Future Prediction of Scenario Based Land Use Land Cover (LU&LC) using DynaCLUE Model for a River Basin

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Abstract

Human activities that cause changes to the surface of the Earth lead to alterations in Land Use and Land Cover (LU&LC) which have an impact on biodiversity, ecosystem functioning, and the well-being of humans. In order to comprehend and manage the effects of human activities on the environment, prediction of scenario-based LU&LC in future periods are crucial. Scenario-based predictions of LU&LC provide valuable insights for decision-makers in the sustainable governance of land and water resources. In the present study, the Dynamic Conversion of Land Use and its Effects (DynaCLUE) modelling platform was used to predict future LU&LC for Munneru river basin, India. Using six different user defined scenarios LU&LC change patterns were analysed in 2030, 2050 and 2080 so as to understand the pressure on the natural resources and to plan sustainable Land Use Planning by preserving the important land use classes. The connection between LU&LC classes and input driving factors was quantified using Binary Logistic Regression (BLR) analysis. The β-coefficient was estimated using LU&LC type as a dependent variable and driving factors as independent variables. The demands of each LU&LC type, spatial policies and constraints, characteristics of each location and land use conversions are used as inputs for prediction of future LU&LC maps. Major conversions in LU&LC observed in this basin from last two decades are the rapid increase in built-up area due to urbanization in the outskirts of cities and towns. The major LU&LC changes projected for the period of 2019–2080 are expansion of built-up area ranging from 42.5% to 88.5%, and a reduction in barren land ranging from 57.3% to 74.5% across all six scenarios in the entire basin. The projected LU&LC maps under different scenarios provide valuable insights that could aid local communities, government agencies, and stakeholders in systematically allocating resources at the local level and in preparing the policies for long-term benefits.

Keywords: Land use change; Binary Logistic Regression; Driving Factors; DynaCLUE model; Prediction and Scenario; River basin management.

1.0 Introduction

Changes in LU&LC can have negative effects on the functioning of ecological systems and also effect the natural processes of the environment (Le at al., 2008, Alonso et al., 2022). Understanding the potential evolution of land use is necessary since human actions greatly influence the distribution of land-cover. Anthropogenic impacts have drastically influenced the way that land is used, and as time goes on, its impact on the environment will have a significant effect on the utilization of land in the future (Sahoo et al., 2018). The LU&LC statistics in the past decades have shown the major land cover conversions such as agricultural land is converted to barren land, built-up and waterbodies, forest to barren land, waterbodies and cropland and other such changes (Hoekema and Sridhar, 2011; Meng et al., 2021, Behera et al., 2018). Due to the intricate and uncertain nature of land use dynamics, modelling the dynamics of change in LU&LC is a crucial aspect of studies related to LU&LC planning, impact on environmental assessment, and evaluation of policies for a specific region (Sujatha and Sridhar, 2021). Development of LU&LC scenarios has become more popular as it provides the possible conversions under anthropogenic and ecological processes in future circumstances (Schirpke et al., 2012, Sleeter et al., 2012, Ghadirian et al., 2023).

Studies have been carried out in numerous locations about the factors causing spatiotemporal changes in LU&LC in a particular area (Luwa et al., 2020; Duraisamy et al., 2018; Dibaba et al., 2020; Buaraka et al., 2022). Numerous studies have focused on particular LU&LC change processes where a single conversion, such as urbanization or deforestation, is dominant (Verburg and Overmars, 2009). To identify the causative factors of these changes and determine the regions where they are most prevalent, several LU&LC models are created and used (Wang et al., 2020; Jazouli et al., 2019; Venkatesh et al., 2020; Varanou, 2003; Waiyasusri et al., 2022).To help planners make more enlightened decisions and maintain a balance between urbanization and conservation of the environment, models that combine and assess many elements of LU&LC change can be utilized.

In recent years, several studies have utilized different models to predict Land Use and Land Cover (LU&LC) scenarios, such as Cellular Automata (CA)-Markov models and historical LU&LC change trend patterns (Behera et al., 2012; Tadese et al., 2021; Karimi et al., 2018; Tong et al., 2012; Loukika et al., 2022). Yao et al. (2023) studied spatiotemporal fluctuations in LU&LC and their effects on water quality in a river flowing through a rapidly developing area in China and LU&LC maps were predicted using CA-Markov model. Okwuashi et al. (2021) carried out the integration of Support Vector Machine (SVM), cellular

automata and Markov chain for urban land use change modelling over Lagos, Nigeria. They concluded that the inability of cellular automata to include driving forces of urban growth is achieved with the integration of SVM to determine the impact of the explanatory variables that drive change in the urban areas. They used the Markov chain to determine the urban transition probabilities between the various time periods. The Dynamics of Land System (DLS) model was also utilized in Najmuddin et al. (2007) to simulate LU&LC changes for the years 2020 and 2030 in the Kabul River Basin (KRB), Afghanistan. The study found significant changes in land use, indicating the importance of understanding the underlying processes driving LU&LC change. Rong et al. (2022) created a land use carbon emission grid, and predicted future land use patterns in China under several scenarios from 2000 to 2018. Mitra et al. (2023) evaluated the influence of several LU&LC and climate scenarios on runoff in Kansabati river basin and LU&LC maps were predicted using IDRISI Land Change Modeller (LCM).

For simulating scenario-based LU&LC maps and understanding the spatial pattern in each location, studying the driving factors is crucial. The DynaCLUE modelling framework, which combines dynamic modelling with empirically measured relationships between land use and its driving elements, has been used in various research studies to simulate LU&LC change (Verburg et al., 1999).Adhikari et al. (2020) used the DynaCLUE model to predict LU&LC evolution in Vietnam by 2100 for a groundwater recharge study. Tizora et al. (2018) used the DynaCLUE model to simulate LU&LC changes in the Western Cape Province, South Africa, and suggested that the model can assist in future land use planning by considering policies that shape land use. Sahoo et al. (2018) simulated Land Use Suitability Zone (LSZ) mapping for future scenarios for agricultural sustainability using DynaCLUE for Dwarakeswar-Gandheswari river basin, India. Similarly, Das et al. (2019) used the DynaCLUE model for evaluating the growth and conversion to urban areas from rural areas in 2025 for the river basin of Mahanadi in India. The Dyna-CLUE model was used to study changes in the LU&LC pattern between 1975 and 2010 in order to gain a better understanding of the conversion process and predicted the future trend in LU&LC for the year 2045 (Behera et al., 2020). Roy et al. (2021) assessed future flood susceptibility in Ajoy river basin, India, with simulated LU&LC scenarios using pixel-wise association properties with the DynaCLUE model.

Loukika et al. (2022) reported that the CA Markov model did not detect any significant changes in future predicted LU&LC maps for the Munneru river basin in India. However, there have been no prior studies analyzing future LU&LC patterns in the basin under different user defined scenarios. The availability of remotely sensed data is very meagre before the year 2000.

So, we may not able to get the LU&LC maps with high resolution for that years. We are more interested to predict the LU&LC maps based on the user defined scenarios for the next 20 years to prepare the sustainable land use plans. We are also concerned about combined impact of climate and LU&LC change in long term basis for the next 60 years in the basin as most of the climate models provide projected data for 100 years. So we analysed LU&LC maps in 2030, 2050 and 2080. Even though it will not exactly resemble the LULC changes in future years as per the climate change scenarios. Hence, we took user defined scenarios to get idea of how LULC change is occurring in the future periods. Therefore, this study presents predictions of future LU&LC maps for 2030, 2050, and 2080 years using the DynaCLUE model under various user-defined scenarios using 20 years of the past LU&LC maps. The LU&LC prediction was performed for six scenarios out of which two scenarios were predicted based on the past trend and remaining four scenarios were based on the restricted/unrestricted conditions of forest deforestation. These predictions can be beneficial for developing basin level watershed management policies in the long-term. The present analysis will assist researchers and policymakers in obtaining better land management practises, which will ultimately aid in the achievement of the Sustainable Development Goals (SDG's) (https://sdgs.un.org/goals).

