
DYNAMISM OF NATURAL ENVIRONMENT IN AND AROUND TAL CHHAPAR WILDLIFE SANCTUARY

Ravinder Kumar*¹, Jeetendra D. Soni², Nimish Narayan Gautam³, Sunita Kumari⁴

1. Government Lohia College, Churu (Rajasthan), India

2. Government Arts College, Sikar (Rajasthan), India

3. India Meteorological Centre, Shillong (Meghalaya), India

4. Government College, Sambhar Lake (Rajasthan), India

Abstract

After having about the geographical setting, it is important to study the dynamism of natural environment in and around the study area. The Tal Chapper, which is known for wildlife sanctuary, is attracting tourists from the various parts of the country and from foreign destinations. The future of tourism growth of this area depends on the various environmental changes in and around this region. Thus, it is imperative to discuss this in detail. Here in this study the environmental changes are studied with reference changing vegetation cover, tal area and other climatic parameters specially temperature and rainfall patterns. This study is an attempt to assess the changes in Land use and land cover (LULC) the last three decades using geospatial techniques during 1990, 2000, 2010 and 2020. Multitemporal Landsat-TM (Thematic Mapper) and Landsat-OLI (Operational Land Imager) was used to estimate LULC patterns here. Multistage unsupervised classification is performed to classify the LULC. The study found that the overall increasing change in grassland 10.73%, built-up 2.67%, agricultural land 2% and plantation 1.98%. fallowland and waterbodies area is shows decreasing change respectively 16.6% and 0.83%. This study will help wildlife sanctuary planners and tourism planners to make suitable decisions for sustainable land use by understanding the LULC change patterns.

Keywords: Geospatial tool, Unsupervised classification, Accuracy Assessment, LULC Change

1. Introduction

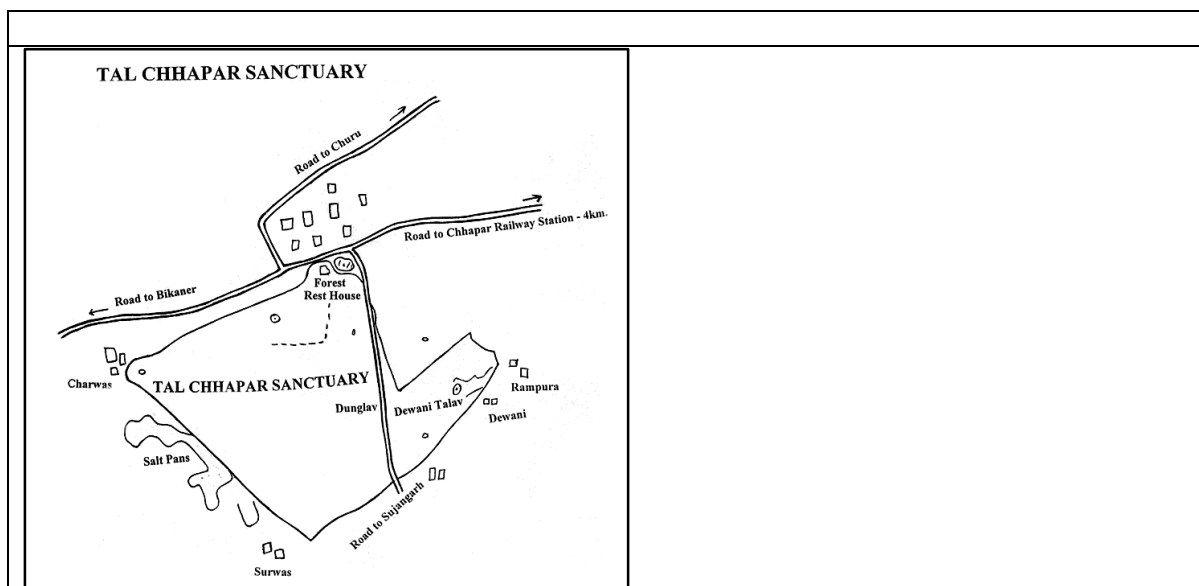
In India ecotourism is still in developing stage and faces a lot of challenges (Das, S.,2011). Ecotourism more often combines elements of wildlife conservation, cultural awareness, education, recreation and adventure. Eco Tourism, therefore, is gaining importance as a tool for conservation (Kiper, T., 2013; Machnik, A., 2021). Located on the boundary of the Great Indian Thar Desert is a unique place to habitat the most elegant Antelope encountered in India "The Black buck". The

Tal Chhappar sanctuary lies in the Sujangarh Tehsil of Churu District, situated in the north-eastern part of Rajasthan and is the only sanctuary in India which houses a good population of blackbucks in an almost treeless, saline and flat land of 719 Ha. The word “TAL” means plain land. The rainwater flows through shallow low lying areas and collects in the small seasonal water ponds. There must be adequate analysis of decadal Land Use Land Cover (LULC) change over the sanctuary area. 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; Chughtai et al, 2021). The significance of this issue has raised awareness about the need to analyse and examine changing activities and their impact on land use and land cover (LULC) Ren et al, 2019. 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 (Yin et al, 2018; Mashala et al, 2023). Quantifying, mapping and predicting of the current change in the use of land resources can be easily achieved by using cost-effective geospatial techniques (Sun et al, 2022; Debnath et al, 2023). Remote Sensing (RS) and Geographical Information System (GIS) are effective tools for simulating LULC changes, which are useful for guiding planning and management (Zadbagher et al, 2018; Degerli et al, 2022). Multiple researches with different approaches have been done to measure the change in landcover, yet well studied documentation is needed to analyse the present LULC pattern change of Tal Chhappar.

2. Study Area

Tal Chhappar sanctuary is located in the Churu district of Northwestern Rajasthan in the Shekhawati region of India. It is 210 km from Jaipur and situated on road from Ratangarh to Sujangarh. The Tal Chhappar lies in the Sujangarh Tehsil of Churu District. This sanctuary is located at 28° 27.5' North latitude and 73° 47.5' East longitude. It covers 719-hectare area. This region is characterized by distinct winter (Oct. to Feb.), Summer (March to June) and Monsoon (July to Sept.). Tal Chhappar is very hot and drought area. The zone has a dry climate with large variation in temperature wind blows South – West during summer. In May and June winds become very hot and that is called “Loo” Maximum temperature reaches up to 48°C in June & minimum temperature falls up to 0°C in month of December – January. The average annual rainfall of this

region is 268 mm. When monsoon run to south-west, the humidity is generally above 60% but in summer season it decrease especially below 30% due to dryness in environment after the period of mid day. During monsoon (July-September) the relative humidity is generally above 60 percent. Summer is the driest period when relative humidity is below 30 percent.



