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SIMULATING THE FUTURE LAND USE AND LAND COVER BY IMPLEMENTING MACHINE LEARNING KNOWLEDGE ON THE SOUTH-WESTERN ZONE OF RAJSHAHI DISTRICT, BANGLADESH

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ABSTRACT

Urbanization causes major urban pressures and changes in habitat, ecology, and environmental diversity. Particularly in developing countries, they are often characterized with strong urban sprawl. This research aimed to detect the temporal LULC change with the driving forces of LULC and forecast the future LULC via simulation in Rajshahi, Bangladesh. The LULC was classified through supervised classification using Erdas Imagine. To predict future land-use/ land cover change, the Land Change Modeler (LCM) of Terrset application was used with the implementation of CA and Markov chain analysis. "Built-up area" and "bare land" increased whereas "water bodies" and "vegetation" landforms decreased from 1991 to 2011. Although, "built-up area" and "vegetation" increased as "water bodies" and "bare land" decreased from 2001 to 2021. The driving forces of the LULC change were identified through correlation. The conventional driving forces were found to be 'population,' 'literacy rate,' 'population density,' 'household income' and 'average household size'. When the outcome of the coefficient is positive, the driving force works proportionally. Average accuracy of the prediction model is approximately 85% and the predicted image was validated with the classified image of 2021 and the average accuracy was 92.03%. LULC for the years 2001, 2011 and 2021 along with the driving forces served as the basis to predict land-use/land cover for 2031, and 2041. This research helps to analyse urban planning policies and environmental management, and to take proper measure for proper control of LULC change

Keywords: *LULC, Machine Learning, Bangladesh*

1. INTRODUCTION

Bangladesh is an overly populated small country in terms of physical size. The rapid growth of population in many cases influences land-use and land cover change which is an ongoing process and expression of human action (Lunetta et al., 2002). Since 1950 there has been an exponential growth in metropolitan population, which has turned the vacant land, water sources, trees, vegetation, and bare land into urban areas (Fattah et al., 2020). Various environmental changes such as filling of wetland, vegetation loss, and spreading of built-up features can be designated through land use and land cover change (Turner et al., 1995). The rapid growth of population, income level, and infrastructure development impose pressure on land related to urbanization, economic development, and social behaviour (Morshed et al., 2020). Due to urban expansion LULC has changed significantly affecting not only biodiversity and ecosystem but also local and regional climate (Kafy et al., 2019). LULC change may or may not improve human well-being. Subsequently, it is essential to point out the incentive of land use and land cover change. LULC is very important in the decision making of future ecological management and environmental planning. Consequently, this study focuses to point out the nature of LULC and better understand the socio-economic driving forces behind this land use and land cover change (Yuan et al., 2005).

Rapid urbanization applies tremendous tension on the neighbourhood and restricted land-based assets, prompting numerous issues, such as environmental pollution, crime, gridlock, poverty, and financial and natural difficulties for the whole nation. The built-up extension has brought about an inexorably quicker change in the landscape formation causing structural intricacy at both class and landscape level. Rajshahi city has witnessed massive changes in the land cover over the past several decades. From 1977 to 2010, it has lost 14.05% cultivable land and increased 194.43% infrastructural land (Islam & Hassan, 2011). Surface water levels as a result has reduced massively in this area. It was found that water bodies were filled up almost 14% from the year

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1992 to 2017 in Rajshahi city (Kafy et al., 2019; 2020). The South-western zone of Rajshahi district and its adjacent river is chosen as the study area. This zone has observed significant variations in its land cover over the past several decades (Islam & Hassan, 2011). From 1991 to 2011, the volume of the population has increased greatly (BBS2001; 2011). As a result, information regarding the characteristics of LULC change and the socio-economic driving forces of these changes is very important, for better planning and policy formulation. Accordingly, this study aims to identify the nature of land-use and land cover change and to gain a better understanding of the socio-economic driving forces behind these LULC changes in the south-western zone of Rajshahi district from 1991 to 2011.

