Predicting the future land use and land cover changes for Bhavani basin, Tamil Nadu, India, using QGIS MOLUSCE plugin

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Abstract

Human population growth, movement, and demand have a substantial impact on land use and land cover dynamics. Thematic maps of land use and land cover (LULC) serve as a reference for scrutinizing, source administration, and forecasting, making it easier to establish plans that balance preservation, competing uses, and growth compressions. This study aims to identify the changeover of land-use changes in the Bhavani basin for the two periods 2005 and 2015 and to forecast and establish potential land-use changes in the years 2025 and 2030 by using QGIS 2.18.24 version MOLUSCE plugin (MLP-ANN) model. The five criteria, such as DEM, slope, aspect, distance from the road, and distance from builtup, are used as spatial variable maps in the processes of learning in MLP-ANN to predict their influences on LULC between 2005 and 2010. It was found that DEM, distance from the road, and distance from the builtup have significant effects. The projected and accurate LULC maps for 2015 indicate a good level of accuracy, with an overall Kappa value of 0.69 and a percentage of the correctness of 76.28%. MLP-ANN is then used to forecast changes in LULC for the years 2025 and 2030, which shows a significant rise in cropland and builtup areas, by 20 km² and 10 km², respectively. The findings assist farmers and policymakers in developing optimal land use plans and better management techniques for the long-term development of natural resources.

Keywords Land use and Land cover · Multilayer Perceptron MLP-ANN · Predicted LULC · Bhavani basin, MOLUSCE, QGIS

Introduction

Biodiversity, distribution of water and radiation budgets, greenhouse gas emissions, carbon cycling, and livelihoods are all impacted by the land-use changes (LULC) worldwide. The visual effect of land use at a given moment is known as land cover. On the other hand, land use refers to the amount of human activity that is directly tied to the land and the utilization of its resources (Ebenezer et al. 2018). The interaction of ecological processes, biogeochemical cycles, biodiversity, and human activities with climate caused gradual changes in LULC (Abdul Rahaman et al. 2017). LULC studies are generally adopted to know the area’s ecology and vegetation (El-Tantawi et al. 2019). The change in LULC of a region, especially the increase in builtup areas, alters hydrological processes such as runoff pattern, peak flow characteristics, water quality, and shifting of stream flows (Ashaolu et al. 2019; Msovu et al. 2019). Humans have either directly or indirectly influenced and altered ground cover (Buğday and Erkan Buğday 2019). The role of the land, or the complete range of direct management activities that impact the land’s existence, such as agriculture, forestry, industry, and other associated activities, determines the land use. On the other hand, land cover refers to the current biophysical state of the Earth’s surface and immediate sub-surface (Srivastava et al. 2020; Wang et al. 2021). Deforestation, desertification, soil erosion, and other forms of environmental destruction are caused by changes in land use and land cover (Bhattacharya et al. 2020). The combined remote sensing (RS) and geographical information
system (GIS) has the best tool for managing land-use change research and natural resources. Analyzing and tracking regional and temporal LULC shifts benefits scientists, environmentalists, agriculturists, legislators, and urban planners. (Guidingan et al. 2019). Remote sensing techniques assist in efficiently preparing natural resources, tracking land management, and long-term change dynamics (Ebenezer et al. 2018; Bhattacharya et al. 2020). LULC transition models, on the other hand, typically attempt to forecast when and how frequently these changes will occur. Land prediction models such as IDRISI’s CA-MARKOV, CLUE S/Dyna-CLUE, DYNAMICS EGO, and Land Change Modeller are used by researchers worldwide. The future prediction model is extremely helpful in determining how previous and future LULC changes may affect soil erosion, especially on farmland (Perović et al. 2018). Several spatio-temporal prediction models, such as the Markov chain (MC) model, the cellular automata (CA) model, and the conversion of land use and its effects (CLUE) model, have been developed in recent years to forecast the LULC and their change detections (Alam et al. 2021). The CA model is widely used for land-use change analysis among the several spatio-temporal dynamic modelling approaches. The CA model has an open structure and can be used with other models to anticipate and simulate land-use patterns. The model has seen considerable use in recent years due to its simplicity, flexibility, and intuitiveness in integrating the spatio-temporal elements of processes (Alam et al. 2021). They are also used in urban planning studies. They can replicate the spatiotemporal complexity of urban areas and deforestation caused by natural disasters or human actions (Saputra and Lee 2019). MOLUSCE (Modules of Land Use Change Evaluation), a new QGIS plugin that can estimate potential LULC changes, is built with the CA model and includes a transition probability matrix used by most researchers (NEXTgis 2017). Four well-known algorithm models are employed in this plugin: Multilayer Perceptron-Artificial Neural Networks (MLP-ANN), Logistic Regression (LR), Multi-Criteria Evaluation (MCE), and Weights of Evidence (WoE). A CA-ANN model in MOLUSCE is a reliable tool for predicting future LULC that may be utilized in land use planning and management. MOLUSCE is also used to investigate temporal LULC shifts and predict future land use, by anticipating prospective land cover and forest cover shifts, and detecting deforestation in sensitive locations. (Rahman et al. 2017; Saputra and Lee 2019; Aneesha Satya et al. 2020). This model predicts the spatial LULC shift by estimating the pixel’s current condition based on its initial situation, adjacent neighbourhood eventuality, and changeover laws. Moreover, this accurately depicts nonlinear spatial stochastic LULC change processes and produce complex patterns (Saputra and Lee 2019). This study on the Bhavani river basin in Tamil Nadu uses the MLP-ANN approach to classify LULC changes from 2005 to 2015 and attempts to forecast potential land-use changes for the years 2025 and 2030.