3. Methodology

Methodology represents both the quantitative and qualitative analysis in which a combination of primary and secondary data was used. Starting section of this chapter deals with the discussion of data sources and the software used for the analysis. First, LULC classification of the year 1990, 2000, 2010 and 2020 was done with the help Maximum likelihood classification. In the later sections, accuracy assessment was performed by applying the post classification comparison approach. The prediction and validation of the same was done using the data of the years 1999, 2000, 2010 and 2020.

3.1. Data Sources

3.1.1. Satellite Images Used

Satellite images used for the study were Landsat-TM (Thematic Mapper) and Landsat-OLI (Operational Land Imager) of February month for the years 1990, 2000, 2010 and 2020 which were acquired from earth explorer USGS (United State Geological Survey) website <https://earthexplorer.usgs.gov>. All the imageries covering Tal chhapar sanctuary with Row 148

and Path 41 were downloaded. Product code for Landsat Images used in this study is represented in the table 3.1. y

Table 3.1: Product code for Landsat Images used in this study.

Landsat-5 image 1990	LT05_L1TP_148041_19900309_20170131_01_T1
Landsat-5 image 2000	LT05_L1TP_148041_20000217_20161216_01_T1
Landsat-5 image 2010	LT05_L1TP_148041_20100212_20161016_01_T1
Landsat-8 image 2020	LC08_L1TP_148041_20200208_20200211_01_T1

3.2. Method

The flowchart of the method used to accomplish the objectives is represented in Figure 3.1.

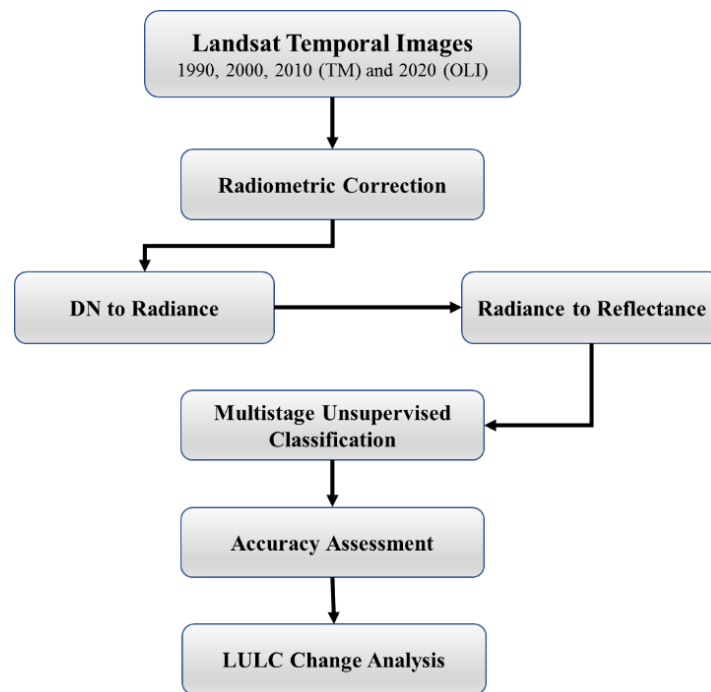


Figure 4.1 paradigm of methodology used for the present study

3.2.1. Pre-processing of satellite data

Landsat-5 (TM) and Landsat-8 (OLI) images were downloaded from USGS having UTM WGS84 43N projection. To obtain the reflectance value, radiometric correction was done. It comprises of two steps (a) DN to Radiance conversion (b) Radiance to Reflectance conversion. Description of both these steps has been mentioned in section 3.2.1.1 and 3.2.1.2.

3.2.1.1. DN to Radiance conversion

DN to radiance conversion is the key step in image processing for putting images from multiple sensors and platforms into a common radiometric scale. Level-1 (L1) product generation involves conversion of pixel value (Q) from level-0 (L0) unprocessed image into the units of absolute radiance in 32 bit floating-point scale. After this, these values are scaled to 8-bit values representing calibrated digital number (Q_{cal}) before output to the distribution media. L1 product (calibrated digital number) converted to sensor radiance (L_{λ}) by using the original rescaling factors provided in metadata file of the satellite data. The equation that has been used for this purpose is given below:

$$L_{\lambda} = \left(\frac{LMAX_{\lambda} - LMIN_{\lambda}}{Q_{calmax}} \right) Q_{cal} + LMIN_{\lambda} \text{ (USGS, 2018; Chander } et al, 2003)$$

Where:

L_{λ} : Spectral radiance at the sensor's aperture in $W/(m^2 \cdot sr \cdot \mu m)$

Q_{cal} : The quantized calibrated pixel value in the form of Digital Number (DN)

Q_{calmin} : The minimum quantized calibrated pixel value (DN=0) corresponding to $LMIN_{\lambda}$

Q_{calmax} : The maximum quantized calibrated pixel value (DN=255) corresponding to $LMAX_{\lambda}$

$LMIN_{\lambda}$: The spectral radiance that is scaled to Q_{calmin} in $W/(m^2 \cdot sr \cdot \mu m)$

$LMAX_{\lambda}$: The spectral radiance that is scaled to Q_{calmax} in $W/(m^2 \cdot sr \cdot \mu m)$

3.2.1.2. Radiance to TOA Reflectance conversion

The radiance images obtained from the above steps were then converted into TOA reflectance using equation given below:

$$\rho = \frac{\pi * L_{\lambda} * d^2}{ESUN_{\lambda} * \cos(\theta)s} \text{ (USGS, 2018; Chander } et al, 2003)$$

Where,

ρ = Unitless TOA or planetary reflectance

L_{λ} = Spectral radiance at the sensors aperture

d^2 = Earth-Sun distance in astronomical units

$ESUN_{\lambda}$ = Mean solar exoatmospheric spectral irradiance

$\cos(\theta)s$ = Solar zenith angle in degrees

3.2.2. Image Classification

The land cover map has been generated using the Max-likelihood classification technique and

ISODATA algorithm. The classification of satellite data depends on satellite data resolutions, sensor's capabilities and the arrangement of different categories of earth surface features in a spatial domain. The classification system to be used is decided by the user for specific applications. In this study unsupervised classification has been chosen, followed by on screen visual interpretation and ground truth incorporation since our requirement was major land cover classes.