For analysing the area cover trends and procedures, researchers were found to use several relevant multi-temporal data from RS (Yildirim et al., 2002), and GIS techniques (Zhang et al., 2002). Spatially explicit time series of LULC change can be developed based on RS (Moglen & Beighely, 2002, Mahi et al., 2021). The commonly used method of change detection will detect the structural difference between various land cover patterns (Chen et al., 2003, Hossain et. al., 2021). Besides correlation and analysis (Hietel et al., 2004), bivariate analysis (Kaufmann & Seto, 2001) such as statistical analysis is used to identify shifts in land use cover based on socio-economic evidence from time series. These time-series studies of the transition in LULC and the unification of the guiding forces responsible for these developments are very beneficial both for the proper strategy and plan-making, as well as for the ongoing sustainable use and legislation of its current land resources (Kelly, 2003, Morshed et al., 2021).

There are a lot of research (Morshed et. al., 2022; Hossain et. al., 2021) conducted on LULC change and future land use prediction but limited focus on socio-economic driving forces and as well as with the location of the south-western zone of Rajshahi. This study will help understand how such massive change occurs. LULC change and its future forecasting will be extremely useful for urban planners and administrators to construct a sustainable city planning for the south-western zone of Rajshahi district and its surroundings.

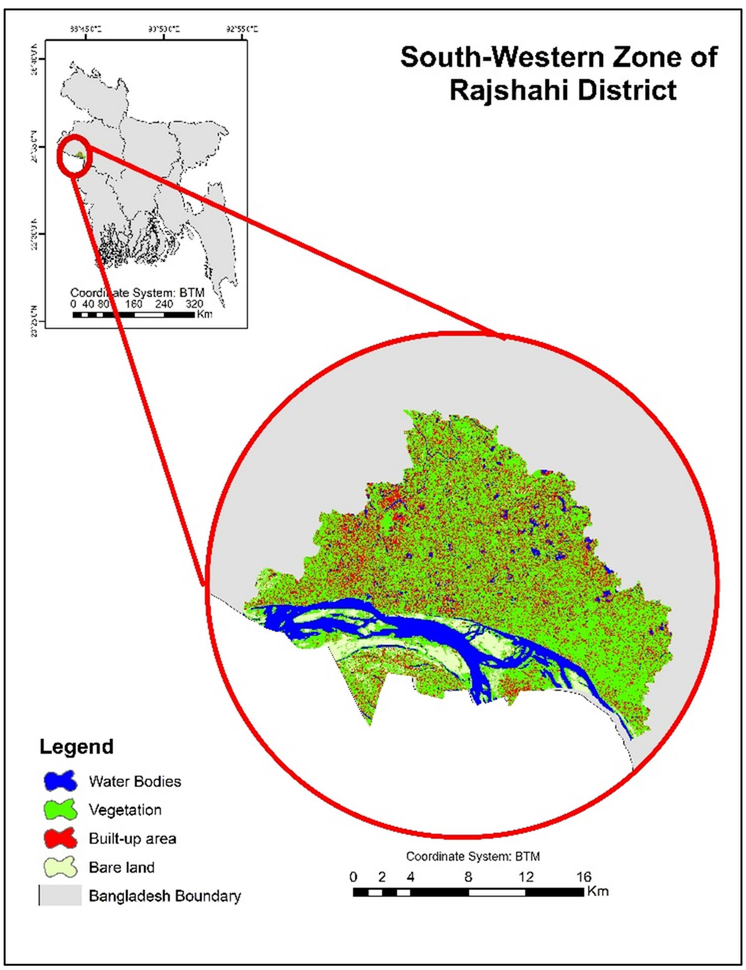

Figure 1: Location of the study area in the south-western zone of Rajshahi.