2.0 Study Area

The Munneru River originates from the left tributary of the River Krishna and is located in the Lower side of the Krishna River basin, India which is also an independent sub-basin. The study area, as shown in Figure 1, is mostly an agriculture-dominated basin, covering a total area of 10,392 Km^2 across the Andhra Pradesh and Telangana states. The Munneru River basin lies between 16.6° N - 18.1° N (Latitudes) and 79.2° E - 80.8° E (Longitudes) (Loukika et al., 2021). The elevation of the basin ranges between 21m to 792m. The average annual rainfall for 119 years (1901-2022) is 1014 mm for the basin. Pakhal Lake, Wyra reservoir, Bhayyaram Cheruvu, and Lanka Sagar reservoir are the four major waterbodies in this basin. Red and black soils are the two most common types of soil in this basin. Khammam, along with adjacent areas like Dornakal and Mahabubabad, receives excessive rainfall, which frequently produces flooding on Munneru. According to 2011 census, the population present in the basin is 32,11,441. The major crops grown in the basin are paddy, cotton, maize and chillies. The study area comprises of five primary types of LU&LC, namely, agricultural lands (72%), built-up (4%) areas, waterbodies (5%), forest areas (13%) and barren lands (6%). The major changes observed in the LU&LC maps during the time period from 2005 to 2019 in the urban areas of Khammam and Nandigama were the conversion of barren lands to built-up land. However, no

significant changes were observed in the remaining LU&LC types, such as agricultural land, forest area, and waterbodies. Rapid urbanization is taking place in some of the cities such as Khammam and Mahabubabad in the newly formed Telangana state. Whereas in Andhra Pradesh state, the new capital city named Amaravati which is near to the basin has the effect of increased urbanization in Nandigama which can cause tremendous impact on the water resources of the basin. As per the observed data, the basin contains sufficient water resources. The climate and LU&LC change in future periods may cause pressure on water distribution to different sectors. There is a need to study the scenarios of LU&LC change and to prepare the policies so that issues related water and environment can overcome.

3.0 Data and Methods

The methodology for predicting future scenario based LU&LC maps was outlined in Figure 2. The LU&LC maps obtained from Landsat 5 and 8 images were classified, and driving factors were selected based on existing literature. Binary Logistic Regression (BLR) analysis was performed to determine the efficient drivers, considering the driving factors and the classified LU&LC maps. The input parameters required for the Dyna CLUE model were prepared based on the BLR analysis, which falls under the non-spatial module. The model was compiled using all the input parameters, calibrated, and validated with the classified map of LU&LC. The future LU&LC maps were predicted under various scenarios, after the validation of the model. The steps of the methodology are thoroughly explained in the following sections.

3.1 Preparation of LU&LC maps and Driving factors

The LU&LC maps for 2005, 2010, 2015, and 2019 were created using Google Earth Engine, as described by Loukika et al. (2021). The driving factors used to project LU&LC maps under various scenarios included distance to road network, waterbodies, and buildings, as well as elevation, lineament density, population density, slope, and precipitation. These driving factors are illustrated in Figures 3 and 4 for the current study.

The layers of driving factors were generated using the GIS platform by combining data from various sources. The building and road network layers were obtained from an open-source website, DIVAGIS (https://www.diva-gis.org/Data). The waterbody layer was extracted from the 2015 LU&LC map in ArcGIS 10.5 Version. The distance to each stream and road network was calculated using Euclidean distance tool, determining the Euclidean distance between the centres of the source cells and each neighbouring cell. The Bhukosh website was used to extract

the lineament features (https://bhukosh.gsi.gov.in), and a spatial map was generated using the kriging interpolation algorithm. A Digital Elevation Model (DEM) layer was created using satellite data (CARTOSAT) which is downloaded from Bhuvan-NRSC website (https://bhuvan-app3.nrsc.gov.in/data/download/index.php) with a resolution of 30 meters, which was used to generate a slope map. Daily precipitation with a resolution of 0.25° × 0.25° was obtained from IMD gridded dataset (https://www.imdpune.gov.in/Clim_Pred_LRF_New/Grided_Data_Download.html) to avail the average annual precipitation. The Kriging interpolation technique was used to prepare the precipitation raster layer using gridded precipitation data. The map related to population density was created using global population data taken from the world population website (https://www.worldpop.org). To maintain uniform projection and cell size with respect to land use classes, the resultant spatial maps were re-projected and rescaled.

3.2 DynaCLUE

The CLUE modelling framework was constituted by the Institute for Environmental Studies (IVM - http://www.ivm.vu.nl) (Das et al., 2019). CLUE uses dynamic modelling and empirically defined relationships between LU&LC and driving forces to simulate changes in land use. DynaCLUE is an improved version of the CLUE model (Verburg and Overmars, 2009; Castella and Verburg, 2007) that allocates spatial demand for various land use categories to individual grid cells. DynaCLUE model version 2.0 has two components: spatial and non-spatial. The spatial component contains geospatial layers, including the LU&LC map and drivers, to examine the impacts of spatial factors on land use change. The data and model parameters were defined in the main parameter file, which is part of the non-spatial module. In the non-spatial component, the land use class requirements for the simulation year are stored, while the allocation file captures the correlation between drivers and LU&LC and is used to compute the suitability of each land cover in a specific location. The preference of location for a particular land use type was determined using the logit model (Verburg, 2010) as illustrated below.

$$\mathrm{Log}\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_{1,i} + \cdots \ldots \ldots \ldots + \beta_n X_{n,i} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

The probability of a specific land use type appearing in a grid cell located at *i* is represented by P_i . The driving factor that affects the land use type is represented by *X*. The β coefficients were determined through logistic regression, with the actual land use class serving as the dependent variable.

3.3 Binary Logistic Regression (BLR) Analysis

The relationship between LU&LC classes and their determining factors and the suitability of each land cover class for every factor, was analyzed using BLR. When conducting statistical analysis on a binary outcome variable, which takes on only two possible values (usually 0 and 1), binary logistic regression is a commonly used method. This method is applicable regardless of whether the independent variables used in the analysis are continuous or categorical.

The compatibility between different types of LU&LC at the cell level is established according to the suitability of a particular location. This suitability is determined by a weighted average method, which is calculated through empirical analysis that reflects current and historical preferences for location based on specific characteristics of the location (Verburg et al., 2008). The location preferences of different LU&LC classes can be understood by performing BLR model. The model established connections between each of the land use class and potential driving factors that drive their location preferences. The influence of each driver on a particular LU&LC can be effectively interpreted using the odds ratio $\left(\frac{P_i}{1-P_i}\right)$ generally referred as Exp(β). The probability of a grid cell being assigned to a particular LU&LC class in a specific location is denoted as P_i . The odds ratio is a measure of how a change in the independent variable by one unit, while holding all other factors constant, impacts the occurring of dependent variable's probability. If the exponential of β is greater than 1, then an increase in the independent variable will lead to an increase in the probability. Conversely, if Exp(β) is less than 1, the probability will decrease (Overmars and Verburg, 2005).

3.4 Input parameters for the DynaCLUE

The parameters used in the non-spatial module and the spatial module creates a set of scenarios and possible outcomes which are utilised by the model for prediction of LU&LC.

3.4.1 Conversion matrix

The conversion of one land cover to another is determined by the conversion matrix, which defines whether such conversions are restricted or allowed. The conversion matrix assigns binary values of 1 and 0 to represent allowed and restricted conversion types, respectively. In the matrix, a value of 1 would indicate that a particular conversion is permitted. Conversely, if the reverse conversion is not permitted, the value assigned to it would be 0.

3.4.2 Conversion elasticity

Conversion elasticity is a parameter included in the main file that indicates how flexible the conversion process of land cover is. The accuracy of simulation between estimated and demand area is defined in convergence criteria. The main file includes information such as the beginning and finishing years of the simulation, number of iterations, number of LU&LC types and the size of the cells. The range of conversion elasticity values is 0 to 1. Therefore, lower conversion likelihoods will occur with larger values and values close to 0 indicate higher conversion possibilities. Built-up areas are assigned a conversion elasticity value of 1 (for no conversion), while forest, agricultural land, and waterbodies have values of 0.8, 0.7, and 0.7, respectively. Barren land has a conversion elasticity value of 0.4.

3.4.3 Convergence Criteria

Convergence criteria is a measure used to determine whether the actual and model-simulated LU&LC areas match. To define convergence criteria, three variables must be specified: iteration mode, first convergence criteria, and second convergence criteria. The iteration mode options are 0 or 1, with 0 indicating criteria in percentage of demand and 1 for absolute values. The average deviation between actually allocated changes and demand changes is the first convergence criterion, and the second convergence criteria is the largest deviation among actually allocated changes and demand changes.

For the present study, the lower limit of the convergence criteria was set at an average and maximum allowable difference of 5 and 18, respectively. To improve the model's prediction accuracy, the conversion elasticity and convergence criteria were repeatedly evaluated. The change matrix was developed by taking into account the long-term changes in LU&LC over the course of a decade, as well as the level of understanding of the interpreter. The simulation model was highly complex and could only function properly with convergence values above a certain threshold. However, setting the maximum convergence value too high could result in inaccurate predictions for certain classes.

