Landuse/landcover monitoring and spatiotemporal modelling using multilayer perceptron and ‘multilayer perceptron’-Markov Chain ensemble models: A case study of Dausa City, Rajasthan

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Abstract. The present work is an attempt to the LULC classification, monitoring, and spatiotemporal prediction using Artificial Neural Network - Multi-Layer Perceptron (MLP) and MLP-Markov Chain (MC) models. Dausa city and its surroundings of Rajasthan, India has been selected for this study for several reasons including arid climatic setting being a sensitive precursor to the climate change scenarios and the huge population pressure experienced by the area. The MLP based supervised classification for two periods 2001 and 2018 have been analyzed using Landsat 7 Thermal Mapper (TM) and Landsat 8 OLI satellite images. The images were classified into six LULC categories viz. Built-up (Settlements), Cultivated Lands (Agricultural/Cropland), Water Body, Uncultivated/Fallow Lands, Barren Lands, and Forest/Vegetation cover. The accuracy assessment for both classified images was performed using confusion matrix led Kappa Coefficient (K) technique. Reasonable accuracies, K=0.82 (2001) & K = 0.91 (2018), have been achieved for datasets selected for both periods of time. The MLP-MC model based spatiotemporal LULC prediction for the year 2045, using the trends in the classified LULC results for the period 2001-2018, prophecies that the ‘built-up land’ would increase to reach 76.10 km2 (67.60% increase) in 2045 with the reference year 2001 whereas the increase in this class of LULC would only be 39.34% during the period 2018-2045. The ‘cultivated land’ (2001-2045: -83.86%; 2018-2045: -65.20%), ‘barren land’, (2001-2045: -54.70%; 2018-2045: -4.86%), ‘water body’ (2001-2045: -96.43%; 2018-2045: -84.42%), and ‘forest/vegetation’ (2001-2045: -81.94%; 2018-2045: -20.59%), categories would experience continuous areal decline over this period, though some at faster pace and other at comparatively lower rate. The projected unprecedented exponential increase in ‘follow land/uncultivated land’ (2001-2045: +372.45%; 2018-2045: +6.39%) presents worrisome future picture of this ecologically sensitive and fragile region. The results of this study indicate and warrant intensive management and policy, and local level participation of communities to help maintain the deteriorating ecological balance in this ecologically sensitive arid ecosystem with fragile agricultural and natural vegetation traits.

Keywords: Land use land cover, Artificial Neural Network, Markov Chain, Remote Sensing & GIS, Dausa City, Rajasthan

1. Introduction

The relationship of landuse/landcover (LULC) change with climate change, ecological function, soil degradation, biodiversity, etc. is well established by now. Still ongoing researches and sizeable amount of research articles on this theme prove the need of a better refinement of understanding of LULC and
other components of the physical and human spheres. The International Geosphere-Biosphere Programme (IGBP) run under the aegis of International Council for Science (ICS) recommended the monitoring and evaluating the LULC change and its pattern at a global, national, as well as local scales with the help of remote sensed (RS) satellite imagery and geographic information system (GIS) tools. Land-use change affects natural biogeochemical cycles at global, regional, and national scales [1]–[4]. It impacts are vividly noticeable in the domains of water resources, green-house processes, atmospheric processes, biodiversity, hydrological cycle, carbon cycle, and ecology [5]–[9]. Also, at regional scale, the LULC changes affects micro-climatic processes, water catchments/watersheds, surface water runoff, and groundwater levels [10]. The land-degradation and land subsidence processes have also been directly related tied to, as one of the important controlling factors, LULC. The study of landuse dynamics, therefore, has been found to be very crucial for protecting the natural way of functioning of different cycles of earth’s system by monitoring and continuous evaluation of LULC pattern, both in spatial and temporal contexts.

The studies of LULC trend and pattern related issues, at local and/or regional, have increasingly been appearing in the research sphere from the last two to three decades [11]–[16]. These research, covering different aspects, in conjunction with its relationship with other domains of four spheres of our planet, at country/global scale have also been carried out by many international agencies i.e. International Geosphere–Biosphere Programme (IGBP), European Space Agency (ESA) Climate Change Initiative (CCI) Land Cover (LC) project, Global Human Settlement Layer (GHSL), United States Geological Survey (USGS), National Remote Sensing Centre (NRSC), etc. But the need to quantify LULC monitoring and their spatiotemporal prediction at finer scale have been emphasized by time to time by these agencies and similar such studies.