**Study area**

The Bhavani river basin is located between latitudes 10° 56’ 3” N and 11° 46’ 14” N, and longitudes 76° 24’ 41” E and 77° 41’ 11” E. A total of 87% of the basin area lies in Tamil Nadu state, and the remaining 9% and 1% are in Kerala and Karnataka state, respectively. The total geographical area of the basin is 5537 km². The Bhavani river rises in the Western Ghats’ Nilgiri hills, flows through Kerala’s Silent Valley National Park, and returns to Tamil Nadu. The Bhavani is a 217-km-long perennial river fed primarily by the southwest monsoon and supplemented with the northeast monsoon. The altitude of the Bhavani basin varies between 177 and 2634 m above the MSL. The average day temperature of the high relief area fluctuates between 20 and 30 °C and for the low relief area ranges between 22 and 44 °C. The average annual rainfall of the Bhavani basin is 811 mm, ranging from 544 mm in Annur, Coimbatore district, to 2251 mm in Gudalur, Nilgiri district (Muthusamy et al. 2013; Ministry of India water resources 2017). The maximum rainfall occurs during October and November in high relief areas. The region is covered by clay soil, loamy soil, and rock outcrop on steep to narrow sloping grounds. Granite and fissile hornblende-biotite gneiss make up the geology of the area. The watershed is characterized by structural hills, denudational hills, narrow gorges, and intermountain valleys from a geomorphological aspect. The major agriculture croANNps are sugarcane, paddy, peanuts, legumes, fodder sorghum, coconut, sesame, turmeric, and banana (Muthusamy et al. 2013; Narayananmurthi 2020) (Fig. 1). Presently, the basin is subjected to environmental degradation due to gradual loss in forest cover. It has also been documented that this watershed is subjected to higher soil erosion due to its nature of topography and terrain conditions (Anand et al. n.d.; Balasubramanian et al. 2017; Saravanan et al. 2015). The deforestation in this basin has further induced soil erosion and because of which the Bhavani Sagar reservoir situated in this basin had lost its gross capacity from 975.18 M.cum in 1964 to 735.82 M.cum in 2006 (CWC report-2006 India-WRIS (indiawris.gov.in)).

**Data and criteria**

The datasets for the study includes the digital elevation model (DEM), distance from the road and distance from builtup, and the three LULC thematic
maps for the years 2005, 2010, and 2015. The LULC maps were obtained from the National Remote Sensing Centre (NRSC), Hyderabad. The road and builtup maps were obtained from the OpenStreetMap website (https://www.openstreetmap.org). The Carto DEM was obtained from the Bhuvan Indian Geo-platform of ISRO. The detailed information of the source of datasets is given in Table 1 and the description of the LULC categories is provided in Table 2.