2. STUDY AREA

The research area on the shore of the Padma River is situated in the south-western zone of the Rajshahi district. This zone is 364.91 sq. km (Figure 1). This field is located between the north latitude of 24'20' and 24'24' and between the east length of 88'32' and 88'40,' 23 m above the mean sea level. This region is less prone to disasters such as floods, cyclones, and earthquakes. Rapid and unequal economic growth is a big problem for Bangladeshi policymakers. Urban area expands irregularly and consists of 2595197, people and 1070 people per sq. km.(BBS, 2011). Massive rural-to-urban resettling and rapid urbanization are among the most important reasons for the growth of the population in this zone (BBS, 2011). During the last fifty years, nearly 27% of the vegetation was lost as a result rapid urbanization (Kafy et al., 2019). Rapid change thus makes this area an appropriate choice for LULC analysis.

3. METHODOLOGY

3.1 Data Description

Only secondary data are collected to determine the land use land cover change, future LULC prediction, and socio-economic driving forces. Secondary data (Satellite image, number of populations, literacy rate, avg. household size, etc.) were collected from various Government and Non- Government Organizations, Website, journals, etc. to find out the land-use and land cover change and its driving forces. Satellite imagery of 1991, 2001, 2011 and 2021 were downloaded from United States Geographic Survey (USGS) for LULC and prediction analysis. The socio-economic data were collected from the Bangladesh Bureau of Statistics (BBS) for the years 1991, 2001, and 2011.

3.2 Satellite Image Processing

Multi-temporal and land cover mapping determine the land use and land cover changes. Landsat Satellite images of 1991, 2001, and 2001 were collected from the United States Geological Survey (USGS). The entire research area is covered by Landsat path 138 and Row 43. The coordinate grid system is in 'UTM' (Universal Transverse Mercator), and datum set is "WGS 1984". The spatial resolution of the images is 30m. The bands were stacked by the 'layer stack' tool in Erdas Imagine software. Afterwards, the study area was masked in ArcGIS 10.5. Sequentially, the images were set as a false-color image in Erdas Imagine. Finally, the primary supervised classification was implied to delineate the current and previous land - cover of the study area. Google Earth image was used as the reference image for determining the land use and land cover classification on the satellite image. Four classes were determined in this classification method. These classes are 'Water bodies', 'Built-up area ', 'Vegetation' and ' Bare land ' (Table 1). For each classified image, reference points are randomly selected to cross-check from both the reference image and classified image.

Table 1: Description of land cover categories.

LULC types	Description
Water Bodies	Wetlands, lakes, ponds, and rivers
Vegetation	Cropland, Park, playground, trees, and grassland
Built-up area	Residential area, industrial area, and commercial area
Bare land	Bare-land, open space, and vacant land

Table 2: Description of downloaded Landsat satellite images.

Year	Date Acquired	Sensor	Path/row
1991	6th February	TM	138/43
2001	28th January	TM	138/43
2011	9th February	TM	138/43
2021	20th February	OLI	138/43

3.3 Future Land Cover Prediction

Satellite images of 1991, 2001, 2011 and 2021 were downloaded from the USGS Earth Explorer and preprocessed for the research work (Table 2). Layer stacking and sub-setting study area were involved in image preprocessing. Classification of the masked area image into four land cover classes through Erdas Imagine. Supervised classification was conducted using the maximum likelihood algorithm. The study area's elevation image was downloaded from USGS earth explorer and masked with ArcGIS10.5 for the study area. From the topographic map, the road-network map is created then converted the map into a raster image. Processed data were put into the Land Change Modeler (LCM) which is a built-in module in Terrset. Change analysis was carried out and the change map gained, helped to develop the transition model. This allowed for the identification of five sub-models. The five sub-models, elevation map, distance map which is created from Terrset, and the transition sub-model were supplied via Multi-Layer Perceptron (MLP), a machine-learning classifier for creation of forecasts. The forecasted LULC map was created through the transition potential model. Land-use for 2021 was predicted through the image of 1991, 2001 and 2011. The predicted LULC of 2021 was checked with the classified image of 2021 (Table 7). Now utilizing the LULC of 1991, 2001, 2011, and 2021 with a range of 30 years, the LULC of 2031, and 2041 were predicted.