To provide more accurate LULC classification maps, different statistical models, in terms of structure and application, have been developed during last 2-3 decades to understand LUCC dynamics. These models range in characteristics from simple statistical models, Maximum likelihood classifier (MLC) based classifications [17], multi-criteria decision-making analysis algorithms i.e. Analytical Hierarchy Processes (AHP) based analysis [18], Fuzzy-AHP based study [19] to advanced machine learning models i.e. Support Vector Machine (SVM) based LULC studies [20]–[24], Bayesian algorithms based researchers [25], [26], applications of Artificial Neural Network (ANN) in LULC classifications [15], [27], [28], etc. All these models have their own set of advantages and disadvantages [29], [30]

Apart of using different models for LULC classification and comparing the accuracy several studies recently found in the interest of projecting the LULC based on earlier maps of two or more than two time periods. The LULC forecast is performed and analysed using the historical remotely sensed satellite images and in-field survey collected samples in Geographic information system (GIS) environment. The LULC patterns are the final mosaic of different landscape elements pertaining to hydrological, climatological and man-made features, which, to a certain extent, determine the forecast of the LULC dependency [30]–[32]. Many studies have been carried out to test the model accuracy performances using different set of simple as well as advanced simulation models [33], [34]. A range of simulation models-based studies have been published for LULC forecast. Some of them are Markov Chain model (MCM) [35], Cellular Automata (CA) Markov Chain (CA-Markov) model [36], Multi-Layer Perceptron Markov Chain (MLP-MC) model [37], [38], multi-actor-based land use modelling (MAS) model [39], multi-criteria evaluation (MCE)-CA model [40], GeoCA-Urban model [41], and SLEUTH model [42]. Among these advanced simulation models, the MLP-MC model is highly recommended for its better performance and accuracy [38].

Inspiring from these studies and after a thorough literature review it has been found that very limited studies have been studied on the selected study area for present work. The present study uses MLP model for LULC classification of historical satellite images of Dausa city and its surroundings of Rajasthan state, India for two periods, 2001 and 2018, to forecast the LULC for year 2045 by using MLP-MC model. There has been found lack of any important study on this aspect of LULC classification using machine learning and future LULC scenario forecasting assessment for Dausa city/district. This research aims to fill research gap by providing accurate and reproducible LULC classified maps for said periods and based on the computed trend of LULC, the prediction for 2045
LULC map of Dausa city and its surroundings has been attempted to have information of LULC transition needed for sustainable development planning and habitat conservation practices as well as ecosystem service assessments. There was one limitation found in the study that the due to arid/semi-arid climate characteristics the

2. Study Area

The Dausa city, satellite city, is located about 55 km from Jaipur metropolitan city which is the capital of Rajasthan state. For present research, a highlighted portion covering Dausa city and its surroundings, of Dausa district has been undertaken to analyse the urban growth and its expansion in future. The study area lies between 26° 38' 41.3'' N to 27° 8' 17.1'' N latitude and 76° 10' 41.7'' E to 76° 32' 55.2'' E longitude, and covers an area of approximately 1277 km² (Figure 1).

Figure 1. Location map of Dausa city and its surroundings

The population of Dausa city, as per 2011 census of India, was recorded as 85,960. Two national highways, NH-21 & 148, connect the city with major urban hubs like Jaipur, Agra, Mathura, etc. The easy and fast road connectivity, apart from connectivity of the nearby cities with air and train routes, attracts many tourism and other activities leading to inflow of people in the area which finally promotes population expansion and urbanization. The climatic conditions of the study area are characteristically hot semi-arid (Köppen climate classification Bsh) with monsoon rainfall during June-July-August months. The arid region records extremely hot summer days, for a very long period, ranges from March to October. The maximum temperature recorded in the region reaches up to ~48°C in the month of May and the average temperature is 32.2°C for a calendar year. The average annual rainfall varies from 50-70 mm. The existing deserts found approximately adjacent to the study area causes the temperature falls drastically during nights, and during winter period (November to February), the average temperature records attain the values in the range from 3°C to 5°C. The scant (and sometimes heavy but for low duration high) rainfall, and high temperature casus very low water availability in river basin throughout the year.
3. Materials and methods