3.2.2.1. Max-likelihood classification

Maximum likelihood classification (MLX) falls under the category of unsupervised classification. In this method, unsupervised classification approach is a per-pixel classification technique performed to process selected initializing option (Principal Axis & Automatic) and Color Scheme Option (Approximate True Color). Unsupervised classification technique was applied for the LULC using temporal images of the years 1990, 2000, 2010 and 2020 in the present study. Firstly the classification of the temporal images was done by dividing them into 30 classes than identifying each of them on FCC image by onscreen visualization. After that, these classes were recoded into five classes and the following LULC classes were generated:

- | | | |
|----------------|--------------|--------------------------|
| 1. Water | 2. Grassland | 3. Plantation |
| 4. Agriculture | 5. Built-Up | 6. Fallow land and other |

At the first stage, some of the classes were mixed with another class. The mixed classes were used to extract the satellite image. The extracted parts were further classified with the help of unsupervised classification and mixed pixels were recoded into their original class. This was further overlaid on the classified image with maximum value overlay rule. This process was repeated again and again till the mixing of classes was minimized at optimum level. This gave a final LULC for study area with improved accuracy.

3.2.2.2. Field Survey

Ground truth survey points serve as an important input for assessing the accuracy and uncertainty of the obtained classification. Using the field survey data, the uncertain features during image classification were physically observed and identified. After the image classification the field visit of study area was undertaken during 10 Feb. to 17 Feb. 2020 and Ground Control Points (GCPs) were collected using hand held GPS (Garmin-H72) with the purpose identify different land

features and GWL change.

3.2.2.3. Accuracy Assessment

Accuracy assessment of classified image serves as another key step in the analysis performed using remote sensing, without which the output classified image may not be valuable for further research work and planning. Ground truth data is must for this process. Accuracy assessment provides complete information on the categorical accuracy. In this study, Accuracy Assessment tool of ERDAS imagine software were used to find the accuracy of classified image (2020). Accuracy assessment was performed by comparing the LULC map created and ground truth information (148 points) collected as reference data obtained from different information sources such as Google earth and handheld GPS (H-72). An interpretation was then made as to how closely the map produced by remotely-sensed data matched with the reference data (Source Map). In order to summarize the classification accuracy results, the most commonly used measures for accuracy assessment such as user accuracy, producer accuracy, overall

Result and Dissection

3.1. Land Use land Cover

3.1.1. Land Use land Cover, 1990

To study the land use land cover of this region Landsat Thematic Mapper (TM) image for month of February, 1990 has been classified using unsupervised ISODAT algorithm and land use land cover is divided into six classes namely water, grassland, plantation, agriculture, built-up and Fallow and other in the study region (Figure 3.2). Fallow and other land class includes non-agricultural land, barren land, wastelands and other category of LULC that does not covered under agriculture, forest, built-up and water bodies. Table 3.1 shows the area of different land use land cover classes obtained after classification.

The land use land cove classes data shows that the Water bodies covers 13.95ha (1.52%), Grassland 133.89ha (14.57%), Plantation 21.22ha (2.31%), Agriculture 5.78ha (0.63%), Built-Up 28.35ha (3.08%) and fallow land and other 715.80ha (77.89%). The maximum area of the study region is covered by Fallow land and other, followed by Grassland, Built-Up, Plantation, Water body and Agriculture (Table 3.1). Grassland class were the second largest class in terms of area as shown in Pi-diagram (figure 3.1) and the map shows the condition of LULC for the year 2000

(figure 3.2). These data, diagram and maps clearly show the peculiar characteristics of the semiarid region. More than 92% of this area showing land use land cover in the categories of clearly depicts the fragile character of this region with sensitive environmental conditions.

Table 3.1 LULC area (ha) for the year 1990

LULC Class	Area (ha)	Area (%)
Water	13.95	1.52
Grassland	133.89	14.57
Plantation	21.22	2.31
Agriculture	5.78	0.63
Built-Up	28.35	3.08
Fallow and other	715.80	77.89

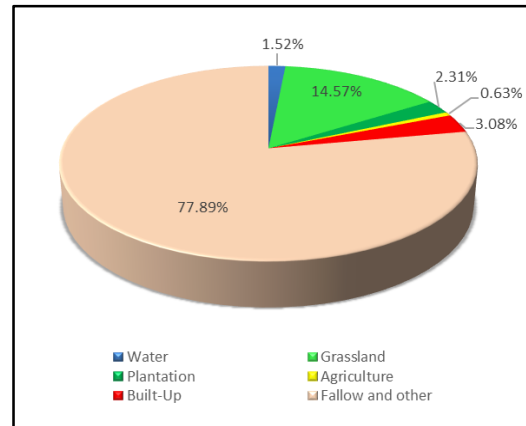


Figure 3.1 Pi-Chart representing LULC (%)

