factors that have an impact on LULC. Using LISS III photos from 2015 to 2023, we sought to examine and track the changes in this article. Giving training pixels based on ground truth allowed for the first categorization of images using supervised classification. In order to investigate LULC change in satellite pictures and evaluate the classification findings' accuracy, post classification comparison methods were utilised. The accuracy of the classification was increased by using auxiliary data and supervised classification. Increased areas of both scrub forest/deciduous forest and water bodies were the main alterations at the watershed level. Additionally, there is less space for types of degraded forest and wasteland. Despite being in a semi-arid environment, the area saw a huge growth in agricultural crops. The findings show that watershed management projects have had a generally good influence on the research region.

Key words: Remote sensing, change detection, supervised classification, and IS

1. INTRODUCTION

The watershed management project has been shown to be an integrated and thorough development plan aimed at India's arid and semi-arid regions. The creation of such projects is supported by government policy as well. More focus was put on rural development, water conservation, and soil preservation in these programmes. The blatant use of India's arid and semi-arid regions' economic and ecological resources ensured sustainable development. The Integrated Watershed Management Programme (IWMP) in India sought to build micro watersheds. At the regional and local levels, changes in LULC and vegetation cover are taken into account as indicators to evaluate the outcomes of recommended schemes. It is simpler to understand how to utilise natural resources effectively thanks to the LULC maps. These maps provide improved information and growth of the future perspective due to watershed management actions. Land degradation and soil erosion are major problems associated with deforestation because of global agricultural development, industrialization, and urban growth. Urbanisation is a natural process resulting from population increase and economic expansion. Changes in land use and cover have a considerable impact on the process of global environmental change. To anticipate and study the environmental consequences brought on by changes in land use and cover, more detailed data on the change in land cover is needed for future planning. Remote sensing provides the ability to identify changes in satellite data using change detection techniques. Remote sensing and GIS provide useful findings by integrating geographic data via modelling. Digital change detection is a method for identifying changes in LULC properties using multitemporal remote sensing data. Numerous specialists have conducted studies on the difficulty of accurately monitoring LULC change across diverse geographical regions. For change detection, a number of techniques have been created, tested, and reviewed. The objectives of the present work are to examine and analyse land cover changes over an eight-year period and to combine supervised classification with visual interpretation using GIS to assess the spatial distribution of LULC.

2. STUDY AREA

The LULC change in a semi-arid location of Dholpur, Rajasthan, has been taken into account in the current research. 563 mm of rain precipitation occurs here annually. Surface water is mostly used for agriculture. In dry and semi-arid parts of India, a lack of rainfall often causes crop failure. The area has a semi-arid climate zone. This region was chosen as the application site as part of the Integrated Watershed Management Programme (IWMP) by the Indian central government to improve soil fertility and conditions. It intends to enhance the socioeconomic standing of the locals by promoting surface water and ground water recharge to allow agriculture during the dry season.

3. DATA AND METHODOLOGY

3.1. Image processing and data from remote sensing

In this investigation, temporal Landsat pictures from 2015 and LISS III images from 2019 and 2023 were employed. These are further rectified geometrically and radiometrically. To counteract the impact of seasonal fluctuations on LULC categorization, satellite images were taken throughout the same season. Using a GPS device, ancillary data such as the LULC's ground truth and ground control points were acquired. Initially, ground control points (GCPs) and topo-sheets were used to georeferenced images. To develop digital topographic maps at a scale of 1:50,000 for geometric corrections and ground truth data, hard copy topographic maps were first digitised. Topographic sheets were geometrically corrected using the geographic coordinate system and GCPs. The accuracy of the picture to map was assessed using the Root Mean Square Error (RMSE) metric. In order to measure accuracy and perform supervised classification, ground truth data was gathered between 2015 and 2023. As registration mistakes might result in an overestimation of LULC change compared to real, per-pixel registration of multitemporal satellite images is crucial for change detection analysis. The process of change detection is done pixel by pixel. Using ground control points from a topo-sheet with a scale of 1:50,000, geometric correction was performed.

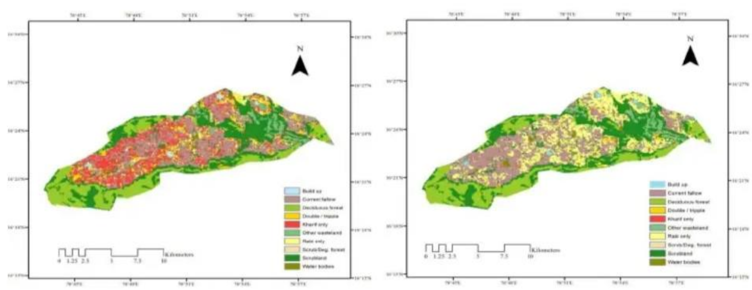
3.2. Image Enhancement and Visual Interpretation

By enhancing the apparent contrast between the characteristics, image enhancement tries to improve the visual interpretability of a picture. The complementing skills of the computer and the human intellect are optimised by this procedure. False colour composites (FCC), which combine photos from 2015 and 2023, were created by using contrast stretching. These FCC were used for visual interpretation to distinguish between the two groups of land cover—agriculture and forest.