3.4. Markov Chain Analysis

The Markov Chain Analysis (MCA) is a subatomic, nonparametric, and cumulative process for modelling used as a tool of predictive transition modelling. The anticipation of potential developments is based on changes that happened in the past. Consider an area that was distributed into several cells which reflect a certain kind of land use at a specific time. In that case, MCA estimates the chance that a cell will experience a transition from one type of land to another within a set period, backed by observable data during periods. The opportunity to adapt from one state to another is interpreted as a likelihood of transformation. MCA generates a transformation matrix, which has the potential that each type of land use can switch to another type, and hence the predicted pixel number (Kumar et al., 2016). The below equation expresses a Markov transition matrix =
P ($0 \leq P_{ij} \leq 1$) (0-1: low to high transition):

$$p = p_{ij} \begin{bmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{n1} & \cdots & p_{nn} \end{bmatrix} \sum_{j=1}^{n} p_{ij} = 1 \tag{1}$$

P = the Markov transition matrix
P_{nn} = state probability of any time.
P_{ij} = the probability from land-use type i to land use type j (Kumar et al., 2016).

3.5. Cellular Automata (CA)

CA may literally be viewed as a physical system of dynamics that modulate cells' complex functions on a gate, based on basic logical laws. In general, CA, by standardized 'n' directional cell grid (for example, n=1, n=2) represents space, for each cell having such details. The simple computing system in CA is defined as a 'cell', and all these cells are typically nonlinear dynamic structures intermingling with one another. The neighbourhood would define the group of cells that will communicate directly with the central cell. The distance was described in the CA method via a grid, time through standardized measures, as well as the functions were discrete integer numbers.(Kumar et al., 2016). This is necessary for establishing the state of the cells and the rules that each cell should adhere to, for proper interaction of cells within the cell system.

3.6. CA Markov

The channel module CA Markov, which is an integrated module of TERRSET application, was used in the estimation of potential land coverage image of Cell Automata and Markov. CA Markov is a method of land cover projection, consisting of a combined Markov chain, cellular automata, and multi-objective land allocation (MOLA). The transformation from previous year to subsequent years is also studied from the research of the Markov chain by evaluating the transition sequence from one class to another. The future usage of the land is then projected using the mode from the analysis of the Markov chain after this model map is created.
CA Markov automatically optimizes the aspect of the system to reduce the attributes to the same degree. This channel takes a Boolean image out of focus per each category from the present land cover. The first recommendations on reasonability expand this to the inaccessible reduction in weight from each type's current spectrum. The results would then be expanded to a byte territory (0-255). This adjustment's net implication is that the weighted suitability never reaches an overweight of 90% of its unique value. This ensures that fair regions are available where no places in neighbouring areas are open. (Kumar et al., 2016).

3.7. Land Change Modeler (LCM)

The Terrset land-change simulation module establishes CA-Markov and the simulations. These are operated and fluidized by a multi-layer perceptron's neural association. Considering possible transitional help, the cycle CA-

Markov will create a future image of LULC (Kumar et al., 2016). Figure 2 shows the methodology followed during this work.

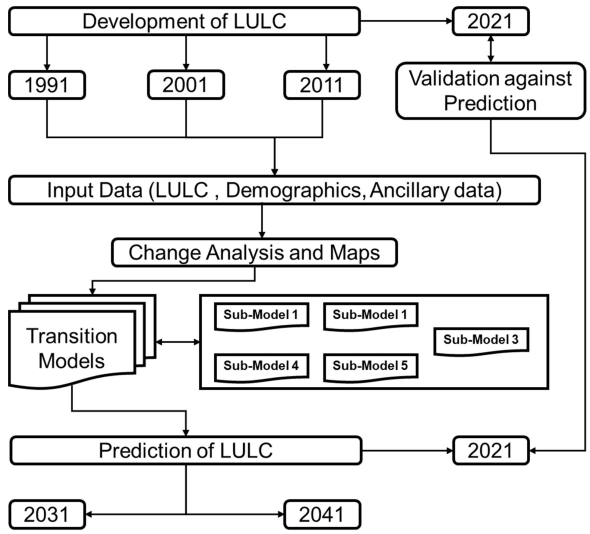

Figure 2: Overall process of LULC prediction.