The criteria used for modelling must be carefully chosen to get the desired accuracy. Though the distance from the road, distance from builtup land, distance from the river, population density, DEM, aspect, and slope were considered by many researchers for LULC studies (Alam et al. 2021; Ashaolu et al. 2019; Guan et al. 2011; Hakim et al. 2019; Nugroho et al. 2018; Saputra and Lee 2019), for this study apart from the three thematic LULC maps, DEM, slope, aspect, distance from the road, and distance from the builtup were considered.

The road lines and builtup land features available in OpenStreetMap were downloaded in the shape file format and were then imported into the ARC GIS 10.4 software. The attribute table of the above mentioned files was converted to raster format using Euclidean distance tool available in spatial analyst to get the distance from the road and distance from the builtup.

**Methods**

In the CA model, the transition probabilities from the MLP-ANN learning process are employed to describe the LULC changes. The MOLUSCE plugin in Quantum GIS 2.18.24 software is used for this method (Fig. 2). The MOLUSCE plugin features six LULC prediction phases (Hakim et al. 2019).
The first step in the model includes the LULC maps for the beginning (2005) and end year (2010). The spatial variable factors such as DEM, slope map, aspect map, distance from road, and distance from builtup are fed in the model to get a land cover change map from which the changing pattern for the study area between 2005 and 2010 is established (Fig. 3). The properties of the explanatory maps are extracted in the same raster format for all datasets, with the exact geographical projected coordinates of UTM 43 N and with a resolution pixel size of 50 m.

To project the change in LULC, the MLP-ANN plugin was used (Buğday and Erkan Buğday 2019; Msovu et al. 2019). The plugin calculates the percentage of area change in a given year. It generates a transition matrix that shows the proportion of pixels shifting from one land use cover to another. The plugin also creates an area change map that shows the change in the land between 2005 and 2010 in all the eight classes, viz., builtup land, cropland, pasture, fallow land, forests, grassland, wasteland, and water bodies. The future LULC maps are predicted assuming that existing LULC patterns and dynamics are getting continued. Also, based on the classified raster images of 2005 and 2010, LULC transitions are predicted for 2025 and 2030.

### Evaluation correlation

The correlation of geographic variables between the two raster images, which are used to examine the correlation among the spatial variables factors, is evaluated using Pearson’s correlation, Crammer’s coefficient, and Joint information uncertainty (Hakim et al. 2019). Then, between the initial year (2005) and the final year (2010), the category of

| Table 1 | Source of dataset maps |
|---------|------------------------|
| Data    | Criteria               | LULC simulation | Year | Description | Source                                                                                     |
| DEM     | DEM                    | Special variable maps | 2019 | Carto DEM 30-m spatial resolution | National Remote Sensing Centre (NRSC) Bhuvan | NRSC Open EO Data Archive | NOEDA | Ortho | DEM | Elevation | AWIFS | LISS III | HySI | TCHP | OHC | Free GIS Data | Download | .tif |
| Road and builtup map | Distance from the road | Distance from builtup | Special variable maps | 2017 | The road map and builtup of Bhavani basin | OpenStreetMap | .shp |
| LULC map | LULC | Input maps | 2005 2010 2015 | A satellite image from LULC map 50-m resolution | National remote sensing Centre (NRSC) Welcome to Bhuvan | ISRO’s Geoportal | Gateway to Indian Earth Observation (nrsc.gov.in) | .tif |

### Table 2 | Eight categories of LULC maps

| Classification | Description |
|----------------|-------------|
| Builtup land   | Buildings and other artificial structures occupy the land |
| Crop land      | Cropped area followed by harvest and a bare soil period. Includes orchards and other type of cropland planted in different seasons |
| Fallow land    | Temporary cultivable land which may remain uncultivated for one or more seasons |
| Plantations    | Plantations, orchards, and tree cash crops for commercial horticulture |
| Forests        | Deciduous forests, evergreen forests, and shrubs forests |
| Grassland      | Herbaceous covers. Trees and shrubs cover less than 10% of the area |
| Wasteland      | Land that is sparsely vegetated shows signs of erosion and land deformation due to lack of adequate water, soil management, and natural causes. These are parcels of land that have been classified as underutilized and could be reclaimed for productive purposes with sufficient effort. Wasteland refers to degraded forests with signs of deforestation (less than 10% tree cover) |
| Water bodies   | Surface water, whether impounded in ponds, lakes, or reservoirs, or flowing as streams, rivers, and other bodies of water. Water bodies may be either fresh or salty |

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in land use/cover area are represented in km² (Ashaolu et al. 2019; Rahman et al. 2017).