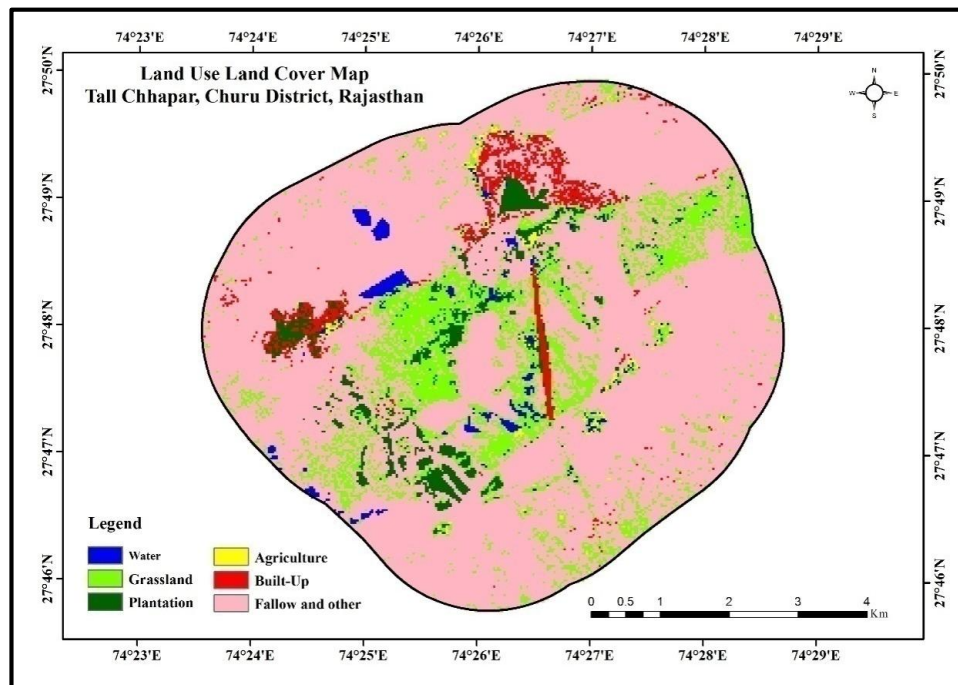


Figure 3.2 LULC of the year 1990

3.1.2. Land Use land Cover, 2000

In the year 2000 the land use land cover is showing a little shift where Water bodies is covered 12.31ha (1.34%), Grassland 140.29ha (15.27%), Plantation 27.75ha (3.02%), Agriculture 6.73ha

(0.73%), Built-Up 33.95ha (3.69%) and Fallow land and other 697.97ha (75.95%). The Maximum area of the study region is again covered by Fallow land and other, followed by Grassland, Built-Up, Plantation, Water body and Agriculture in descending order (Table 3.2).

Table 3.2 LULC area (ha) for the year 2000

LULC Class	Area (ha)	Area (%)
Water	12.31	1.34
Grassland	140.29	15.27
Plantation	27.75	3.02
Agriculture	6.73	0.73
Built-Up	33.95	3.69
Fallow and other	697.97	75.95

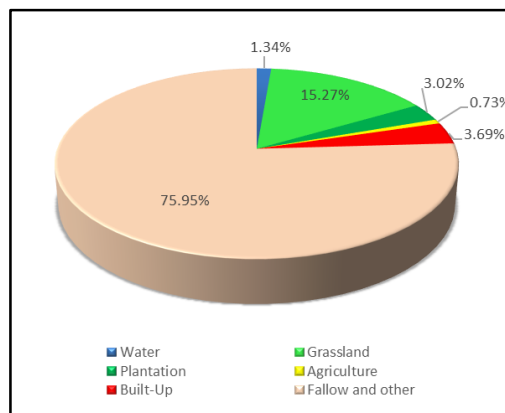


Figure 3.3 Pi-Chart representing LULC (%) Grassland class was found to be the second

largest class in termed of area as shown in Pi-diagram as found in the year 2000 (figure 3.3) and map shows the condition of LULC for the year 2000 (figure 3.4).

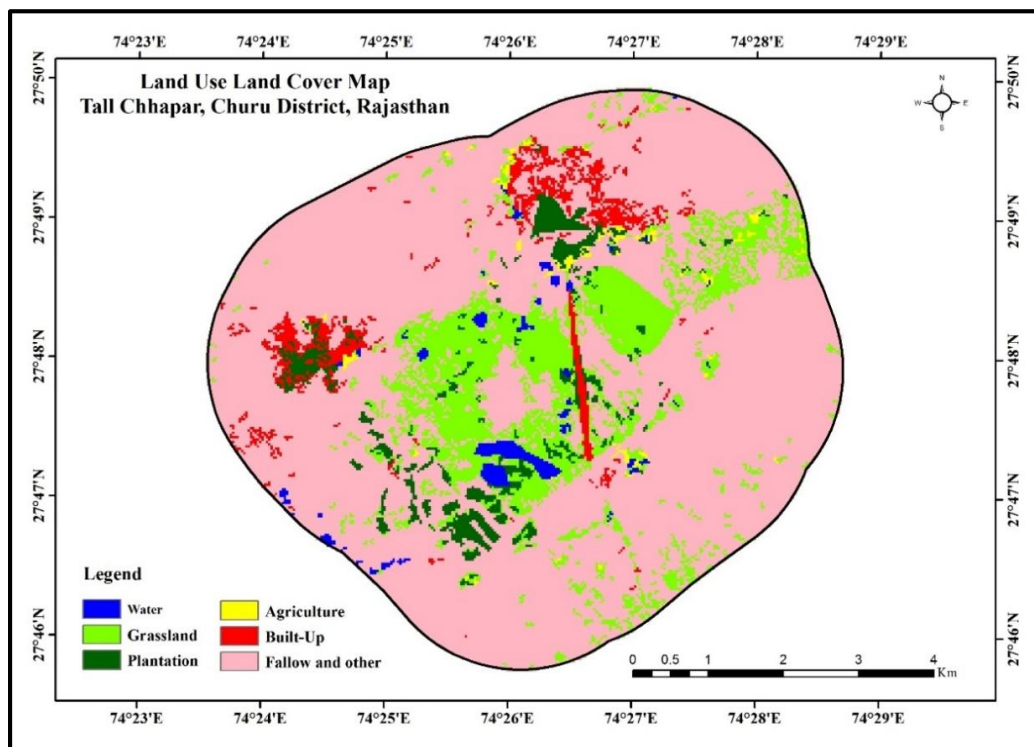


Figure 3.4 LULC of the year 2000

3.1.3. Land Use land Cover, 2010

For the year 2010 again the land use land cover situation has been analysed. For this year the areas covered by various categories are again showing a shift from the previous cases of year 1990 and 2000. For the year 2010 the Water bodies have covered 7.36ha (0.81%), Grassland 261.09ha (28.41%), Plantation 35.43ha (3.86%), Agriculture 13.94ha (1.52%), Built-Up 36.44ha (3.96%) and Fallow land and other 564.74ha (61.45%).