3.3. Image Classification

Geographical classification use satellite pictures to digitally classify various land cover classifications. By employing a statistical approach to group pixels belonging to the same population according to their DN values, satellite remote sensing-based categorization establishes classes. These use either supervised or unsupervised approaches. Images were classified using the maximum likelihood classification (MLC) approach, which is supervised classification. The most used supervised classification technique is MLC. The technique of classifying images aims to automatically categorise all of the pixels in a picture into different types of land cover. The maximum likelihood classifier makes use of the variance- and covariance-based spectral response patterns for each category to most correctly classify unknown pixels.

Using satellite photos of the research region and ground checkpoints, supervised categorization was carried out. Each category's training pixels are chosen for automatic digital categorization. Built-up, kharif, rabi, double/triple crop, fallow land now, deciduous forest, degraded forest, barren land, scrub forest, and water bodies are the main classifications in this region (fig. 1).The accuracy of the measurement was then evaluated using ground control points derived from field data.The location locations were chosen using a stratified random approach to determine various land cover classes. Using GIS, additional data and visual interpretation were combined to increase the current study's categorization accuracy.



3.4. Land Cover/use Change Detection

The regions of land cover change between the photos from 2015 and 2023 are clearly identified using the change detection technique. The technique of image processing and categorization as well as the kind of change that is happening determine how changes in the research area are detected. A comparison matrix for the post-classification is usually used after change detection. These two photos were registered and categorised separately. The accuracy of the classification analysis relies mostly on the independent classification technique and registration accuracy in the post-classification process of comparing two distinct date pictures. Field observation data from the current case study made it evident how the acquisition dates for the images changed. In this work, a post-classification change detection technique was utilised to compare individual photos. This technique reduces mistakes brought on by atmospheric and sensor variations between two photos. The geographical distribution of land use and cover change is shown via cross tabulation analysis. Each class type's area and the percentage changes between 2005 and 2013 were computed (figs. 2 and 3).

3.5. Classification Accuracy Assessment

When data from aerial photos and ground truth are merged, accuracy evaluation is more dependable. When categorised, it is the indicator of the accuracy of information gleaned from satellite photos. Several GCPs were obtained for the current investigation during a field visit in 2023. This data is used as a source. To avoid bias error while identifying individual photos, sampling is carried out using a random stratified sample technique. There was also done a visual interpretation procedure to identify the various land use classifications. For LULC mapping, a total of 300 and 352 pixels were chosen as training pixels for the years 2015 and 2023, respectively. Error matrices were used to determine the overall accuracy, user accuracy, and producer accuracy. According to Bishop and Fienberg's 2007 equation 1, the Kappa coefficient was determined.

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+})(x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+})(x_{+i})} \qquad (1)$$

Where,r = number of rows in the matrix

xii =number of observations in row i and column i (the diagonal elements)

*x+i*n and *xi+* = marginal totals of row r and column i N = number of observations.

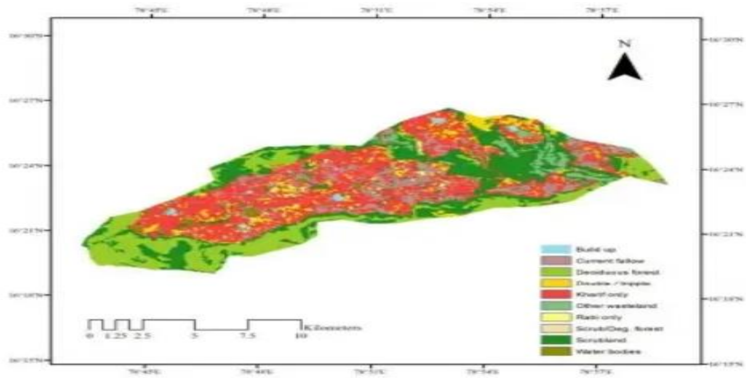


Figure 3 Land use land cover map 2023

Table 1 Area and percentage of change of different land cover classes of 2015 and 2023 classified images

