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Simulation of Future Development Pattern and Identify Its Impact on The Degradation of Agricultural Land: A Machine Learning Based Remote Sensing Approach In Rajshahi District

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Abstract :

In the last few decades, rapid urban development has a significant impact on land use/landcover (LULC) parameters, i.e., water bodies, built-up area, agricultural and bare land. According to the yearly report of the Rajshahi district, almost 10% of the total agricultural land has been lost in the last 20 years due to the tremendous development pressure and massive LULC change. Monitoring and prediction of urban growth and the LULC change scenario is the essential element in current strategies for conserving agricultural land and natural resources for ensuring sustainable urbanization and food security in the future. This study aims to identify the loss of agricultural land using maximum likelihood supervised image classification algorithm and LULC indexes such as normalized difference vegetation index (NDVI), normalized difference built-up index (NDBI) and normalized difference bare soil index (NDBSI) for the year 1999, 2009 and 2019 using Landsat 4-5 TM and Landsat 8 OLI satellite images in Rajshahi district. The study also simulates the urban growth and loss of agricultural land for the year 2029 using machine learning-based cellular automata (CA) approach. The result suggests that almost 12% of the built-up area is increased in the last 20 years, and based on the simulation, the built-up area will be increased to 15% in 2029 in the Rajshahi district. 13% of agricultural land already converted to built-up areas, and in 2029 the percentage will increase by almost 21%. The loss in agricultural land will become unstable the biodiversity, ecosystem services and create unemployment as well as food insecurity in the district. District authority needs to implement effective strategies with the help of urban planners, environmental engineers, and policymakers to conserve district agricultural wealth and natural resources, which will ensure sustainable, planned, and inclusive urban development in the Rajshahi district.

Keywords: *Urban development, land use/land cover change, agricultural land, machine learning, and Rajshahi.*

I. Introduction

In recent times, developing countries are facing challenges due to the urbanizations of cities. Rapid urban expansion is meant to occur mostly in small and medium-sized cities in a region. According to the UN reports, by 2050, more than 2.5 billion people living will be included in the metropolitan areas, and 90% will be included in the Asian and African areas (UN, 2015). In the Asian region, mainly south Asian countries, including Bangladesh, are mostly developing with the flow of digitalizing the world. Industrialization and population growth created metropolitan cities in Bangladesh. As population growth rates rising rapidly, LULC changes in a city are happening significantly.

In recent decades, urban developments and rapid population increases have been observed in the Rajshahi district mainly from the beginning of the 21st century to the present. Population of Rajshahi metropolitan areas were 663000 in 1999, 774000 in 2019, and 893000 in 2019 (Bank & United Nations, 2019; BBS, 2013). Rapid population growth and urban areas' expansion drives urbanizations and leads to LULC changes. The application of Remote Sensing (RS) and GIS have created efficient and practical methods for estimating variations in LULC in a specific area (Ahmed & Ahmed, 2012). Multiple methods and algorithms were used to forecast LULC, i.e., Markov Chain (MC), Cellular Automata (CA), Logistic Regression (LR), and Artificial Neural Network (ANN). Several types of research have used LULC's Markov-cellular automata (CA) model for Spatio-temporal modeling, which has proven to be an effective tool for land use preparation, management, and environmental change study in different regions.

Located in the northeastern part of Bangladesh, just beside the river Padma, the Rajshahi district is one of the fastest rising megacities facing population migration with rapid urban expansion. The use of the CA model and ANN algorithms can be useful in the analysis of short and long term LULC in this field. Current research on the field determined the LULC changes for the years of 1999, 2009, and 2019. Finally, the simulation of the future LULC model for the years 2029 and their impacts on agricultural land of the study area was evaluated in the respective years using the ANN-CA techniques.