In present study, the remotely sensed satellite Landsat satellite data of two different times has been utilized to prepare the LU/LC maps for the Dausa City and its surroundings. For two different years, 2001 and 2018, the L1TP level (level-1, pre-processed) satellite tiles for Landsat-5 Thematic Mapper (TM) and Landsat-8 Operational Land Imager (OLI) were downloaded from the earth explorer portal, a platform provided by the United States Geological Survey (USGS) to their users to order archived or latest satellite images, cartographic products, and aerial photographs for different purposes of studies and research. The L1TP products are already pre-processed meaning thereby they are radiometrically calibrated, orthorectified with optimum GCPs (ground control points) and correction of relief displacement computed has also been performed during pre-processing, using digital elevation model (DEM) [43]–[46]. The details of satellite data are provided in table 1. The complete methodology flowchart is given in figure 2.

Table 1. Characteristics of the Landsat satellite data in detail used in the study

| S. No. | Landsat Image scene ID | Cloud coverage (%) | WRS Path/Row | Acquisition date | Spatial reference |
|--------|------------------------|--------------------|--------------|-----------------|-------------------|
| 1.     | LE07_L1TP_147041_20011103_20170202_01_T1 | Scene cloud cover: 0.0 Land cloud cover: 0.0 | 147/41 | 03-11-2001 | Projection: UTM Zone: 43N Datum: WGS84 Ellipsoid: WGS84 |
| 2.     | LC08_L1TP_147041_20181126_20181210_01_T1 | Scene cloud cover 1.01 Land cloud cover 1.01 | | 26-11-2018 | |

Figure 2. Flowchart of methodology
3.1. Pre-processing of satellite images

The collected imageries were projected in Universal Transverse Mercator (UTM), Zone-43 projection with datum of World Geodetic System (WGS) 1984, developed by Defence Mapping Agency (DMA) as global reference [47] for coherence of spatial data being produced at global scale. Further, the Region of Interest (ROI) has been extracted and false colour composite (FCC) was generated for period, 2001 and 2018, datasets using the procedural exercise of band combination.

3.2. Training Samples

In order to collect consistent training samples from the images, they should be cloud and shadow free or very low share of cloud clusters encourage better quality of sample collections. For both periods, 2001 & 2018, the selection of cloud coverage less than 2% (table no. 1) has been achieved by removing the low-quality sample collection constraint. In addition, before sample collection the two constraints have been followed: absence of cloud or shadow pixel(s) and avoidance of shared boundary classes collection [48]. For collection of samples the following criteria have been followed after comparing both datasets (2001 & 2018 images) and identifications of change pixels from one class of earlier period maps to any other classes in the later period maps [13]: (1) selection of maximum possible classes/places in ROI, (2) inclusion of change pixels in training samples, and (3) minimum-distance rule for avoiding overlap or duplication in collection. Hence, for training of the datasets (images) in the model, the samples were collected in six categories viz. Built-up (Settlements), Cultivated Lands (Agricultural/Cropland), Water Body, Uncultivated/Fallow Lands, Barren Lands, and Forest/Vegetation cover.

3.3. Multi-Layer Perceptron neural network

An artificial neural network (ANN) is an inter-connected network of several processing units which are prepared on basis of human brain’s neurons to solve a complex problem. Neural networks, non-linear complex models, help to convert a data, remotely sensed imagery in this case, into a desired output (LULC classified image). Generally, there are six ANN models, popularly used for studies of pattern recognition in images; Carpenter/Grossberg classifier, Hamming network, Kohonen’s self-organising feature maps, Hopefield network, single layer perceptron, and the last one is multi-layer perceptron [49]. The most popular among them, the multi-layer perceptron (MLP), described by Rumelhart et al., (1986), is popularly being used in studies involving remote sensing data. As described in figure 3, it consists of minimum three layers which are interconnected to the preceding and subsequent layer and there is no connectivity of nodes, processing elements, with each other in same layer. In the structure of this model, the first layer is called input layer, holds the input or assigned values by user, distributes the values to the next layer for processing. The processed values are saved in output or last layer of the structure and between input & output layers, the hidden layer receives the feeds (values) forwarded by input layer for finding the better output to be transferred to the final output layer. A user can define the number of hidden layers; generally, one hidden layer is sufficient to solve a complex problem but for deep learning exercise or to solving more complex problems, the number may be increased accordingly [51]–[53].The hidden layer nodes are a critical part of MLP structure for functioning; in absence of it, the MLP is unable to learn from the previous records as well as it cannot perform further iterations to solve any problem.
Figure 3. Schematic of MLP Neural Network. Source: (Shafiullah and Abido, 2018)