3.8 Determination of Driving Forces and Their Relationship with LULC Types

The driving forces of LULC change are identified through correlation coefficient and significance level. When a socio-economic factor gains a satisfactory correlation coefficient and significance level (below 5%) then it is considered as a socio-economic driving force (Murry et al., 2007). When the coefficient is near 1 or -1, then it is called strongly correlated. When it is positive then it means it is proportionally correlated and vice-versa (Long et al., 2007). The socio-economic driving forces are 'Population', 'household income', 'average house-hold size', 'literacy', and 'population density'. Literature review and reconnaissance survey were very helpful to establish those socio-economic driving forces. Sometimes one LULC type can act as a driving force for another LULC type. For example, the growth of built-up areas can work as a driving force to reduce the vegetation. The driving forces are classified according to the LULC change types.

4. RESULT AND DISCUSSION

4.1 Characteristics of Land-use and Land Cover Change

Land-use and land cover changed greatly over the period from 1991 to 2001 in this zone. From 1991 to 2001, "water body", "built-up area" and "agriculture land" decreased by 7.93%, 0.02%, and 12.20%, respectively. On the other hand, "bare land" is increased by 50.55%, 71.53%, and 113.44%, correspondingly, in the same period. These patterns nearly remained unchanged for the period 2001 to 2011. "Water bodies" and "bare land" have dropped by 11.92% by the end of 2011. On the other hand, "agriculture land" and "built-up area" increased by 1.95%, 22.97%. In 1991, vegetation class covered the primary type of LULC in the south-western zone of the Rajshahi district at 54.68 % of the total area, followed by "water bodies", "built-up area" and "bare land" at 12.45%, 26.02% and 6.85%, respectively. Between the ten years' timeframe from 1991 to 2001, the vegetation declined by 44.69 sq. km (22.40%) and the built-up area gain 24.72 sq. km. (26.04%) form the total land-use and land cover. In 2001, built-up area and vegetation covered the primary type of LULC in the south-western zone of Rajshahi district at 32.80%, and 42.43% of the total area, followed by "water bodies" and "bare land" at 11.06%, 13.71%, respectively. Between 2001 to 2011, the built-up area increased 27.50 sq. km (22.97%) from the total land-use and land cover between the ten years' timeframe. Table 5 summarizes the major LULC conversion between 1991 to 2041 (predicted).