3.4.4 Demand Estimation

Land-use demands pertain to the anticipated pattern of land use classes within a specific research area over time. The estimation of land-use demand involves creating a continuous dataset of aggregate land use classes. There are several methods for estimating demand, including linear extrapolation of system dynamics, socioeconomic models, and historical

trends. In this study, linear interpolation is used as the method for estimating demand. This involves calculating the aggregated land use changes by extrapolating from the land use details at two time extremes and determining the demand for the years in between. The demand was generated by using linear interpolation and extrapolation techniques for intermediate and future years with the classified LU&LC's of 2005, 2010, 2015 and 2019.

3.5 LU&LC Scenarios

Based on the land use and land cover (LU&LC) maps from previous years, six different user-defined scenarios were considered for projecting future LU&LC maps, as shown in Table 1. The BLR analysis results and the input parameters were fed into the model for the prediction of the LU&LC maps. For Scenario 1, the transitions in LU&LC observed during the period 2005-2015 were used to predict maps of LU&LC for 2030, 2050, and 2080. The trend observed during the period 2010-2019 was utilised to predict LU&LC maps for the years 2030, 2050, and 2080 in scenario 2. The model projections were carried out under two different demand conditions: the first set included scenarios with less changes (Scenario 3) and moderate changes with restricted deforestation (Scenario 4), while the second set included scenarios with less changes (Scenario 5) and moderate changes without forest preservation (unrestricted deforestation) (Scenario 6).

The scenarios were formulated by considering historical patterns observed in the basin and utilized to forecast future demands under conditions of restricted and unrestricted deforestation. The 2005 LU&LC map was used as base map and 2019 map was simulated and validated with 2019 classified map. Subsequently, the 2019 map was used as the initial map for future simulations. The third and fourth scenarios were considered based on the observed trend, which suggests that agricultural and built-up areas will continue to expand over time without disturbing the ecological balance by restricting the changes in forest area. The extent of this increase was determined by averaging historical changes, resulting in a minimum annual increase of 2 Km^2 and a maximum annual increase of 6 Km^2 in the built-up area. The fifth and sixth scenarios were formulated assuming unrestricted deforestation, resulting in a reduction of forested areas and corresponding increases in agriculture, built-up areas, and barren land. In addition to the aforementioned expansion of built-up areas, the agricultural area is expected to experience a minimum annual increase of 10 Km^2 and a maximum annual increase of 20 Km^2. The driving factors were taken into account to determine the probability of transitioning to a specific land use and land cover (LU&LC) class. Based on these driving factors, future

demands specified in DynaCLUE were assigned to regions where there is a likelihood of transitioning to a different LU&LC class.

4.0 Results and Discussions

4.1 BLR Analysis

The logistic regression-derived β-coefficients are presented in Table 2, showing the odds ratio of driving factors influencing land use. Lineament and precipitation have a positive impact on water body conversion. A high lineament density indicates a lack of hard rock, which reduces the likelihood of water body conversion into other irreplaceable land uses. Conversely, a high lineament density provides a free-flowing passage, thereby increasing the chances of water body transition. Increased precipitation increases water body storage capacity, reducing the likelihood of conversion to other land use classes. The slope and population density are negatively correlated with water body land use. This indicates that water body occurrence decreases with increasing vertical altitude and steepness, and increasing population density increases dependency on water bodies, leading to a reduction in water percentage and a negative correlation with population density. The slope, precipitation, and distance to water bodies have a positive relationship with forest land. Forest occurrence increases with steepness, and precipitation contributes to forest growth.

In the Munneru river basin, agricultural land usage is predominantly found on flat terrain close to streams, as demonstrated by the inverse correlation between distance to water bodies, slope, and distance to roads. In contrast, precipitation and lineament density show a positive relation with agricultural lands, as an increase in these factors contributes to water storage and passage in the surface and subsurface, leading to an increment of farmlands. Urban area expansion, on the other hand, is primarily attributed to the rise in population density in various regions of the study area, as indicated by the strongest positive factor contributing to the increase in urban area being population density, followed by distance to road driver. Distance to water body projects a positive relation with barren land, as the distance between cultivated lands or agricultural land to water body increases, the chances of irrigation reduce, thereby leaving the land barren.

To study the spatial variation occurring in LU&LC types of the Munneru river basin, the results of the binary logistic regression model were analyzed. These results are then used as input for the Dyna CLUE model to simulate the changes that may occur in future years. Since not all the drivers may be influential, the drivers showing a significant value of less than 0.01 are considered in the present study.

The Relative Operating Characteristic (ROC) is a statistical tool used to evaluate the goodness of fit for logistic regression. Figure 5 shows the ROC curves for the five LU&LC classes. The ROC value ranges from 0 to 1, with values closer to 1 indicating an excellent fit and 0.5 representing a random fit. Based on Figure 5, it can be observed that water bodies have a perfect fit, accompanied by forest area, built-up, agricultural land, and barren land.

4.2 LU&LC Dynamics

We divided the the study area into five major LU&LC classes including Built-up, waterbodies Agriculture, Forest and Barren land. The LU&LC maps of the years 2005, 2010, 2015 and 2019 were presented in Figure 6. The classification accuracy was determined to be 91.2%, 92.6%, 94.3% and 95%, respectively, with the kappa coefficients of 0.85, 0.91, 0.92 and 0.93. The LU&LC statistics of the classified maps were summarized in Table 3.

Within the study area, the agricultural land was found to be dominant accounting for 68.49% in 2005, 68.92% in 2010, 71.01% in 2015 and 71.96% in 2019. Forest was the second most common land cover with 13.63% in 2005, 13.63% in 2010, 13.57% in 2015 and 13.57% in 2019. Barren land decreased by 0.97% in 2010, 1.88% in 2015 and 0.99% in 2019 compared to the 2005 LU&LC map. There was little change observed in waterbodies, which covered 5.35% of the area in 2005, 5.36% in 2010, 5.16% in 2015 and 5.16% in 2019. Barren land was found to be converting to built-up area, with an increase of 0.54% in 2010, 0.04% in 2015 and 0.04% in 2019 compared to the 2005 LU&LC map. Overall, the study area's LU&LC statistics revealed a relative stability in the LU&LC patterns over the studied period.

4.3 Predicted LU&LC maps under different scenarios

The LU&LC maps for the Munneru river basin were projected under six different scenarios and plotted. Figure 7 displays the LU&LC maps for Scenario 1 and Scenario 2 for the projected years. A detailed explanation of each scenario was provided. Table 4 shows the percentages of LU&LC types for the respective years under various scenarios in the study area.

4.3.1. Scenario 1

The prediction of LU&LC for Scenario 1 follows the same trend as the previous period from 2005 to 2015. The predicted LU&LC map, when compared to 2019, shows that the built-up area will rise by 13.5% in 2030, 39.5% in 2050, and 59.5% in 2080. The reduction in barren land is expected to be 30.3% in 2030, 51.3% in 2050, and 66.2% in 2080. Agricultural land is projected to increase by 2.5% in 2030, 2.7% in 2050, and 3.3% in 2080. The forest area is not

expected to undergo significant change in future periods. However, the waterbodies are predicted to decrease by 3.7% in 2030, 6.6% in 2050, and 9.7% in 2080. The major changes in predicted LU&LC are an increase in built-up and agricultural land, followed by a reduction in barren land, forest, and waterbodies. From the results obtained from scenario1, there may be additional requirement of water in the basin due to extension of built-up and agricultural areas. The current policy should be revised for meeting the water demand due to increase in built upland and agriculture land.

4.3.2. Scenario 2

In scenario 2, LU&LC map was predicted using the past trend of LU&LC during the period 2010-2019. The predicted LU&LC map under scenario 2 shows an expansion in built-up area and agricultural land, and a decrease in barren land, forest, and waterbodies. The predicted LU&LC map when compared to 2019 indicated rise in built-up area of 10.4% in 2030, 19.6% in 2050, and 42.8% in 2080. It was observed that there was a reduction in barren land of 34.7% by 2030, 54.1% by 2050, and 68% by 2080. Agricultural land was increased by 4.3% in 2030, 3.6% in 2050, and 4.3% in 2080. Similar study states that to simulate extreme agricultural area, system dynamics-based scenarios might be coupled with the CA model (Ghadirian et al., 2023). The forest area did not show any significant change in the future periods. The waterbodies area was decreased by 7.7% in 2030, 4.3% in 2050, and 8% in 2080. Scenario 2 showed the same trend patterns as scenario 1, but the percentage changes varied. As per the recommendations followed in scenario 1, more or less the same type of practical implications will be applied in the basin for scenario 2.