In order to accomplish the modifications of neuron weights (calculated from assigned values), the MLP functionalities involve forward and backward propagation. During training of the dataset, each sample is fed into the input layer and the receiving node calculates the weighted signals from all nodes to which it is connected in the preceding layer. Formally, the input layer that a single node receives is weighted according to the equation:

$$\text{net}_j = \sum_{i=1}^{m} w_{ij} O_i$$  

(1)

Where, \( w_{ij} \) represents the weight between nodes \( i \) & \( j \). \( O_i \) refers output from node \( i \). The output from a given node \( j \) is computed by:

$$O_j = f(\text{net}_j)$$  

(2)

In the function of MLP, the number of hidden layer nodes can be calculated as follows:

$$N_h = INT(\sqrt{N_i \times N_o})$$  

(3)

Where, \( N_h \), \( N_i \) and \( N_o \) are the number of hidden, input and output layer nodes respectively.

3.4. LULC classification and accuracy assessment

The LULC classification for both periods 2001 & 2018 were carried out using supervised-MLP learning method by using collected training samples. Out of total collected samples, 70% were apportioned for training and the rest 30% was used for testing of the MLP model. For each class, 1000 samples were chosen with 10,000 iterations for better performance of the model. The complete parameter and performance of both period classifications is provided in the table.

Accuracy assessment was also performed for both classified maps through confusion matrix table derived kappa coefficient. The model performance has been assessed from two perspectives viz. 1) how well the model has performed in actual and how well it could performed by chance can be calculated through Cohen’s Kappa [54]. The Kappa coefficient is calculated through following formula;

$$K = \frac{N \sum_{i=1}^{n} m_{ii} - \sum_{i=1}^{n} (G_i C_i)}{N^2 - \sum_{i=1}^{n} (G_i C_i)}$$  

(4)

Where, \( i \) denotes the class number, \( N \) refers the total number of obtained values through classification in comparison to the true values, \( m_{ii} \) is the obtained values belong to the truth class \( i \), also been classified as class \( i \), \( G_i \) & \( C_i \) refer total number of predicted and observed values in class \( i \).

In addition, the overall accuracy, producer’s accuracy and consumer’s accuracy is also calculated from confusion matrices by using following methods;
Overall Accuracy = \frac{\text{Total number of correctly classified pixels}}{\text{Total number of reference pixels}} \quad (5)

Where, total number of reference pixels refers the sum of the obtained diagonal pixel counts in confusion matrix for each class.

Producer’s Accuracy = \frac{\text{Correct classified pixel counts within a class}}{\text{Total number of reference pixels of that class}} \quad (6)

Where, the total number of reference pixels of that class refers the sum of the column for particular category in the confusion matrix table.

Consumer’s Accuracy = \frac{\text{Correct classified pixel counts within a class}}{\text{Total number of classified pixels in that class}} \quad (7)

Here, the total number of classified pixels in that class refers the sum of the row for particular category in the confusion matrix table.

The error assessment of MLP model has been computed by the root mean square error (RMSE) test. The RMSE method is considered as standard statistical metric to assess a model’s performance in various fields of Science, Technology, Applied sciences, etc. [55]. The RMSE used in this study was aimed to exercise a comparison between the predicted and observed output values. The equation of RMSE can represented mathematically as follows:

\[ \text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \quad (8) \]

Where, P and O refer to predicted and observed values respectively. ‘n’ is the total number of input cases.

Further, the LULC change map was prepared and the derived LULC change map used to calculate selected LULC transitions and then the LULC transitions were utilized transition potential modelling for prediction of LULC by using the Markov Chain analysis.