	2015 (hectares)	Percentage	2023 (hectares)	Percentage
Built-u p	94.7 1	0.54	93.77	0.52
Kharif crop	2724.24	15.48	5468.87	30.60
Rabi crop	802.50	4.56	180.63	1.0I
Double cropland	I 059.97	6.02	1319.94	7.39
Current fallow land	4254.30	24.17	1967.21	1 1.0 I
Deciduous forest	3262.69	18.54	3283.39	18.37
Degraded forest	26.66	0. 15	20.07	Cl.I I
Wasteland	615.60	3.50	610.89	3.42
Scrub forest	4637.83	26.35	4775. 19	26.72
Waterbodies	12 1.36	0.69	149.90	0.84

4. RESULTS AND DISCUSSION

Visual analysis of the photos provided some identification of land cover types across time. In picture 2023, fresh irrigation canals were shown. In the agricultural sector, a significant shift in Kharif and Rabi crops has been seen. The total accuracy was enhanced by superimposing classification findings on visual interpretation analyses. This may be explained by the fact that present fallow land is sometimes mistaken with barren land. Accuracy levels for land cover are set between 95 and 96%.

Overall accuracy was determined to be 96% in this research for 2015 and 96% for 2023. Agriculture and deciduous forests have the best accuracy since the categorised picture may be visually interpreted. The region that is now fallow and barren was found to have the lowest accuracy since it is semi-arid and has minimal vegetation, which contributed to the misunderstanding. GIS and remote sensing data enable the study of geographical data in conjunction with auxiliary data derived from ground truth. When photos are cross-tabulated, it is possible to compare the landcover classes of one image with those of a second image from the same class.

In 2015, there were 2724 hectares of kharif crop land; in 2023, there were 5468 hectares. The integrated watershed management programme in this region caused the fallow land to drop from 4254 to 1967 by 2013 (table 2). Water canals and technologies for collecting rainwater increased the availability of water and increased the area that could be farmed. Scrub woodland and deciduous forest both exhibit increasing distributions in terms of area. An enormous growth in water bodies has been seen as a result of rainwater gathering. Because of a government-run project to improve forest cover and boost local economies, degraded forests have had their area reduced. By converting waste land to agricultural or scrubby-forest land, the soil's fertility and water-holding capacity are improved. IWMP's overarching goal is to rebalance the environment, which promotes sustainable growth. This clarifies the critical function of GIS and remote sensing in identifying land cover change since they are potent tools for analysing the crucial data on the spatial distribution of landcover changes. Classification accuracy is crucial since mistakes might result in pixels being misclassified. The current analysis demonstrates a favourable shift towards sustainable development via the general increase in vegetation classes and the decrease in garbage and damaged forest.

Table 2 Cross-tabulation of land cover classes between 2005 and 2013 (area in hectares)

2023										
Land use	**Built-up**	**Kharif crop**	**Rabi crop**	**Double cropland**	**Current fallow land**	**Deciduous forest**	**Degraded forest**	**Wasteland**	**Scrub forest**	**Waterbodies**
Built-up	77.57	8.62	0.00	0.32	4.79	0.00	0.00	2.55	2.55	0.00
Kharif crop	2.55	1809.54	59.69	367.40	299.41	17.56	0.32	19.47	193.75	1.92
Rabi crop	2.23	393.25	14.36	198.22	111.40	9.90	0.00	1.28	81.40	4.79
Double cropland	2.23	575.20	15.00	307.07	52.35	19.79	0.00	3.83	100.87	2.55
Current fallow land	5.43	2166.72	8J.08	309.94	1303.29	17.56	0.00	43.41	3I2.50	88.42
Deciduous forest	0.00	2171	0.00	9.58	0.64	2921.95	0.96	0.00	352.08	0.00
Degraded forest	0.00	0.96	0.00	0.64	0.00	8.30	16.28	0.00	0.96	0.00
Wasteland	2.23	24.90	0.00	0.64	23.62	0.96	0.00	436.98	135.34	0.00
Scrub forest	3.19	451.03	I1.81	123.85	129.28	282.17	2.55	107.25	3590.99	3.83
Waterbodies	0.00	27.77	0.00	0.00	42. 13	0.00	0.00	0.64	6.70	46.28

5. CONCLUSION

In the eight years from 2015 to 2023, modifications in land cover classifications have place. Land cover changes over a certain time period are studied using optical remote sensing data from the LISS III satellite. When combined with GIS and remote sensing, visual interpretation and ground truth from field trips provided more precise findings for examining and analysing the geographical distribution of various land cover classifications. A large IWMP programme to modify the land cover has been implemented in the study region. Agriculture courses and the amount of forest cover both significantly increased. Natural vegetation now occupies a larger area.

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