4.3.3. Scenario 3

The LU&LC maps for Scenario 3 and Scenario 4 for projected years depicted in the Figure 8. Scenario 3 involved restricted deforestation and a limit of 2 km^2 per year for changes in built-up area. The predicted LU&LC map, when compared to the 2019 map, showed an increase in built-up area of 5.9% by 2030, 29.8% by 2050, and 49.1% by 2080. It was also observed that the barren land decreased by 16.5% by 2030, 45.6% by 2050, and 57.3% by 2080. Agricultural land increased by 0.7% in 2030, 2.4% in 2050, and 2.6% in 2080. The forest area did not show any significant change during the study period. Waterbodies decreased by 2.9% in 2050 and 5.9% in 2080. This scenario is proposed based on forest conservation policies and shifting of people to nearby cities (increase in urbanization). The major changes predicted

in LU&LC were increased built-up followed by a reduction in barren land. In 2080, the conversion of barren into urban-area is higher when compared to 2030 and 2050.

4.3.4. Scenario 4

Scenario 4 involved restricted deforestation and a change in built-up area of 6 km^2 per year. The predicted LU&LC map indicated a growth in built-up area by 17.6% in 2030, 55.9% in 2050, and 88.6% in 2080 when compared to 2019. It was observed that the reduction in barren land was 30.1% by 2030, 51.8% by 2050, and 65.9% by 2080. Agricultural land was increased by 1.7% in 2030, 1.9% in 2050, and 1.1% in 2080. The forest area did not show any significant change in the future periods. Waterbodies decreased by 2.9% in 2030, 6.9% in 2050, and 4.3% in 2080. Higher rate of urbanization is the main assumption for formulating this scenario while the conversion of forest area to other LULC is restricted. Hence we need to optimize the resources like water and land according to the rate of growth in urbanization.

4.3.5. Scenario 5

The LU&LC maps for Scenario 5 and Scenario 6 for projected years depicted in the Figure 9. In Scenario 5 involved unrestricted deforestation whereas, the built-up area was allowed to increase by 2 Km^2 and agricultural land by 10 Km^2 annually. The predicted LU&LC map showed an increased growth in built-up area by 4.7% in 2030, 29.8% in 2050, and 49.5% in 2080 compared to 2019. The scenario also resulted in a reduction in barren land by 20.8% in 2030, 39.1% in 2050, and 59.7% in 2080, while agricultural land increased by 2.2% in 2030, 2.6% in 2050, and 4.7% in 2080. Forest area decreased by 3.5% in 2030, 3.1% in 2050, and 11.3% in 2080, and waterbodies area decreased by 1.4% in 2030, 6.6% in 2050, and 5.0% in 2080. The primary change observed in the predicted LU&LC was the increased built-up area, followed by a reduction in barren land, forest, and waterbodies. In this scenario, deforestation is permitted, resulting in an increase in built-up and agricultural areas. Therefore, it is essential to educate people on forest conservation policies to ensure that there is a balance in the ecosystem. Governments may pass laws that support reforestation, forest conservation and programmes for restoring the forest. Such measures can lessen deforestation, protect biodiversity, and lessen the effects of climate change.

4.3.6. Scenario 6

The predicted LU&LC map in scenario 6, which involved unrestricted deforestation and moderate changes, led to a phenomenal built-up area growth when compared to 2019.

Specifically, there was an increase of 17.7% in 2030, 50.6% in 2050, and 88.5% in 2080. The reduction in barren land was also notable, with a decrease of 30.8% by 2030, 67.7% by 2050, and 74.5% by 2080. Agricultural land increased by 3.1% in 2030, 3.9% in 2050, and 5.8% in 2080. However, forest area decreased by 7.5% in 2030, 5.1% in 2050, and 20.8% in 2080, while waterbodies decreased by 2.3% in 2030, 7.2% in 2050, and 7.1% in 2080. In the fifth scenario, deforestation of the forest is permitted with the aim of maximizing the expansion of built-up and agricultural areas. To ensure the effective preservation and protection of forest resources, it is necessary to implement awareness programs targeting the local populations. Governments can employ land use planning where it is most suited, such as those with already-existing infrastructure, easy access to transportation, and services. By doing so, urban sprawl and the conversion of forest land to built-up area can be lessened.

Comparing scenario 1 and scenario 2, there were no significant changes observed in the predicted LU&LC maps for 2030, 2050, and 2080. In scenario 4, which involved demand conditions and unrestricted deforestation, there was more expansion of agricultural and built-up area than in scenario 3. Specifically, the expansion of built-up area was 6 Km^2 per year. In scenario 5 and scenario 6, where there was an expansion in agricultural and built-up area of 20 Km^2 and 6 Km^2 per year, respectively, similar trends were observed. As there was unrestricted deforestation and high changes in built-up area, scenario 6 exhibited a high percentage of surge in built-up area, a reduction of barren and forest land. In 2080, the decrease of forest land was 9.5% more in scenario 6 than in scenario 5. Similarly, the percentage decrease of barren land was 14.8% more in scenario 6 compared to scenario 5. Overall, the change of barren land to built-up area exponentially increased from 2019 to 2080 under all six scenarios. This trend is in agreement with similar studies (Venkatesh et al., 2020; Das et al., 2019). However, unlike other studies where agricultural land and forest areas were frequently affected by a declining trend (Rimal et al., 2018; Li et al., 2020), agricultural land in the present study had a progressive growth, which was similar to other studies (Waiyasusri et al., 2022).

The determination of conversion elasticity in the CLUE model relies on the user's understanding of the situation, and the chosen value for conversion elasticity significantly impacts the resulting patterns of land use (Verburg et al., 2002). This is because conversion elasticity directly affects the paths of change and the historical patterns of land use. The inherent uncertainty in simulating land use change due to the subjective nature of conversion elasticity calls for the development of a more quantitative approach. It is essential to propose a new solution that utilizes existing historical land use data to better define and quantify

conversion elasticity (Luo et al., 2010). Furthermore, enhancing the calibration process of the CLUE model by improving the settings of model parameters becomes crucial in order to address this challenge effectively. However, it is suggested to apply the current methodology in other geographical regions to improve its efficiency. The results of this study using the DynaCLUE model are ideal for tracking alterations in LU&LC in a region. The model takes into account the key drivers evaluated within a specific scenario that align with the defined objectives. Consequently, the outcomes of each scenario offer optimal solutions for making informed decisions regarding systematic land-use planning in the study region.

5.0 Conclusions

The present study analyzed the future predicted LU&LC maps using the DynaCLUE model for the years 2030, 2050 and 2080 in the Munneru Basin, India, considering six different scenarios. To achieve this, the DynaCLUE model was first validated using the 2019 classified LU&LC map, and then used to predict future periods under different scenarios with user-defined demand conditions. The relationship between LU&LC and driving factors was established using binary logistic regression analysis. The results revealed that both barren land and forest area were transitioned into agricultural land and built-up area, with the maximum change observed from 2019 to 2030 in the form of decreasing barren land and minimal changes in the forest area. This trend was also observed for 2030 to 2050 and 2050 to 2080. Scenarios 5 and 6, which involved unrestricted deforestation, exhibited greater changes in the forest area, leading to an increase in agricultural land. From 2019 to 2080, the maximum growth of built-up area and agricultural land was noticed in scenario 6, and the maximum reduction of barren land and forest land was also observed in this scenario. It was also noted that there was a drastic decrease in barren land in 2080, with half of the area getting converted to agriculture or built-up area. This is not unexpected as food security and dwelling concerns are looming to an extent in several parts of the world (Kang and Sridhar, 2021). To deal with future shortages of water, it is critical to optimize water utilization by building reservoirs and improving water usage efficiency productivity. Finally, population control and balanced socioeconomic development will aid in sustainable land use management. The model's results predict potential future variations in land use change. Rapid degradation of forest and water regions suggests that the government need to develop comprehensive land use planning to promote rational utilization of land resources. The proposed policies for sustainable land management obtained from scenario based LULC changes can be better implemented by involving the all the local stakeholders. The findings of this research have the potential to assist in the creation of policies

that promote sustainable land use management. Additionally, this study will analyze the effects of changes in LU&LC under various scenarios within the river basin, with the goal of developing a comprehensive model for integrated water resources management.