3.5. Markov Chain Analysis for Prediction of LULC

Markov chain (MC) analysis, a stochastic process, is being widely used for spatial modelling and for prediction of LULC based on trends in the change of historical LULC pattern [14], [35], [49], [56]. The MC analysis for prediction of LULC for a region uses different sets of matrices, represent multi-directional LULC changes between all LULC categories [35] and provides the probability matrix of transitions from one land category to another category. The transition probability matrix defines change trends from past to present and into the future probabilities of for a certain class type of LULC for each grid [49]. Correspond to the potential driver(s) and taken into consideration of different sets of variables, the probability matrix can be defined as a set of conditional probabilities for the transition of LULC from one state to a new state. The MC equation, adopted from Muller and Middleton (1994) for predictability of LULC distributions at the beginning (M) and at the end (M_{t+1}) can be expressed mathematically as follows:

\[ M_{t+1} * M_t = M_{t+1} \quad (9) \]

Where, \( M_{t+1} \) = transition matrix which represents the LULC changes occurred during the period. \( M_t \) = the probability of any given point being classified as any category of LULC at time t.

The MC transformation matrices are used to predict the future LULC, but the MC based analysis only provides inadequate changes of spatial distribution whereas, the ensemble of MLP-MC based model provides higher accuracy level than MC based analysis [49]. Hence, the predicted map was prepared by using the ensemble of MLP-MC based model.

Parameters and performances of classified images are provided in Table 2.
Table 2. Parameters and Performance of classified images

| Parameters                  | 2001       | 2018       |
|-----------------------------|------------|------------|
| Input layer neurons         | 3 (bands)  | 3 (bands)  |
| Hidden layers               | 1          | 1          |
| Hidden layer 1 neurons      | 4          | 4          |
| Output layer neurons        | 6          | 6          |
| Samples per class           | 1000       | 1000       |
| Final learning rate         | 0.0100     | 0.0100     |
| Momentum factor             | 0.5        | 0.5        |
| Iterations                  | 10000      | 10000      |
| Training RMS                | 0.2161     | 0.1421     |
| Testing RMS                 | 0.2243     | 0.1315     |

4. Results & Discussion

The result section has been described in three parts: LULC change analysis & accuracy assessment; LULC transitions, selection of LULC transitions and modelling, and prediction of future map using MLP-MC based model.

4.1. LULC Change Analysis & Accuracy Assessment

From the LULC change analysis, it has been observed that the water body in the area has reduced from 3.37 km² to 0.06 km². The built-up lands increased 22.84 km² from 112.57 km² in 2001 to 135.41 km² in 2018. Moreover, the forest cover has been drastically decreased from 330.58 km² to 75.19 km² which may have occurred due to the expansion of urbanization led deforestation in the area. The cultivated or croplands have also shrank by -53.62% from 2001 to 2018 but the uncultivated or fallow lands have observed exponential increase. It has increased from 169.89 km² to 754.44 km² in 2018. This indicates shift in the practice of agriculture during the 18 years and possibly because the cultivation of the lands could not take place in during the later years. The complete LULC statistics for both periods are given in table 3.

The LULC map for 2001 and 2018 are represented in the figure 4 & 5 respectively. By comparing both figures, it can be understood that the urbanization has been spread more in the central part of Dausa city than in its surrounding places.
Table 3. Area and area change statistics for 2001 & 2018 LU/LC

| LU/LC Classes            | 2001          | 2018          | 2001-2018     |
|--------------------------|---------------|---------------|---------------|
|                          | Area (km²)    | Area (%)      | Area (km²)    | Area (%)      | Area Change (%) |
| Water Body               | 3.37          | 0.26          | 0.77          | 0.06          | -2.60 -77.12    |
| Cultivated Lands         | 250.78        | 19.63         | 116.31        | 9.10          | -134.47 -53.62  |
| Built-up Lands           | 112.57        | 8.81          | 135.41        | 10.60         | 22.84 20.29     |
| Uncultivated/Fallow Lands| 169.89        | 13.30         | 754.44        | 59.06         | 584.55 344.08   |
| Barren Lands             | 410.29        | 32.12         | 195.35        | 15.29         | -214.94 -52.39  |
| Forest/Vegetation Cover  | 330.58        | 25.88         | 75.19         | 5.89          | -255.38 -77.25  |

Figure 4. Land use land cover for 2001
Total gains and losses for each landuse class are demonstrated in figure 6. The exponential gain, as compared to meagre loss, is clearly visible in uncultivated/fallow lands and built-up lands during the study period. On the other hand, the maximum loss is recorded in barren lands, more than 30%, and less than 10% gain is recoded. The cultivated lands gained about 10% but lost ~15% in 2018. Water body is reduced to negligible amount from 2001 to 2018.