Table 3.3 LULC area (ha) for the year 2010

LULC Class	Area (ha)	percentage
Water	7.36	0.81
Grassland	261.09	28.41
Plantation	35.43	3.86
Agriculture	13.94	1.52
Built-Up	36.44	3.96
Fallow and other	564.74	61.54

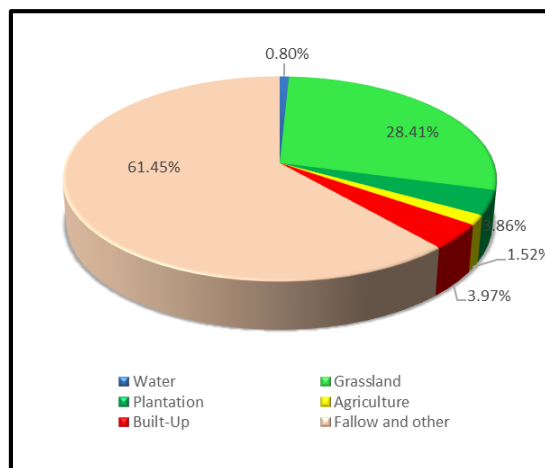


Figure 3.5 Pi-Chart representing LULC (%)

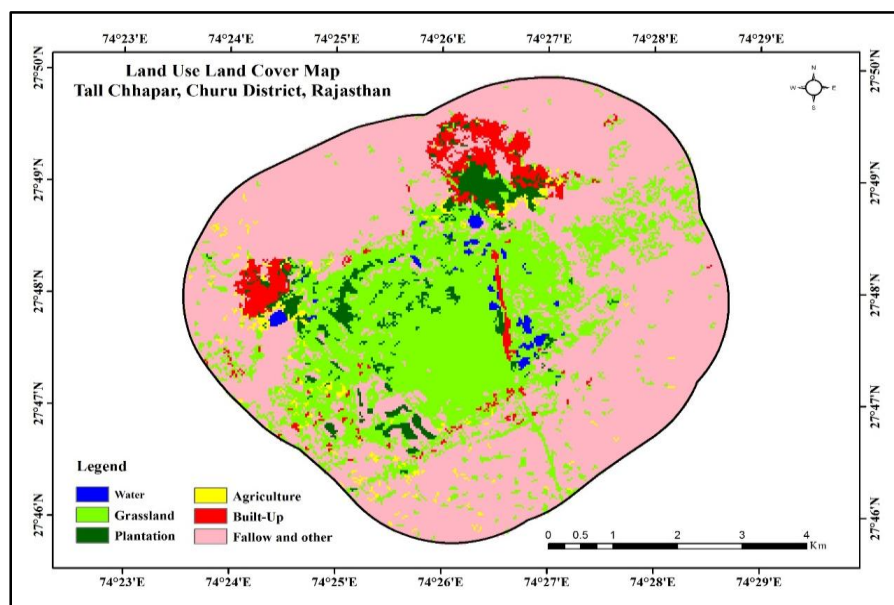


Figure 3.6 LULC of the year 2010

Again this time also the maximum area of the study region has been found in the Fallow land and other category and followed by Grassland, Built-Up, Plantation, Agriculture and Water bodies respectively (Table 3.3). Grassland class was found to be the second largest class in terms the area as shown in Pi-diagram (figure 3.5) and map showing the condition of LULC for the year 2000 (figure 3.6).

3.1.4. Land Use land Cover, 2020

For the year 2020 the Landsat Operational Land Imager (OLI) has been used to get LULC of study area for the month of February, 2020. The LULC categories have been mapped into similar six classes namely water, grassland, plantation, agriculture, built-up and Fallow and other in the study region (Figure 3.8). The area of each class was represented in table 3.4. Table data shows that Fallow land and other class is still a dominant category of the land use land cover in the study area with 61.29% coverage. Out of total 919 ha area of Tal Chhapar, 6.30ha (0.69%) is covered by water bodies. Grassland area has covered 232.52ha covering about 25.30% of the total geographical area of study region. Plantation area has covered 39.41ha (4.29%). 24.68ha area (2.69%) is covered by Agriculture area and Built-Up has covered 52.87ha (5.75%). The Fallow land and other class has observed 563.22ha (61.29%) (table 3.4). LULC for the year 2009 was also classified into similar classes using Landsat TM data and was used for the prediction purpose only.

Table 3.4 LULC area (ha) for the year 2020

LULC Class	Area (ha)	Percentage
Water	6.30	0.69
Grassland	232.52	25.30
Plantation	39.41	4.29
Agriculture	24.68	2.69
Built-Up	52.87	5.75
Fallow and other	563.22	61.29

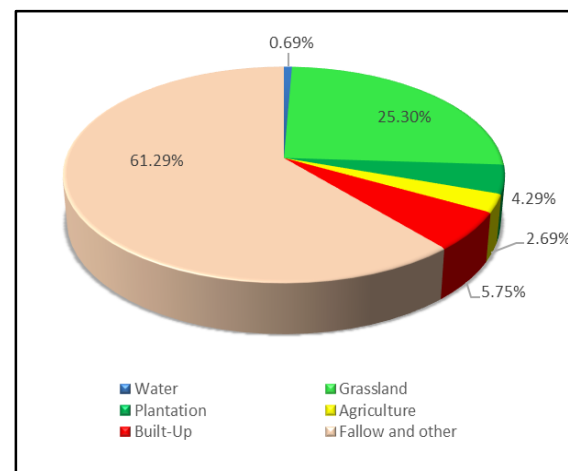


Figure 3.7 Pi-Chart representing LULC (%)