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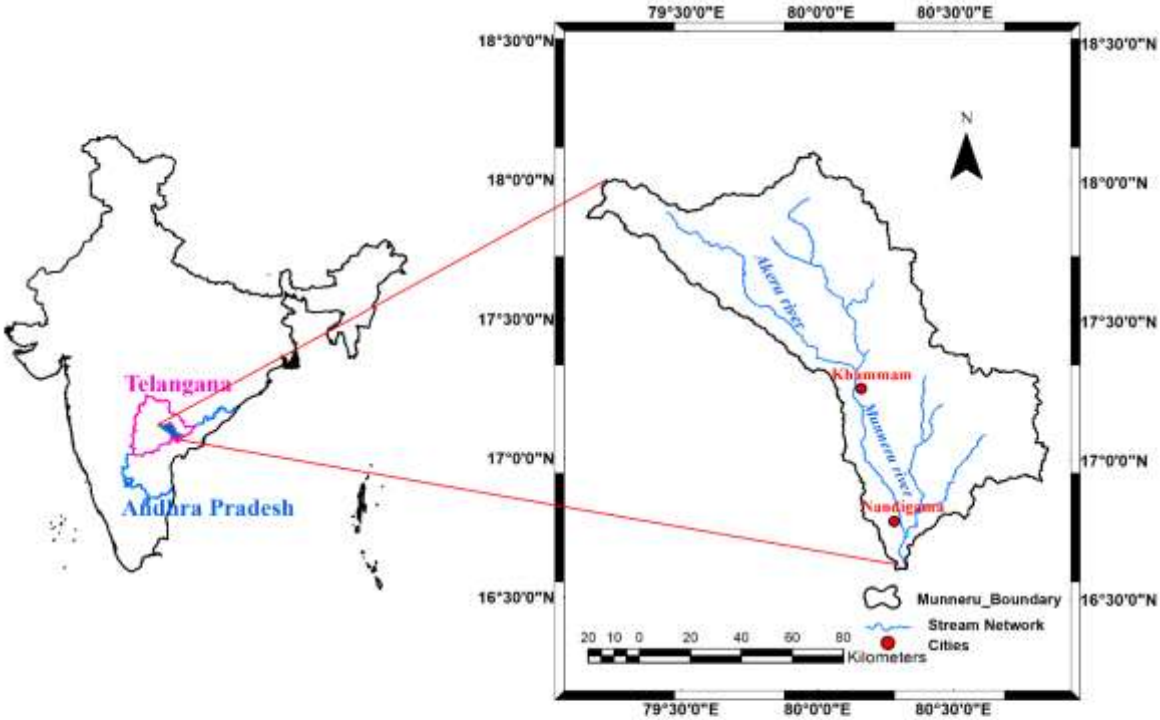

Figure 1. Munneru basin location map

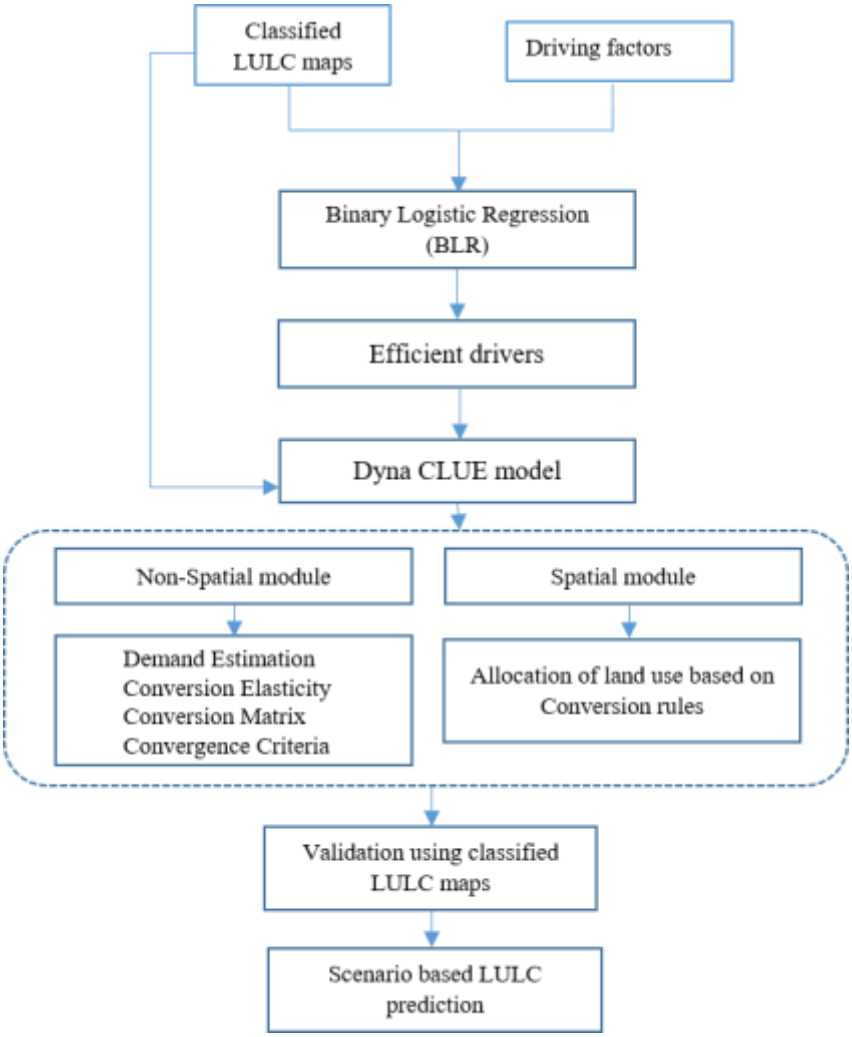

Figure 2. Methodology flowchart of the present study

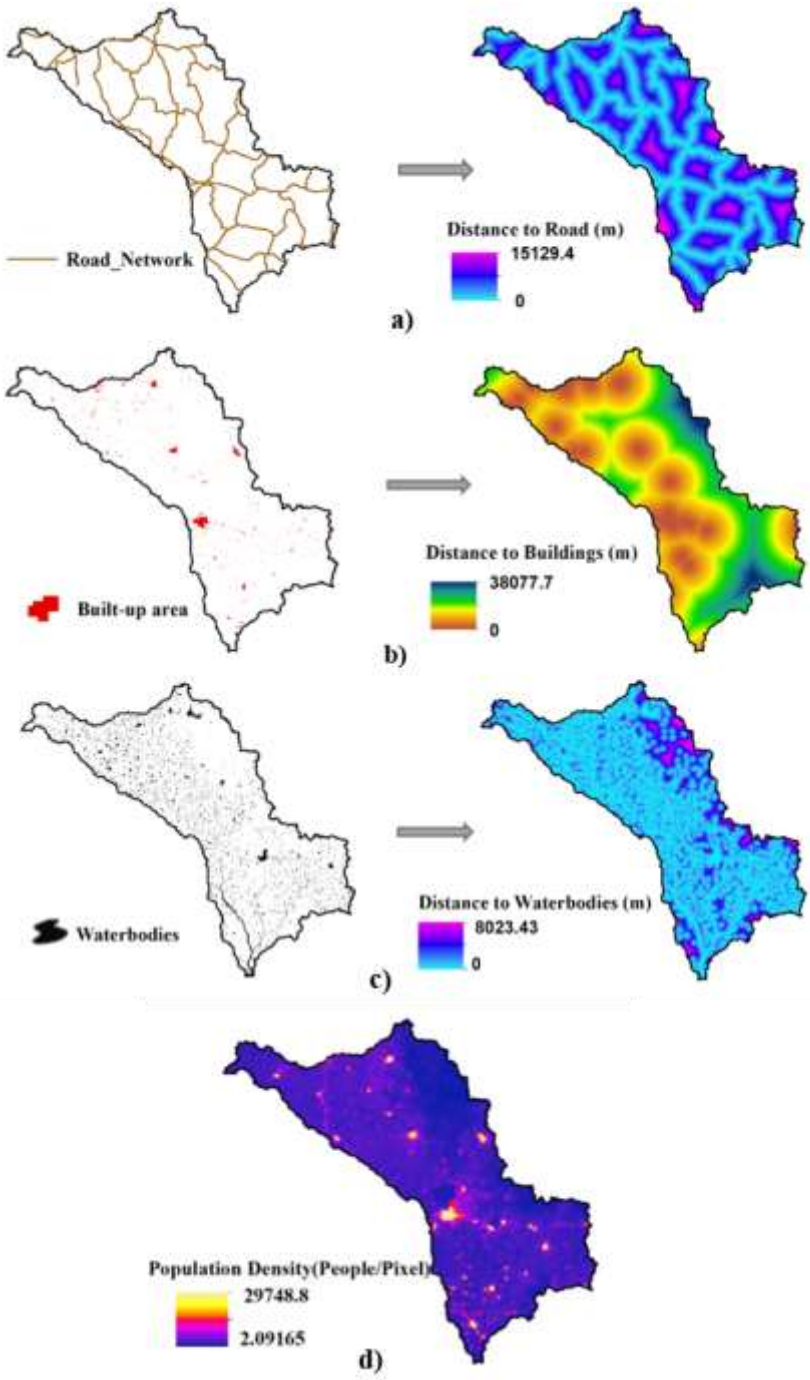

Figure 3. Driving factors considered for LULC projection (a) Distance to Road (b) Distance to Buildings (c) Distance to Waterbodies (d) Population Density