In the figure 7, the LULC change from one class to another has been presented. Total forty-two types of changes from one class to another were recorded. Among them, the more important changes from any of the classes to built-up land are displayed along with figure 7. The major change has been observed from uncultivated lands to built-up lands wherein ~ 38 km² area has been converted into built-up land. Another important change of approximately 20 km² and 19 km² was recorded from barren lands and cultivated lands into built-up respectively.

![Figure 5. Land use land cover for 2018](image-url)
Figure 6. Gain and losses between 2001 and 2018 (in %)

Figure 7. Land use land cover change from 2001 to 2018
The calculated results from confusion matrices for both periods, 2001 & 2018, are presented in the table 4. In the table of accuracy assessment for classified images, the following calculated parameters are presented: Consumer’s Accuracy (CA), Producer’s Accuracy (PA), Overall Accuracy and Kappa Statistics (KIA).

| LU/LC Classes          | 2001  | 2018  |
|------------------------|-------|-------|
|                        | CA (%)| PA (%)| CA (%)| PA (%)|
| Water Body             | 93.33 | 84.85 | 100.00 | 80.00 |
| Cultivated Lands       | 81.03 | 62.67 | 88.89  | 80.00 |
| Built-up Lands         | 88.24 | 85.71 | 93.18  | 100.00|
| Uncultivated/Fallow Lands | 74.72 | 85.81 | 90.54  | 97.81 |
| Barren Lands           | 80.71 | 86.92 | 86.49  | 84.21 |
| Forest/Vegetation Cover| 97.30 | 84.71 | 99.31  | 92.86 |
| Overall Accuracy       | 83.83 | 91.11 |       |       |
| Kappa Statistics (KIA)  | 0.82  | 0.91  |       |       |

The maximum CA is recorded for Forest/Vegetation Cover (97.30%) followed by Water Body (93.33%), Built-up lands (88.24%) and so on for the 2001 LULC image. The maximum PA is observed for Barren lands (86.92%) followed by Uncultivated/Fallow Lands (85.81%), Built-up lands (85.71%), etc. On the other hand, due to better quality of image and sample collection, the higher accuracy is recorded for 2018 dataset. The highest CA is recorded to be 100% for water body followed by Forest/Vegetation Cover (99.31%) and Built-up Lands (93.18%). In terms of PA, the 100% accuracy is recorded for built-up lands followed by Uncultivated/Fallow lands (97.81%) and Forest/Vegetation Cover (92.86%). The overall accuracy is found 83.83% and 91.11% for 2001 and 2018 images respectively. The reasonable KIA = 0.82 is also recorded for 2001 data and K=0.91 found for 2018 image.

4.2. Selection of LULC transitions and modelling

LULC transitions from all the six classes to other classes, between 2001 and 2018, were analysed in this study. Through the MLP method, the transition potential modelling has been conducted with considerable accuracy [37]. The evidential likelihood dataset, as a driving force, has been taken into consideration while calculating the conducting the transition potential modelling. Finally, the major and important transformations from one class to another have been taken into consideration for further sub-modelling for prediction. The following seven class-transitions have been recorded: Barren to Built-up lands, Cultivated to Barren lands, Cultivated to Built-up lands, Uncultivated/Fallow to Built-up lands, Forest/Vegetation Cover to Barren lands, Forest/Vegetation Cover to Built-up lands, and transition of water body to Built-up lands. The computed transition probability matrix, from 2001 to 2018, to predict the LULC for 2045, through MLP-MC analysis, is given in table 5.
### Table 5. Transition probabilities matrix from 2001 to 2018

|                | Water | Crops | Built-up | Fallow | Barren | Forest |
|----------------|-------|-------|----------|--------|--------|--------|
| Water          | 0.017 | 0.132 | 0.167    | 0.440  | 0.073  | 0.172  |
| Crops          | 0.026 | 0.120 | 0.120    | 0.612  | 0.075  | 0.048  |
| Built-up       | 0.016 | 0.151 | 0.163    | 0.511  | 0.103  | 0.056  |
| Fallow         | 0.026 | 0.111 | 0.121    | 0.608  | 0.090  | 0.045  |
| Barren         | 0.014 | 0.111 | 0.118    | 0.616  | 0.098  | 0.044  |
| Forest         | 0.014 | 0.129 | 0.118    | 0.499  | 0.055  | 0.185  |