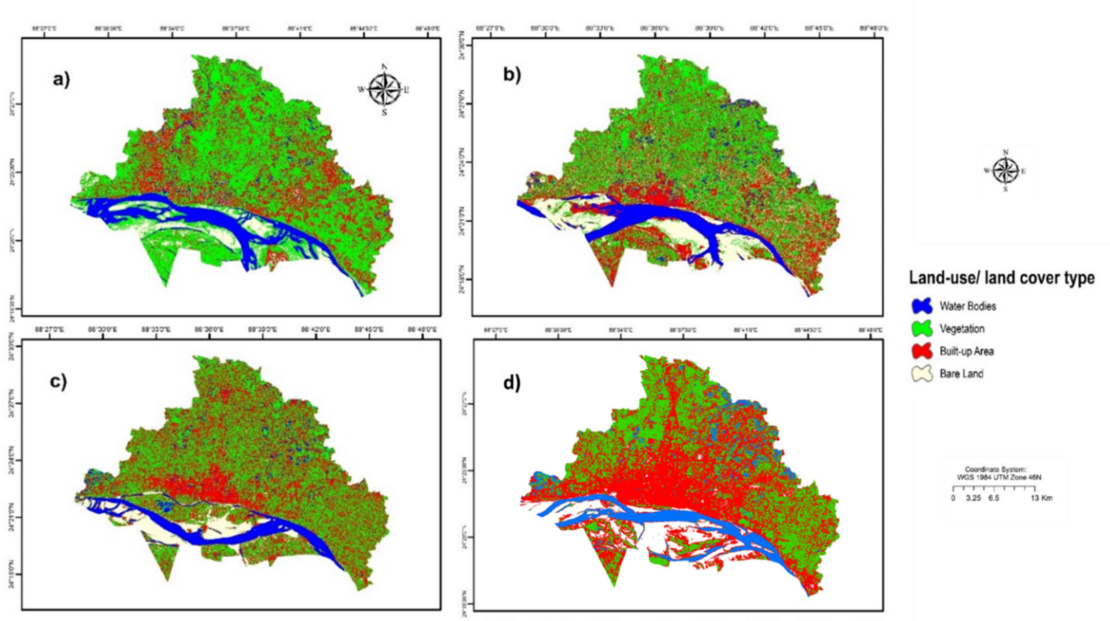

Figure 3: LULC maps of the south-western zone of Rajshahi District for years a) 1991, b) 2001, c) 2011 and d) 2021.

4.2 Land-use/ Land Cover Prediction

The MLP and MCA model were used for the forecasting of future LULC of 2021, 2031, and 2041. The classified image of 1991-2001, 2001-2011 and 2011-2021 were used in this simulation (Figure 3). Through the MLP and MCA model the transition potential map for all the land-use and land cover were created. The forecasted area of 2021 shows that 47.63% area is covered by built-up area, which is an increase of 18.10% from 2011. Furthermore, vegetation and bare land decreased 15.87% and 10.57% respectively. In 2031, more than half of the total area is predicted to be covered by the built-up area (50.63%). Vegetation, water bodies, and bare land decreased by 2.14%, 0.29%, and 0.56%, respectively from 2021. Similar scenario is predicted to happen in 2041 (Table 4). Built-up area and vegetation cover most of the area at 53.77% and 31.87 %, respectively, water bodies and bare land cover 9.44% and 4.93% area of total land-use (Figure 5).

Table 5 shows that built-up area will have increased by 106.62% in a span of 50 years. On the other hand, water bodies, vegetation, and bare land will have decreased by 24.22%, 41.71%, and 28.10%, respectively. The developed region which significantly affects the climate is separated from the LULC image. From the figures and tables, the degree of urban development and its pattern is apparent, which is extremely valuable for environmental management.

4.3 Validation

The model validation was examined using the reliability, functionality, and acceptance of the model (Figure 4). Kappa coefficients and Chi-square statistical analysis were conducted on the predicted and satellite driven LULC map of 2021. The kappa values varied between 0 and 1, which indicated the accuracy of the predicted map. The kappa coefficient values were achieved from Erdas Imagine and ArcGIS software. The result of percentage-correctness and overall kappa index values were 97.12 and 0.95, respectively.

Chi-square estimates on the predicted and actual LULC were calculated for discrepancies and further validation. It was calculated by using the following equation-

$$X^2 = \sum \frac{(O-E)^2}{E} \qquad (2)$$

The details of the results are provided in Table 3.

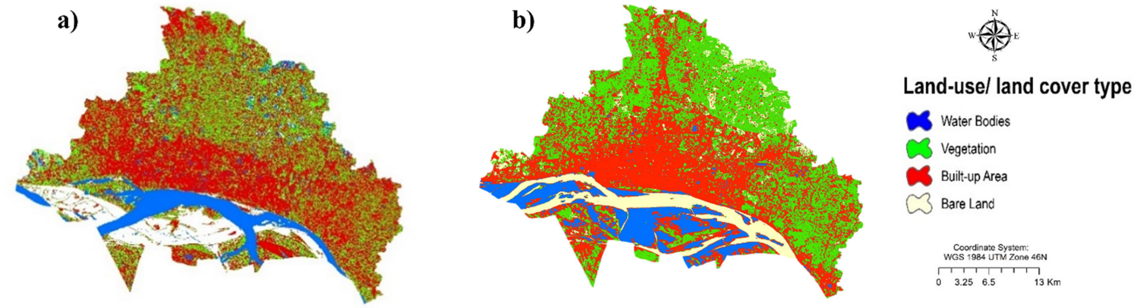

Figure 4: LULC type (a) Prediction model (b) Current status.

Table 3: Land-use prediction validation with 2021 (Area in sq. km).