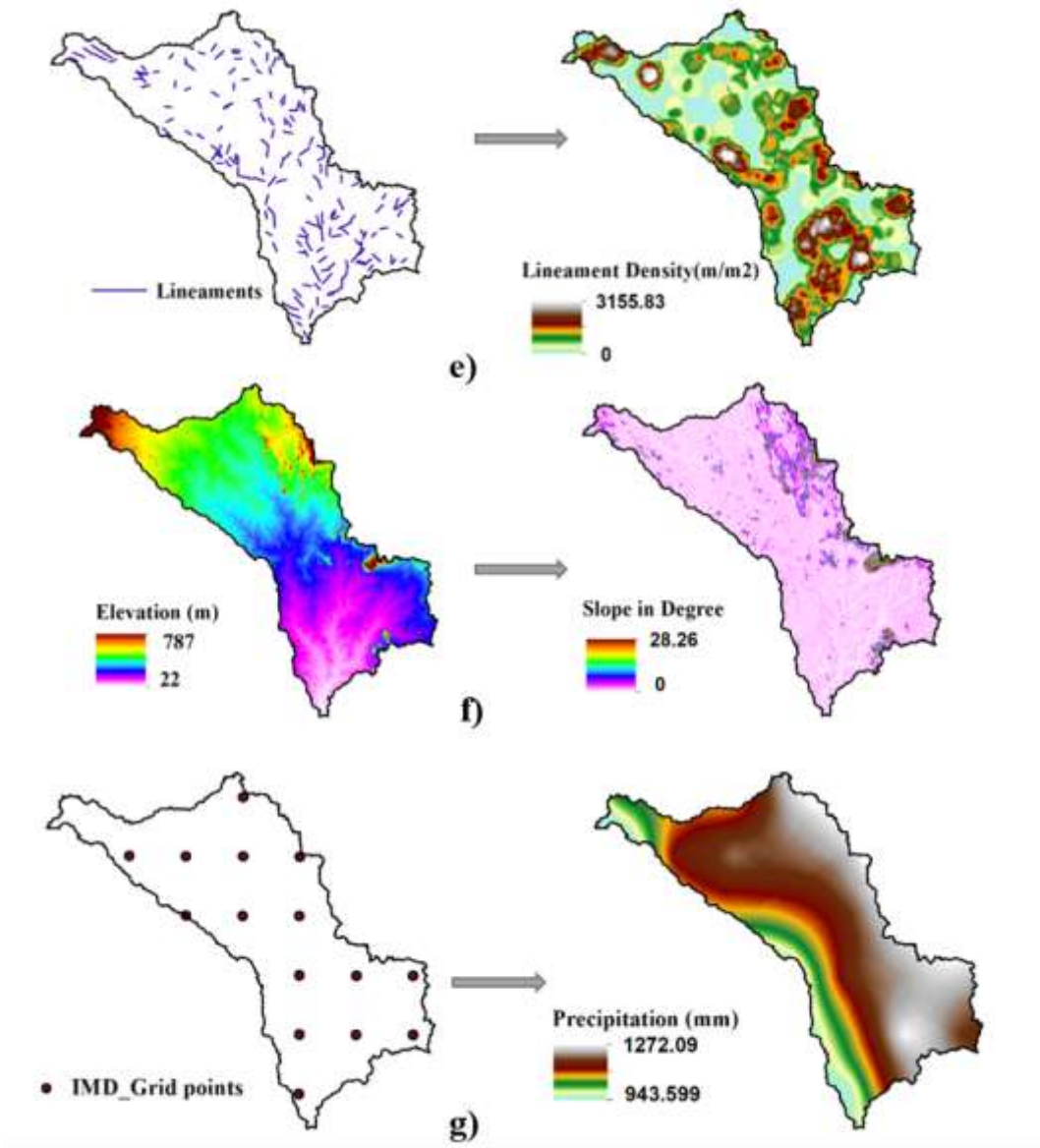

Figure 4. Driving factors considered for LULC projection (e) Lineament Density (f) Slope (g) Precipitation

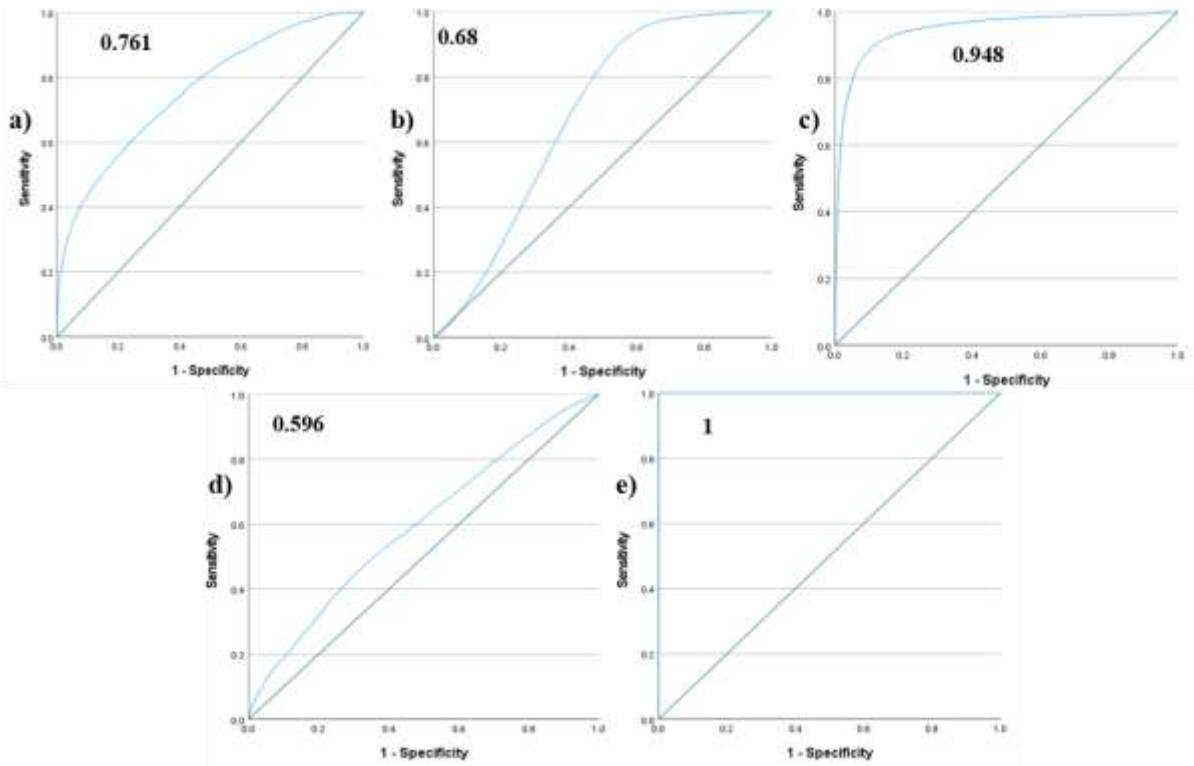

Figure 5. ROC curve for LULC classes a) Built-up b) Agriculture c) Forest d) Barren land e) Waterbodies