### 4.3. Prediction using MLP-MC based model

The MLP-MC model based predicted LULC map for 2045 of the Dausa city and its surroundings is presented in figure 8.

### Table 6. Predicted LU/LC area and area change statistics

| LU/LC Classes             | 2018-2045 | 2001-2045 |
|---------------------------|-----------|-----------|
| Water Body                | Area (km²) | Area (%) | Area Change (km²) | % Change |
| Water Body                | 0.12      | 0.01     | -0.65             | -84.42  | -3.25     | -96.43 |
| Cultivated Lands          | 40.48     | 3.17     | -75.84            | -65.20  | -210.31   | -83.86 |
| Built-up Lands            | 188.67    | 14.77    | 53.26             | 39.34   | 76.10     | 67.60  |
| Uncultivated/Fallow Lands | 802.64    | 62.83    | 48.20             | 6.39    | 632.75    | 372.45 |
| Barren Lands              | 185.85    | 14.55    | -9.50             | -4.86   | -224.44   | -54.70 |
| Forest/Vegetation Cover   | 59.71     | 4.67     | -15.48            | -20.59  | -270.86   | -81.94 |

From the map, it is observed that the urban sprawl is spreading more towards northern part than southern counterpart. Also, the forest cover and cultivated lands are visible in patches. From the pixel counts, it has been calculated that, in future, the built-up lands would increase by approximately 53.26 km² from 2018-2045 and would cover ~188.67 km² of land in 2045. The cultivated lands will diminish to 40.48 km² in 2045 with a loss of 75.84 km² from 2018. Barren lands will also reduce to 185.85 km² with loss of 9.50 km². The complete change matrix is given in table 6.
5. Conclusion

The LULC classification accuracy depends on the resolution and image quality of the input satellite images [57]–[59]. More advanced satellites images having greater quality than earlier satellite images, therefore, provide better accuracy in LULC classification. The higher resolution, of course, of a satellite or aerial photograph would be helpful for a user to collect more accurate samples and prepare LULC map with considerable accuracy. Moreover, the prediction is directly dependent on the quality of classification of earlier set of images [60]. The higher resolution and high accuracy of images will help to increase the prediction and hence more accurate future maps. Also, the success of a model is mostly dependent on the accurate LULC classification [49] and thereafter the transition classes could be used for prediction.

This study utilized MLP model to produce LULC maps for 2001 and 2018 and simulated LULC for 2045 using MLP-MC analysis. For the purpose, Landsat 5 TM & 8 OLI satellite images with 30-meter resolution for two different periods 2001 & 2018 were used for supervised MLP classifications. Sufficient numbers of samples were collected in each LULC class for both images and then the MLP model was applied for LULC classification. Due to low quality images and problem to clearly identify
an entity in the image at the time of sample collection, the accuracy for the 2001 LULC map was found to be less than 90%; the same technique was applied on 2018 Landsat image but the identification of LULC classes at the time of sample collection was found to be more easy due to high quality of images, although the resolution for both datasets is 30-meter, the accuracy for 2018 image was found to be more than 90%. Using both images, the LULC change map was also prepared. Afterwards, seven major transitions derived from LULC change analysis between 2001 and 2018 maps were taken as ingredient for prediction of LULC of 2045. The MLP-MC method was used to simulate the LULC for 2045. From the results, a major transformation in settlement (built-up) and cultivated lands is observed. The maximum changes are observed in the central and northern parts of the city. Due to high rate of urbanization the settlement would be also expanding in the outer fringes of the city. The present work can be helpful for the urban planners at local and national level to prepare future layout of the city towards sustainable development.

6. References

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