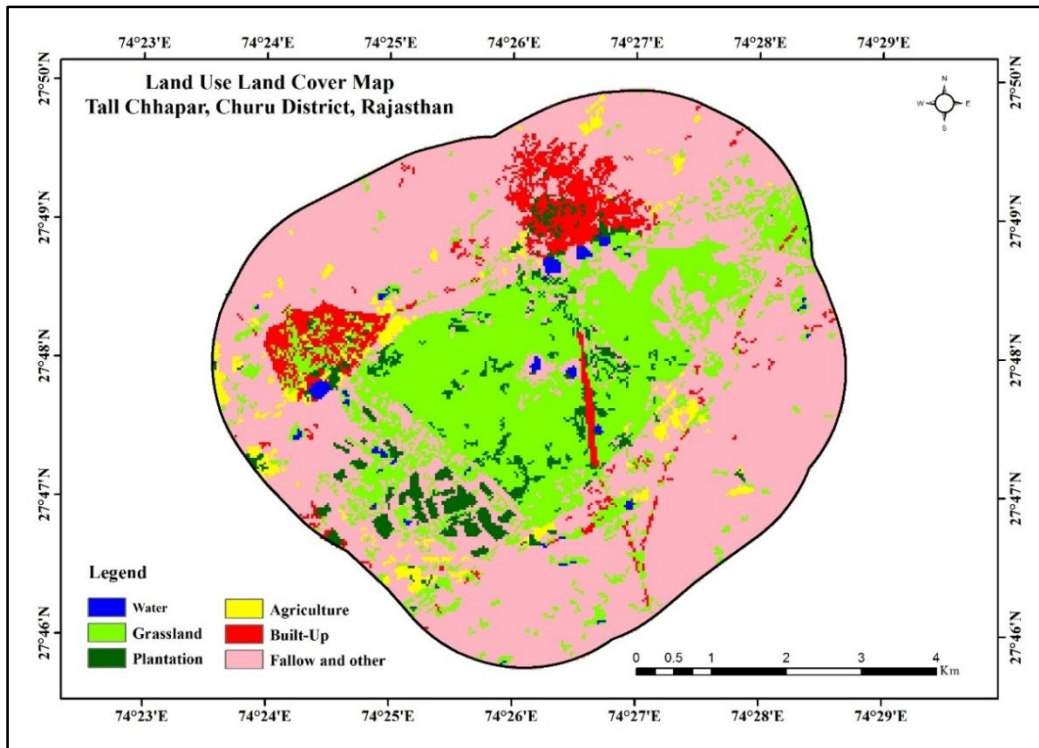


Figure 3.8 LULC of the year 2020

3.2. Accuracy Assessment

It is important to follow accuracy assessment when remote sensing data are used for the analysis. Here, after incorporation of ground truth information in the classified image of the year 2020, accuracy is assessed. Total 194 sample points including ground truth locations and some reference locations from Google earth are used for the assessment of accuracy. Class wise distribution of the points taken has been represented in Table 3.6. Out of total 03 points have been taken for the accuracy assessment of water class, 02 are showed correctly classified on the map. 47 locations are checked for Grassland class and 46 are found correct. Total 08 locations are taken as reference for the case of plantation area out of which 07 reference points are found correctly classified. Total 05 locations are taken as reference for the case of agriculture out of which 05 reference points are found correctly classified. The accuracy of the built-up class is assessed based on 13 reference points and out of which 10 points are found correctly classified. 118 reference points are taken for Fallow land and the other classes out of which 115 points are found correctly classified.

Table 3.6 LULC Confusion Matrix

LULC Class	Water	Grassland	Plantation	Agriculture	Built-Up	Fallow and other
Water	2	0	0	0	0	0
Grassland	0	46	1	0	0	2
Plantation	1	0	7	0	0	0
Agriculture	0	0	0	5	0	0
Built-Up	0	0	0	0	10	1
Fallow and other	0	1	0	0	3	115

Table 3.7 LULC Accuracy Assessment

LULC Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Water	3	2	2	66.67%	100.00%
Grassland	47	49	46	97.87%	93.88%
Plantation	8	8	7	87.50%	87.50%
Agriculture	5	5	5	100.00%	100.00%
Built-Up	13	11	10	76.92%	90.91%
Fallow and other	118	119	115	97.46%	96.64%
Total	194	194	185		
Overall Classification Accuracy = 95.36%			KAPPA (K [^]) STATISTICS = 0.92		

Table 3.7 represents the different parameters of accuracy assessment such as Producer accuracy (PA), user’s accuracy (UA), overall accuracy and kappa coefficient. The overall accuracy of classified image of February 2020 is found 95.36% with Kappa coefficient 0.92. The producer and user accuracies of individual classes are extremely high, ranging in Water 66.67% (PA) and 100% (UA), Grassland 97.87% (PA) and 93.88% (UA), Plantation 87.50% (PA) and 87.50% (UA), Agriculture 100% (PA) and 100% (UA), Built-Up 76.92% (PA) and 90.91% (UA) and Fallow land other 97.46% (PA) and 96.64% (UA) respectively. Points from Google earth and ground truth (GPS Point) information covering different LULC classes made it possible to assess the classification results reliable and to get good accuracy.

3.3. LULC Change Analysis

Post classification comparison technique of change detection is used for the temporal LULC change analysis (%) in this research work. Table 3.8 represents the changes in LULC between the years 1990- 2000, 2000 – 2010 and 2010 - 2020. Firstly, the change analysis between the years 1990 to 2000 is done. Negative change in water 0.18% and Fallow and other 1.94% whereas the positive change in grassland 0.70%, Plantation 0.71%, Agriculture 0.10% and Built-up 0.61% (figure: 3.9). Change analysis between the years 2000 to 2010. Negative change in water 0.54% and Fallow and other 14.50% whereas the positive change in grassland 13.14%, Plantation 0.84%, Agriculture 0.78% and Built-up 0.27% (figure: 3.10). Change analysis between the years 2010 to 2020. Negative change in water 0.12% and Grassland 3.11%, Fallow and other 0.17% whereas the positive change in Plantation 0.43%, Agriculture 1.17% and Built-up 1.79% (figure: 3.11) has been observed.

Table 3.8 Temporal LULC change analysis (%)

Years LULC Class	1990 (A)	2000 (B)	2010 (C)	2020 (D)	Change (B-A)	Change (C-B)	Change (D-C)
Water	1.52	1.34	0.80	0.69	-0.18	-0.54	-0.12
Grassland	14.57	15.27	28.41	25.30	0.70	13.14	-3.11
Plantation	2.31	3.02	3.86	4.29	0.71	0.84	0.43
Agriculture	0.63	0.73	1.52	2.69	0.10	0.78	1.17
Built-Up	3.08	3.69	3.97	5.75	0.61	0.27	1.79
Fallow and other	77.89	75.95	61.45	61.29	-1.94	-14.50	-0.17