LULC type	2021 actual (O)	2021 predicted (E)	O - E	(O - E) ^2	Accuracy (%)	((O - E) ^2)/E
Water bodies	40.52	36.88	3.64	13.27	91.01	0.359756135
Vegetation	123.85	128.67	-4.82	23.23	96.11	0.180565509
Built-up area	164.86	168.26	-3.40	11.56	97.94	0.06873149
Bare land	35.68	31.10	4.58	20.98	87.16	0.67462959

(Chi squared equals 7.815 with 3 degrees of freedom at P value 0.05).

Table 4: Predicted land-use / land cover (Area in sq. km)

LULC Classes	Predicted 2031		Predicted 2041	
	Area (sq. km)	Area (%)	Area (sq. km)	Area (%)
Water bodies	35.48	9.72	34.43	9.44
Vegetation	124.98	34.25	116.30	31.87
Built-up area	184.75	50.63	196.2	53.77
Bare land	19.7	5.40	17.98	4.93

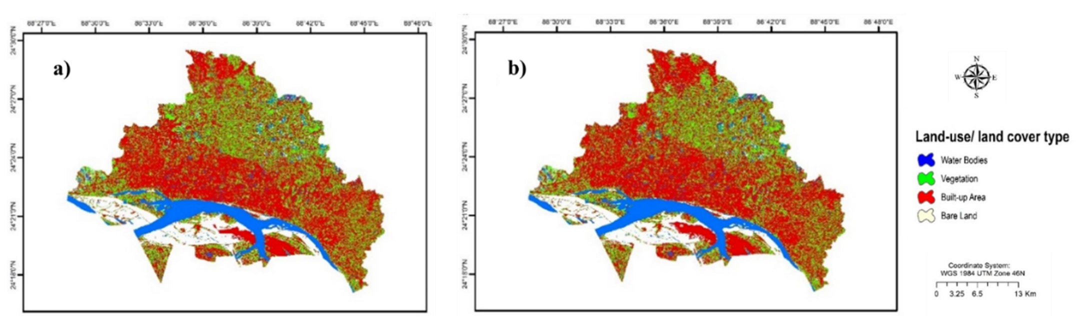

Figure 5: Forecasted LULC maps of the research area for years a) 2031 and b) 2041.

Table 5: LULC change from 1991 to 2041. (Area in sq. km).

LULC Classes	Change% (2011-2021)	Change% (2011-2031)	Change% (2011-2041)	Change% (1991-2041)
Water bodies	2.73	-0.22	-3.18	-24.22
Vegetation	-15.87	-20.82	-26.32	-41.71
Built-up area	18.10	25.53	33.31	106.62
Bare land	-10.57	-19.04	-26.11	-28.10

4.4 Significant Driving Forces of Land-use/ Land Cover Change

The built-up area in the south-western zone of Rajshahi district is increasing gradually. In 1991, 2001, 2011, and 2021 the built-up area was 79.50, 119.68, and 147.17, and 164.86 Sq. km. respectively. Population growth is the main driving force behind the increase in the built-up area. The population in the south-western zone of Rajshahi district was 1887015, 2286874, and 2595197 in 1991, 2001, and 2011 respectively. As the population increases, so does the population density. On the other hand, the average household size is decreasing, as household income increased. The literacy rate has a significant impact on the increase in the built-up area in Rajshahi. People from other districts, along with their family migrate here to complete their education.

Table 6: Driving force of LULC change in the built-up area.

Driving Forces	Effect Characteristics	Pearson Correlation Coefficient	Level of Significance
Population	+ +	0.999	0.021
Literacy	+ +	0.984	0.113
Density	+ +	0.999	0.023
Household income	+ +	0.922	0.253
Avg. Household size	- -	-0.985	0.115

[Here the signs represent the positive/negative correlation for table 6, 7 & 8]

In the study area, the amount of water bodies is in rapid decline. It has decreased by 11.14% in the year of 2001 and consequently by 11.92% in 2011. As the population density increased, land use was forcefully converted. Hence it is estimated that the bank of the river was land grabbed and filled during that passage of time. Household size shows signs of decreasing, but this does not mean that the number of houses has decreased. On the contrary, there is evidence of increase shown by the increased built-up area beside the riverbank. Therefore, built-up area rose on the bank of the river, and this is further suggested by the significance level of change between built-up area and water bodies.