**Transition potential modelling**

While there are several methods for calculating potential transition maps, this plugin includes (MLP-ANN), Weights of Evidence (WoE), Logistic Regression (LR), and Multi-Criteria Evaluation (MCE). For calibrating and modelling LULC changes, each methodology takes LULC change information and geographic factors as inputs. (Buğday and Erkan Buğday 2019; El-Tantawi et al. 2019; Guidingan et al. 2019). To model LULC forecast, the MLP-ANN technique was used for this study to forecast the LULC map for the year 2015. The Kappa coefficient was measured while validating the accurate and predicted LULC maps.

**MLP-ANN**

LULC data is used as an input in MLP-ANN for calibrating and modelling LULC change. This strategy is justified in handling problems where the algorithm must deal with enormous amounts of uncertain or difficult-to-implement input data. As a result, a continuous index is created that describes the terrain on a scale of 0 to 1. Since ANN incorporates fuzzy logic requirements, an endless range of 0 and 1 is determined based on terrain usability. The interactions between linked neurons and the alteration of the weight connections between them are the essential elements of ANN (Bhattacharya et al. 2020). The following parameters have been finally arrived while predicting the LULC map for the year 2015, viz., neighbourhood-1, iterations-1000 nos., hidden layer-10 nos., momentum value-0.06, and learning rate-0.001 (El-Tantawi et al. 2019; Perović et al. 2018; Das and Sarkar 2019).

**Validation**

The assessment of LULC was measured widely by the Kappa coefficient. The validation is carried out between the predicted and accurate LULC maps of 2015 by calculating the overall Kappa value. The Kappa coefficient is calculated using the expression given below (Ullah et al. 2019; Alawamy et al. 2020; Aneesha Satya et al. 2020)

\[
\text{Kappa} = \frac{p_o - p_e}{1 - p_e}
\]

where \( p_o \) denotes the proportion of actual agreements and \( p_e \) denotes the proportion of expected agreements.

\[
p_o = \sum_{i=1}^{c} p_{ij}
\]
Fig. 3 Explanatory maps: DEM, slope map, distance from road, distance from builtup, and aspect map
\[ p_e = \sum_{i=1}^{c} p_i T p T_j \]

where \( p_{ij} \) denotes the \( i \)th and \( j \)th cells in the contingency table, \( p_i T \) denotes the sum of all cells in the \( i \)th row, \( p T_j \) denotes the sum of all cells in the \( j \)th column, and \( c \) indicates the raster category count. The contingency table is a matrix that represents the frequency distribution of variables and is used in this study to show how the \( i \)th and \( j \)th cells are related. In this matrix, the interactions of each cell are tabulated and calculated. The result explains the agreement of every criterion of each cell (Saputra and Lee 2019).

Several simulations were done to predict the LULC change map for 2015 utilizing various combinations of spatial variables factors. Two to three spatial variables were combined to predict LULC map (Table 3).

Table 3 discusses the overall accuracy and maximum Kappa coefficients for the various spatial variable combinations. The analysis found that the combinations of DEM, distance from the road, and builtup got the maximum Kappa value of 0.69 and the maximum percentage of correctness 76.28% (Fig. 4). The maximum Kappa value of 0.63 was considered as a good accuracy by many researchers (Alam et al. 2021; Aneesha Satya et al. 2020; Perović et al. 2018; Rahman et al. 2017). Hence, it was concluded that these variables have a high influence in predicting LULC map of this basin. The LULC map of 2025 and 2030 were then predicted using the 2005 and 2010 LULC map with the same spatial variable combinations.