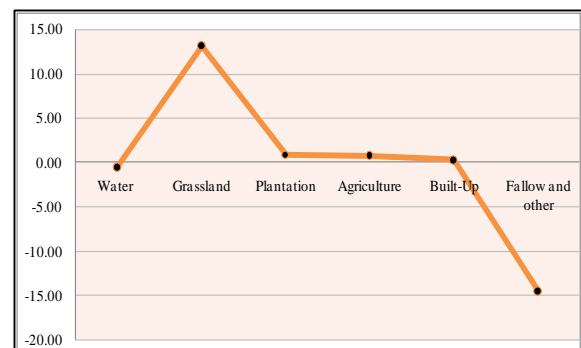
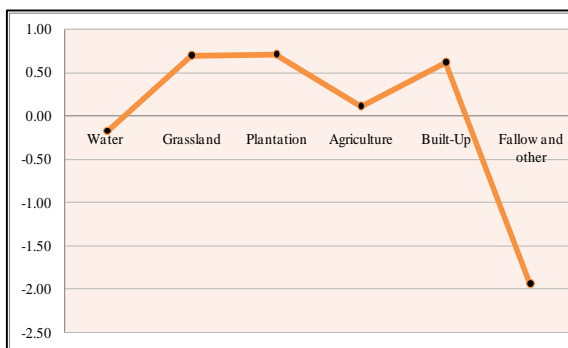


Figure: 3.9 LULC Change for the year 1990 - 2000

Figure: 3.10 LULC Change for the year 2000 - 2010

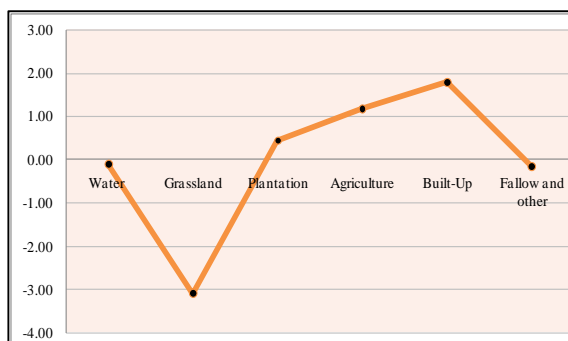


Figure: 3.11 LULC Change for the year 2010 - 2020

3.4. LULC Change inside Tal Chhappar

Post classification comparison technique of change detection is used for the temporal LULC change analysis in inside Tal Chhappar. Table 3.9 represents the changes in LULC between the year 1990 - 2000, 2000 – 2010 and 2010 – 2020 in hectare (ha). First, in change analysis between year 1990 to 2000, negative change is observed in plantation 5.04ha, Agriculture 2.59ha, Built-up 0.07ha and Fallow and other 106.72ha, whereas the positive change is found in Water 13.01ha and Grassland 101.41ha. for the change analysis between the years 2000 to 2010, negative change has been observed in water 14.97ha, Built-up 4.76ha and Fallow and other 189.59ha, whereas the positive change in grassland 200.64ha, Plantation 8.46ha and Agriculture 0.21ha. Change analysis between the years 2010 to 2020, is showing negative change in water 13.15ha and Fallow and other 11.54% whereas the positive change in Grassland 2.52ha, Plantation 16.71ha, Agriculture 4.62ha and Built-up 0.84 (figure: 3.12).

Table 3.9 Temporal LULC change inside Tal Chhappar Sanctuary (hectare)

Years → LULC Class ↓	1990 (A)	2000 (B)	2010 (C)	2020 (D)	Change (B-A)	Change (C-B)	Change (D-C)
Water	20.07	33.08	18.11	4.97	13.01	-14.97	-13.15
Grassland	241.55	342.96	543.60	546.12	101.41	200.64	2.52
Plantation	38.53	33.50	41.96	58.68	-5.04	8.46	16.71
Agriculture	4.62	2.03	2.24	6.85	-2.59	0.21	4.62
Built-Up	16.57	16.50	11.75	12.59	-0.07	-4.76	0.84
Fallow and other	397.65	290.93	101.34	89.80	-106.72	-189.59	-11.54