Table 7: Driving force of LULC change in water bodies.

Driving Forces	Effect Characteristics	Pearson Correlation Coefficient	Level of Significance
Population	- -	-1.000	0.019
Household income	- -	-0.923	0.252
Literacy	- -	-0.984	0.115
Density	- -	-0.999	0.025
Avg. Household size	+ +	0.984	0.114

Based on the analysis, it has been found that vegetation was changed in two phases from the period of 1991 to 2011. Vegetation decreased in 2001 as compared to 1991 and increased in 2011 as compared to 2001 by 22.40% and 1.95% respectively. Several reasons help deduce the situation. Firstly, most of the people in the region during that time frame were engaged in farming. As population increased, combined with increase in literacy rate, which enabled more efficient farming and consequently more landcover in vegetation. Here also we can see that the household income is positively correlated with vegetation and has the lowest level of significance.

From this study, it is found that bare land was changed in two phases from the period of 1991 to 2011. Bare land increased both 2001, and 2011 bare land decreased compared to 1991. It can be observed that only population and population density strongly correlated with bare land, and the value is near -1, which states negatively correlated. Population increased thus; the open space decreased between the time frames. Other driving forces are poorly correlated.

Table 8: Driving Forces of LULC Change in vegetation.

Driving Forces	Effect Characteristics	Pearson Correlation Coefficient	Level of Significance
Population	+ +	0.956	0.189
Density	+ +	0.974	0.144
Household income	+ +	0.999	0.021
Avg. Household size	- -	-0.903	0.283

Table 9: Driving Forces of LULC Change in bare land.

Driving Forces	Effect Characteristics	Pearson Correlation Coefficient	Level of Significance
Population	- -	-0.981	.124
Literacy	- -	-0.324	.790
Household income	--	-0.243	0.843
Density	- -	-0.945	0.216
Avg. Household size	+ +	0.029	0.981

5. CONCLUSION

The research aimed towards identification of the nature of land-use and land cover change and the changes that ensued over the years. The South-Western zone of Rajshahi district was chosen for the study. Hereafter, the Landsat satellite images of the years 1991, 2001, and 2011 were classified through a typical supervised method. The better understanding of the socio-economic driving forces behind the LULC were highlighted through correlation. It was found that population, household income, avg. household size, density, and literacy are the major driving forces of LULC change. A socio-economic factor was considered as a driving force to the respective LULC type when the level of significance went below 5%. Correlation coefficient and level of significance are calculated between the LULC types and the socio-economic factors. Through the correlation, the driving forces were identified for each LULC types. The explosive growth of population increased the need for non-agricultural land and combined with driving forces like household income led to more urban housing. Other driving forces also contributed to the increase in non-agricultural activities and consequently built-up area increased and other land uses gradually decreased. The study of simulation can help in understanding the results of current planning policies or their inadequacy. Forecasting of future urban growth is normally troublesome without devices that grasp the urban system's multifaceted nature. Through this research, an endeavor is made to mimic the future urban extension from the past information utilizing geo-simulation methods. For this LULC of the past dates 1991, 2001, and 2011 were created utilizing ERDAS programming. Utilizing the LULC picture of 1991, 2001 and 2011 the LULC picture of 2021 was predicted utilizing Terrset programming. This product employed the Cellular Automata and Markov Chain analysis method. The predicted LULC picture of 2021 was validated utilizing the calculated LULC. Utilizing the land-cover images of 1991, 2001 and 2011, LULC of 2021, 2031, and 2041 was predicted. The future LULC image can be immensely helpful for the metropolitan territory's appropriate administration to take decisive action against urban sprawl. Subsequently, the utilization of geo-simulation methods like Cellular Automata and Markov Chain was fused and demonstrated in this research. Further research could consider abrupt human influences, higher image resolution and human decision making as these are some of the limitations in any simulated predictions.

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