### Results and discussion

Table 4 displays the changeover probability matrix of LULC categories from 2005 to 2010. Except for the diagonal cells with high values, which show no changes because they remain in the same category, the value in the table ranges from 0 to 1, with higher values signifying more significant changes.

The trend of LULC change from 2005 to 2020 is summarized in Tables 5 and 6 depicts the LULC analysis for every five years. Figure 5 depicts the spatial variation of LULC from 2005 to 2020. In 2005, the forests were dominated by 47.79% of the total area, followed by cropland (16.65%), plantations (15.50%), fallow land (9.27%), wasteland (7.34%), water bodies (2.03%), builtup land (1.40%), and grassland (0.03%). It was observed that except for water bodies and grassland, changes in the trend were detected for all LULC classes between the years 2005, 2010, 2015, and 2020. Compared to 2005, the percentage of area covered by forest land, fallow land, wasteland, and water bodies by 0.31%, 3.28%, 1.67% and 0.02%, respectively. A percentage increase was observed for builtup land and cropland by 1.47% and 3.8%, respectively. No change in the area was observed for plantations and grassland category for the periods. The increase in builtup land was due to the increase in population in the three major districts of Bhavani basin, viz., Nilgris, Coimbatore and Erode. It can be learnt that the projected population in these districts have increased by 16% between 2011 and 2021 (censusindia.gov.in). This increase had an indirect effect on the conversion of fallow land to cropland by 3.8%. The decrease in forest land was attributed to the anthropogenic effects such as deforestation, land degradation, and desertification.

The change in land cover classes between 2015 and 2025 is depicted in Table 7. It is observed that the builtup and cropland might increase by 24.09 km² and 14.13 km², respectively, while fallow land, forests, and wasteland might decline by 10.1 km², 11.79 km², and 16.14 km², respectively. Land use land cover changes as a percentage

| Spatial variable combinations | Percentage of Kappa correctness | Kappa coefficients |
|-------------------------------|---------------------------------|--------------------|
| DEM, distance from road, distance from builtin | 76.28 | 0.69 |
| DEM, distance from road | 73.12 | 0.60 |
| DEM, distance from builtin | 70.45 | 0.58 |
| DEM, distance from builtin, slope | 71.01 | 0.56 |
| DEM, slope, aspect | 68.86 | 0.54 |

Fig. 4 Validation graph between observed 2015 and predicted 2015 LULC map
of the total land area are also analysed. A positive value implies that the categorization has improved, while a negative value denotes the categorization has deteriorated.

Table 8 shows how the land cover classification might change between 2015 and 2030. By 2030, an increase in area is observed for builtup land and cropland by 28.47 km² and 15.21 km², respectively. For other categories, except for plantations and grassland, a decrease in size is forecast. Figure 6 shows the areal LULC changes of different classes from 2005 to 2030 in an incremental span of five years and Fig. 7 shows the expected LULC changes in 2025 and 2030.

The percentage difference in LULC categories from 2005 to 2025 and from 2005 to 2030 showed an increase in a builtup area and cropland by 1.58%, and 3.86%; 1.66% and 3.88%, respectively, whereas for other categories, a decrease in percentage (< 3%) was noticed.

From the analysis, it is learnt that when the area of one classification increases, it decreases the area of other classes and vice versa. An increase in cropland and builtup areas in the future implies that these categories have to be given importance in designing policy formulations for the basin.

Table 4 Changes over Probability matrix LULC between the years 2005 and 2010

| Classes     | 2005    | 2010    | 2015    | 2020    |
|-------------|---------|---------|---------|---------|
| Builtup land| 0.9791  | 0.0101  | 0.0063  | 0.0014  |
| Crop land   | 0.0016  | 0.8772  | 0.1034  | 0.0014  |
| Fallow land | 0.0013  | 0.4396  | 0.5379  | 0.0012  |
| Plantations | 0.0005  | 0.0016  | 0.0004  | 0.9972  |
| Forests     | 0.0000  | 0.0008  | 0.0001  | 0.9987  |
| Grassland   | 0       | 0       | 0       | 0       |
| Wasteland   | 0.0882  | 0.0768  | 0.0135  | 0       |
| Water bodies| 0.0006  | 0.0095  | 0.0022  | 0       |