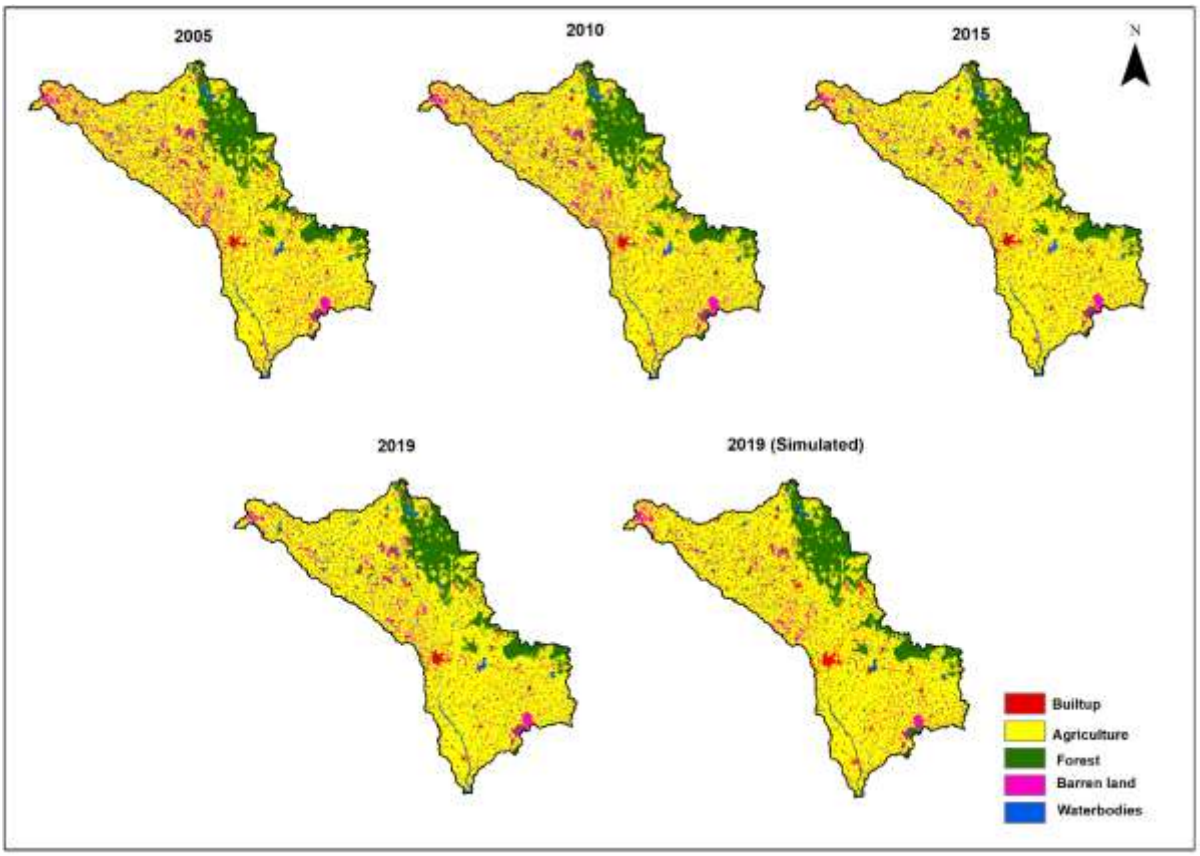

Figure 6. Classified LULC maps for 2005, 2010, 2015, 2019 years and the simulated (2019) LULC map

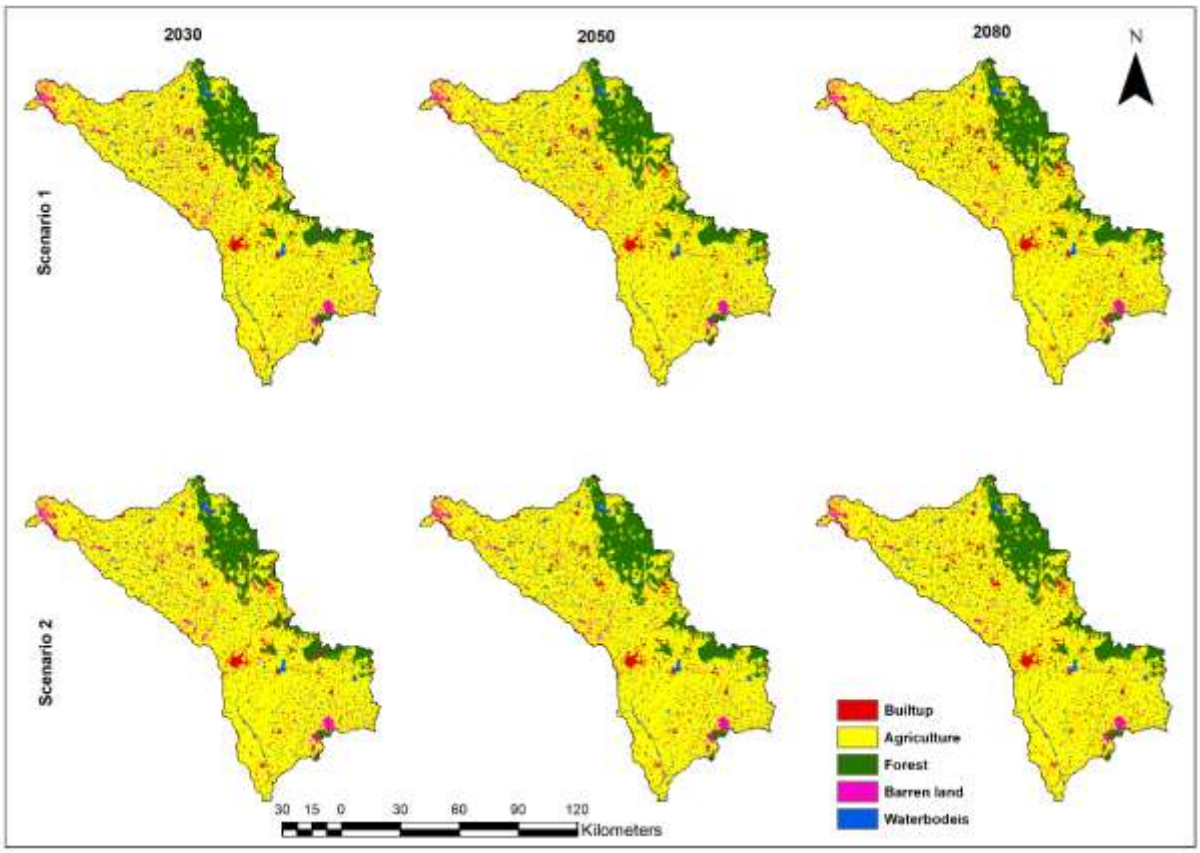

Figure 7. Predicted LULC's for 2030, 2050 and 2080 years with Scenario 1 and Scenario 2

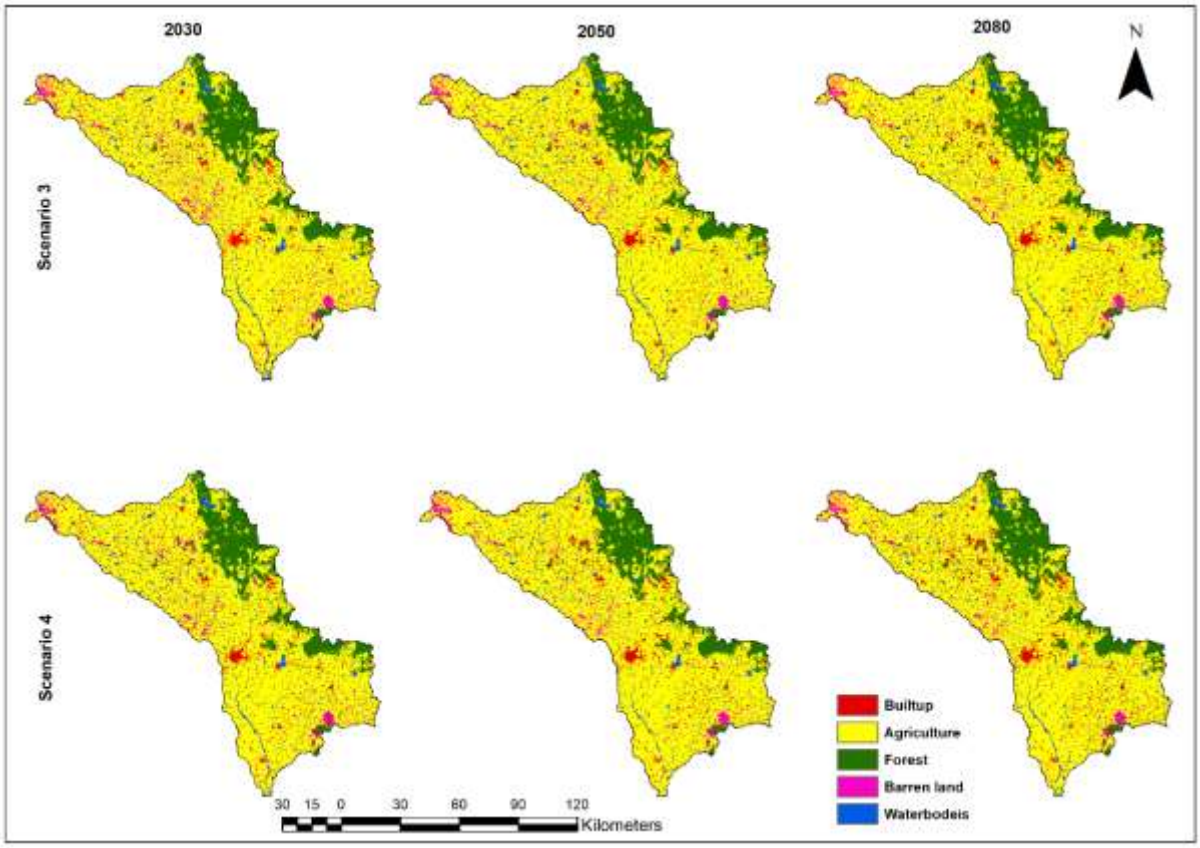

Figure 8. Predicted LULC's for 2030, 2050 and 2080 years with Scenario 3 and Scenario 4