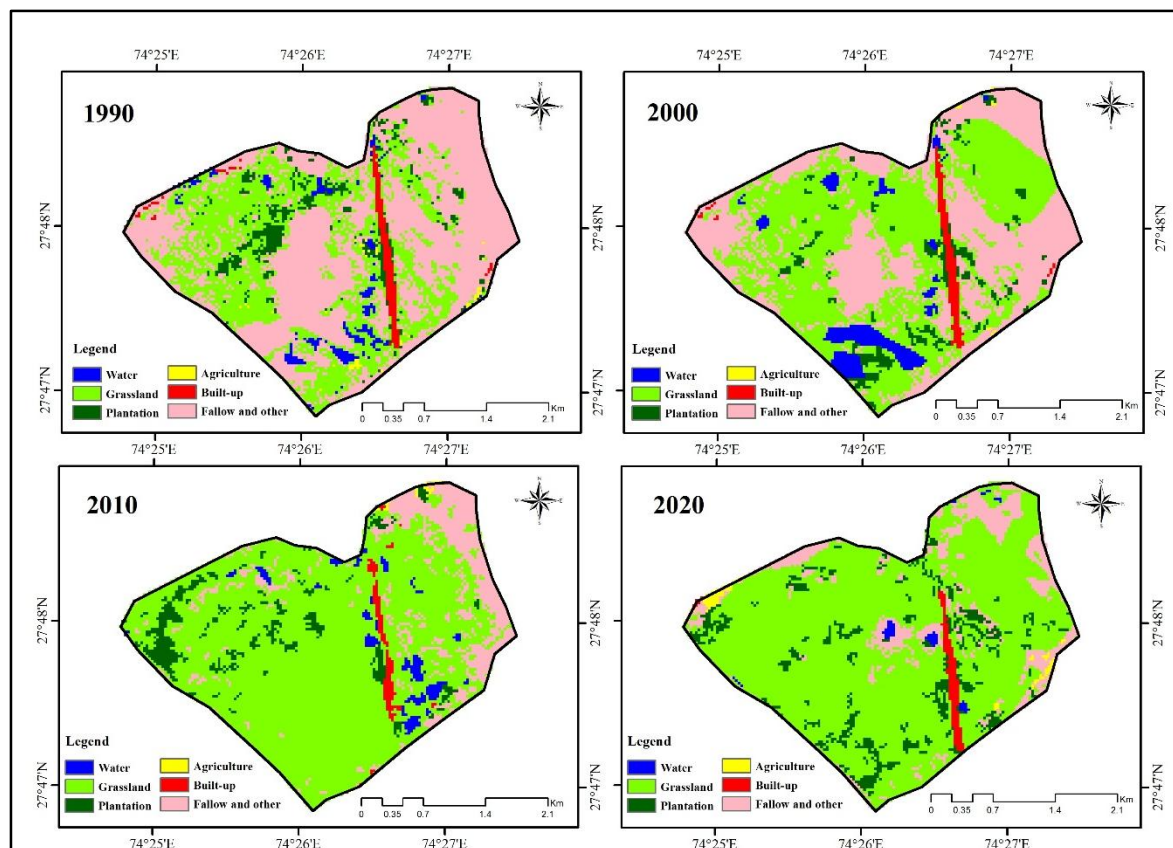


Figure: 3.12 Temporal LULC Change inside Tal Chhapar Sanctuary

Here the land use land cover data for the period of three decades clearly showing a shift from the year 1990 to 2020 (table 3.5). There are two alarming indications which are showing serious concerns in terms of environmental degradation in the study area. First, the depleting water resources, which is clearly reflected from the data on water bodies. In 1990 there was 1.52% LULC under this category which has been reduced to 0.69% in 2020. This more than 50% decline is a serious issue and it is indicating the shortage of availability of adequate water for the maintenance of ecosystem of this region. This is because of increasing water use for agricultural purposes as the share of agriculture in LULC increased from 0.63% to 2.29% in last three decades from 1990 to 2020.

Second, the increase in built-up area from 3.08% to 5.75% is also a cause of concern. This is because of increasing population pressure in the study area as well as developmental initiatives in this region in terms of expansion of infrastructure. In this period the area under grassland increased from 14.57% to 25.30% (it has reached to the level of 28.41% in the year 2010), and plantation land use shows increase from 2.31% to 4.29%. the increase in land use land cover in these

categories is take place due to shrinking land use land cover in the Fallow and other category from 77.89% to 61.29%.

Table 3.5 LULC area (in %) for the year 1990 to 2020

LULC Class	1990	2000	2010	2020
Water	1.52	1.34	0.81	0.69
Grassland	14.57	15.27	28.41	25.30
Plantation	2.31	3.02	3.86	4.29
Agriculture	0.63	0.73	1.52	2.29
Built-Up	3.08	3.69	3.96	5.75
Fallow and other	77.89	75.95	61.54	61.29

Conclusion

Found that there no regular change in the amount of rainfall received in this region. But it is found that the share of land use land cover under Water body category is showing drastic decline. This is mainly because of increasing use of underground water for irrigation purpose. The share of agriculture in total land use land cover has increased by more than three times in the last three decades along with expansion of irrigation facilities mainly by tube wells. The area under grassland and plantation is also increase for this period of analysis. All these expansions are taking place on the cost of reducing area under fallow land and other. The built-up area is almost doubled. This is showing an alarming situation and need quick intervention for the protection of environment in the study area.

References

- Mishra, V. N., & Rai, P. K. (2016).** A remote sensing aided multi-layer perceptron-Markov chain analysis for land use and land cover change prediction in Patna district (Bihar), India. *Arabian Journal of Geosciences*, 9, 1-18.
- Mariye, M., Jianhua, L., & Maryo, M. (2022).** Land use and land cover change, and analysis of its drivers in Ojoje watershed, Southern Ethiopia. *Heliyon*, 8(4).
- Steplin Paul Selvin, S., Ganesh Kumar, A., Sarala, L., Rajaram, R., Sathiyam, A., Princy Merlin, J., & Sharmila Lydia, I. (2018).** Photocatalytic degradation of rhodamine B using zinc oxide activated charcoal polyaniline nanocomposite and its survival assessment using aquatic animal model. *ACS Sustainable Chemistry & Engineering*, 6(1), 258-267.
- Das, S. (2011).** Ecotourism, sustainable development and the Indian state. *Economic and Political*

Weekly, 46(37), 60-67.

- Kiper, T. (2013).** Role of ecotourism in sustainable development. InTech.
- Machnik, A. (2021).** Ecotourism as a core of sustainability in tourism. *Handbook of sustainable development and leisure services*, 223-240.
- Chughtai, A. H., Abbasi, H., & Karas, I. R. (2021).** A review on change detection method and accuracy assessment for land use land cover. *Remote Sensing Applications: Society and Environment*, 22, 100482.
- Ren, Y., Lü, Y., Comber, A., Fu, B., Harris, P., & Wu, L. (2019).** Spatially explicit simulation of land use/land cover changes: Current coverage and future prospects. *Earth-Science Reviews*, 190, 398-415.
- Yin, H., Pflugmacher, D., Li, A., Li, Z., & Hostert, P. (2018).** Land use and land cover change in Inner Mongolia-understanding the effects of China's re-vegetation programs. *Remote Sensing of Environment*, 204, 918-930.
- Mashala, M. J., Dube, T., Mudereri, B. T., Ayisi, K. K., & Ramudzuli, M. R. (2023).** A Systematic Review on Advancements in Remote Sensing for Assessing and Monitoring Land Use and Land Cover Changes Impacts on Surface Water Resources in Semi-Arid Tropical Environments. *Remote Sensing*, 15(16), 3926.
- Sun, T., Cheng, W., Abdelkareem, M., & Al-Arifi, N. (2022).** Mapping Prospective Areas of Water Resources and Monitoring Land Use/Land Cover Changes in an Arid Region Using Remote Sensing and GIS Techniques. *Water*, 14(15), 2435.
- Debnath, J., Sahariah, D., Lahon, D., Nath, N., Chand, K., Meraj, G., ... & Singh, S. K. (2023).** Geospatial modeling to assess the past and future land use-land cover changes in the Brahmaputra Valley, NE India, for sustainable land resource management. *Environmental Science and Pollution Research*, 30(49), 106997-107020.
- Zadbagher, E., Becek, K., & Berberoglu, S. (2018).** Modeling land use/land cover change using remote sensing and geographic information systems: case study of the Seyhan Basin, Turkey. *Environmental monitoring and assessment*, 190, 1-15.
- Degerli, B., & Çetin, M. (2022).** Using the remote sensing method to simulate the land change in the year 2030. *Turkish Journal of Agriculture-Food Science and Technology*, 10(12), 2453-2466.