Table 5 LULC analysis from 2005 to 2020

| Classes     | 2005     | 2010     | 2015     | 2020     |
|-------------|----------|----------|----------|----------|
| Builtup land| 77.56    | 114.85   | 141.48   | 159.68   |
| Crop land   | 924.67   | 1074.73  | 1125.21  | 1136.24  |
| Fallow land | 515.19   | 379.78   | 340.48   | 332.57   |
| Plantations | 861.04   | 861.29   | 861.28   | 861.28   |
| Forests     | 2654.74  | 2654.71  | 2644.89  | 2637.5    |
| Grassland   | 1.61     | 1.61     | 1.58     | 1.58     |
| Wasteland   | 407.7    | 355.75   | 328.48   | 314.73   |
| Water bodies| 112.64   | 112.69   | 112.01   | 111.83   |

Table 6 LULC analysis for every five years from 2005 to 2020

| Classes     | 2005–2010 | 2010–2015 | 2015–2020 |
|-------------|-----------|-----------|-----------|
| Builtup land| 37.29     | 26.63     | 18.2      |
| Crop land   | 149.86    | 50.48     | 11.03     |
| Fallow land | −135.45   | −39.3     | −7.91     |
| Plantations | 0.25      | −0.01     | 0         |
| Forests     | −0.03     | −9.82     | −7.39     |
| Grassland   | 0         | −0.03     | 0         |
| Wasteland   | −51.97    | −27.27    | −13.75    |
| Water bodies| 0.05      | −0.68     | −0.18     |
The prediction of LULC plays a vital role in creating plans for balancing conservation, competing users, and developmental pressures. The MLP-ANN is utilized to simulate and predict the LULC maps of the Bhavani basin, Tamil Nadu. The three spatial variable factors, viz., DEM, distance from the road and distance from builtup, had a considerable effect on predicting this basin’s LULC map. The Kappa value of 0.69 shows a maximum level of accuracy between the observed and predicted LULC maps.
predicted 2015 LULC maps. The LULC map of 2025 and 2030 were predicted using the 2005 and 2010 LULC map with the same spatial variable factor combinations. The predicted LULC for the years relative to 2015 showed a significant increase in cropland and builtup areas by 24 km² and 14 km² in 2025 and 28 km² and 15 km² in 2030 respectively. Meanwhile, fallow land, forest land, and wasteland areas are expected to decrease by 10 km², 11 km², and 16 km² in 2025 and 10 km², 15 km², and 17 km² in 2030. The results demonstrate that the conversion of forest land and other land categories would be converted to builtup land and cropland areas due to anthropogenic pressures.

The forest region in the Nilgiri hills of the Western Ghats is a crucial forest cover in Tamil Nadu, which needs significant preservation and conservation. Forests disturbance, particularly land conversion, had resulted in forest degradation. Rather than being retained as forest, human interests in the region drive the land to be transformed to different uses, such as farmland or industrial types which had resulted in LULC modifications. Farmers in general prefer to grow crops and plantations rather going for reforestation to increase their earnings. This situation necessitates to understand changes in LULC and its long-term consequences, notably loss in forest biodiversity. This kind of study assists us in detecting specific land-use changes and projecting which land use will be affected in future to know the possible biodiversity loss and ecological concerns. The findings assist farmers and policymakers in developing optimal land use planning and management methods for the long-term development of natural resources.

**Author contribution** MK wrote the manuscript in consultation with SR. MK carried out all technical details, prepared the map, and performed GIS analysis. SR contributed to the verification of the analysis and the results. Both authors contributed to shaping the work by discussing the results and contributed to the final manuscript.

**Availability of data and materials** The Land use and Land cover (LULC) maps used for the current study are obtained from the National Remote sensing Centre (NRC), Hyderabad, (https://bhuvan.nrsc.gov.in/bhuvan_links.php), and the road maps are obtained from the open street map (https://www.openstreetmap.org). The CARTO DEM for this study is obtained from Bhuvan Indian Geo-platform of ISRO (https://bhuvan-app3.nrsc.gov.in/data/download/index.php).
Declarations

Ethical approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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