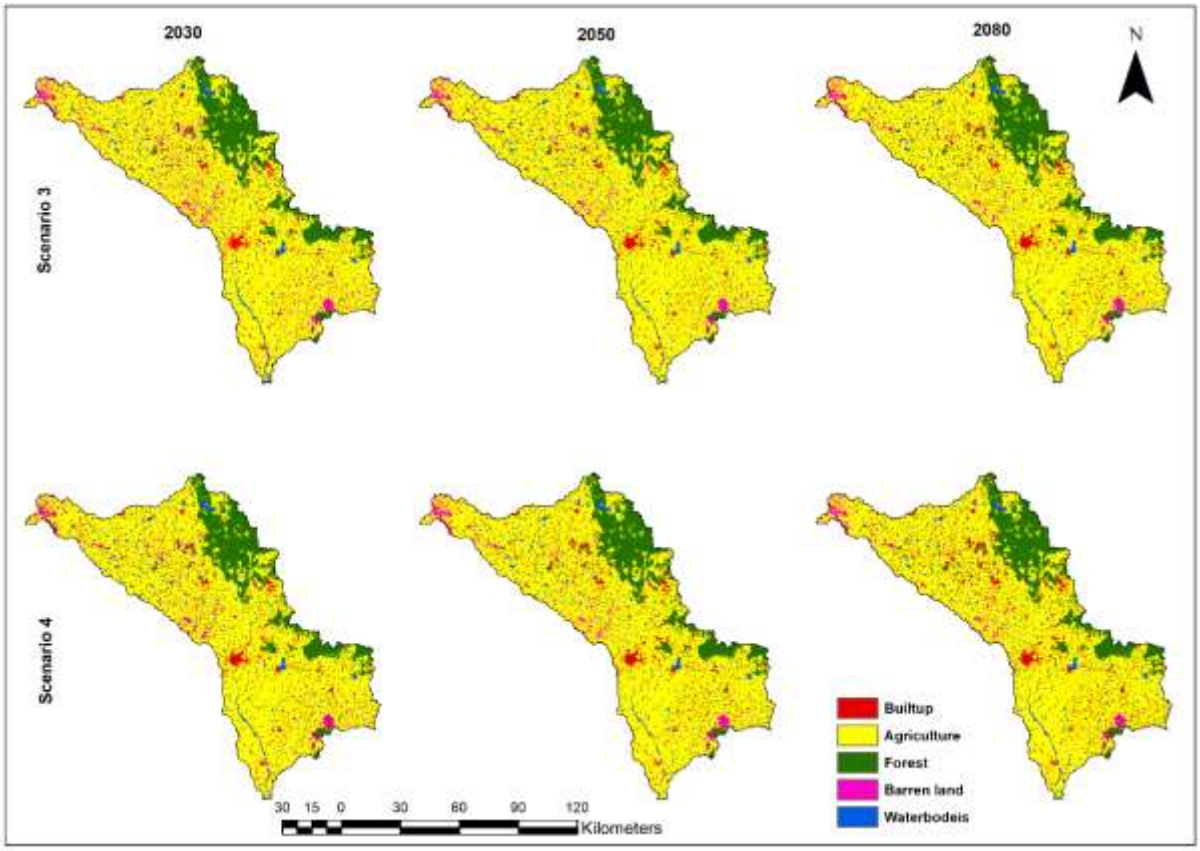

Figure 9. Predicted LULC's for 2030, 2050 and 2080 years with Scenario 5 and Scenario 6

Table 1. Scenarios considered for projection of future LULC maps

Scenario	Description
Scenario 1	Similar Change as in the period 2005-2015
Scenario 2	Similar Change as in the period 2010-2019
Scenario 3	Increase in Built-up area (2 Km^2 per year) with unchanged forest area
Scenario 4	Increase in Built-up area (6 Km^2 per year) with unchanged forest area
Scenario 5	Increase in Built-up area and agricultural land (2 Km^2 per year and 10 Km^2 per year) with change in the forest area
Scenario 6	Increase in Built-up area and agricultural land (6 Km^2 per year and 20 Km^2 per year) with change in the forest area

Table 2. Binary logistic regression analysis for input drivers

Driving Variables	β - coefficient and its exponential	LULC Type				
		Built-up	Agriculture	Forest	Barren land	Waterbodies
Distance to Buildings	β	-0.0000175	-0.0000051	-0.0000495	0.0000173	-0.000661
	Exp(β)	0.999982	0.999995	0.9999505	1.0000173	0.99933
Precipitation	β	-0.0011895	0.0029684	0.0210682	-0.0053235	0.00018
	Exp(β)	0.998811	0.997036	1.0212917	0.9946906	1.00018
Lineament Density	β	-	0.038473	-	-0.000173	0.000273
	Exp(β)	-	1.03922	-	0.9998	1.000273
Population density	β	0.0009886	-0.0002526	-0.0095129	-	-0.012298
	Exp(β)	1.000989	0.9997475	0.9905322	-	0.9877
Distance to road	β	0.0000805	-0.0000158	-0.0000091	-0.0000143	-
	Exp(β)	0.999919	0.9999843	0.9999909	0.9999857	-
Slope	β	-0.1655022	-0.6310085	0.3173325	-0.0837166	-0.048153
	Exp(β)	0.847468	0.532055	1.3734592	0.9999383	0.95298
Distance to waterbodies	β	-0.0002498	-0.0002498	0.0008879	-0.0000617	-0.1274863
	Exp(β)	0.99975	0.9997503	1.0008883	36.0041096	0.88

Table 3. Area wise distribution of classified LULC maps

LULC/ Area in ha	2005	2010	2015	2019	2019 (Simulated)
Built-up	31513.53	37152.84	37588.03	38020.95	37565.82
Agriculture	711774.26	716209.59	737938.14	747823.42	737793.26
Forest	141596.25	141596.25	141032.96	141006.20	140865.60
Barren land	98673.53	88584.11	69013.54	58724.23	69024.40
Waterbodies	55642.43	55657.21	53627.33	53625.20	53781.20

Table 4. Percentage of LULC types in the study area for the Base year (2019) and for the years 2030, 2050 and 2080 under different scenarios

Year	Scenario	Change in LULC (%)				
		Built-up	Agricultural Land	Forest Land	Barren Land	Waterbodies
2019	Base	3.7	71.9	13.6	5.6	5.2
2030	Scenario 1	4.2	73.6	13.3	3.9	5.0
	Scenario 2	4.1	74.9	12.5	3.7	4.8
	Scenario 3	3.9	72.4	13.7	4.7	5.3
	Scenario 4	4.3	73.1	13.6	3.9	5.0
	Scenario 5	3.9	73.4	13.2	4.5	5.1
	Scenario 6	4.4	74.1	12.6	3.9	5.0
2050	Scenario 1	5.2	73.8	13.5	2.8	4.8
	Scenario 2	4.4	74.4	13.6	2.6	4.9
	Scenario 3	4.8	73.6	13.5	3.1	5.0
	Scenario 4	5.8	73.2	13.5	2.7	4.8
	Scenario 5	4.8	73.7	13.2	3.4	4.8
	Scenario 6	5.8	74.7	12.9	1.8	4.8
2080	Scenario 1	5.9	74.2	13.3	1.9	4.7
	Scenario 2	5.3	74.9	13.2	1.8	4.8
	Scenario 3	5.5	73.7	13.5	2.4	4.9
	Scenario 4	7.0	72.6	13.5	1.9	4.9
	Scenario 5	5.5	75.2	12.1	2.3	4.9
	Scenario 6	7.0	76.0	10.8	1.4	4.8