II. Materials & Methods

Study Area

Rajshahi district is located in the northwestern region of Bangladesh between 24°12' to 24°42'N latitude and 88°15' to 88°50'E longitude (Fig. 1). The study area stands upon the northern bank of the river Padma. Rajshahi city is a central urban, commercial and educational hub of Bangladesh. Rajshahi district has an area of about 2428 km^2 (BBS, 2013). As it is an agricultural-based region, 1047 km2 area consists of agricultural land followed by 780 km^2 bare land, 344 km^2 urban area, and 257 km^2 area represents water bodies (Kafy et al., 2020). The total number of populations in the district is 25,95,197, with a population density of 1070 people per km^2. While in 2001, the region had a population of 22,86,874 with density per km^2 is only 941. Large scale rural-to-urban migration and rapid urbanization are among the most significant reasons for population growth in this region. The history of land use in this area shows that over 7% of agricultural land has been lost in the last 20 years due to rapid urbanization (BBS, 2013).

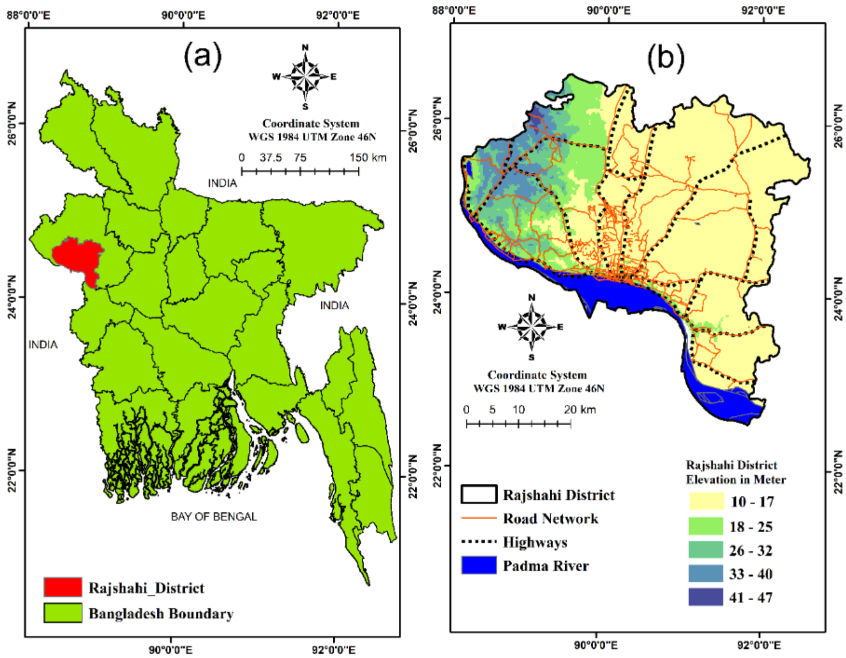

Figure 1: Study area location map a) Rajshahi District in Bangladesh b) Rajshahi District

Data Set

The research deals with multi-temporal Landsat 4-5 TM and Landsat 8 OLI satellite images from the USGS website where the path is 138, and the row are 43 (Table 1) for the years of 1999, 2009, and 2019. All images have a spatial resolution of 30 m. The images (Level 1 Terrain Corrected product) were projected to UTM zone 46 North projection using WGS-84 datum. To prevent the seasonal variation, all Landsat images were downloaded at a maximum interval of one month. To ensure greater classification accuracy, the images were collected to less than 10% cloud coverage. Table 1 offers details on the images taken from the USGS web data repository.

Table 1: Details of Downloaded Satellite Images

Date (d/m/y)	Sensor	Cloud Cover	Path / Row
28 / 03 / 1999	Landsat 5 TM	~1%	138 / 043
23 / 03 / 2009	Landsat 5 TM	~0%	138 / 043
19 / 03 / 2019	Landsat 8 OLI	~9%	138 / 043

Land use land cover (LULC) classification

After downloading the images, a standard pretreatment procedure using the atmosphere and the radiometric correction was performed before deriving the LULC classification. The data were then analyzed by ArcGIS, ENVI 5.3, IDRISI Silva, and QGIS software for LULC and LST estimation and simulation. The Support Vector Machine (SVM) algorithm was used to classify the LULC maps, which is a non-parametric classifier with a set of relevant learning algorithms. The LULC changes were simulated using the ANN-CA algorithms to forecast changes in the year 2029. The changes were predicted to determine the effect of agricultural land.

The images obtained from Landsat were classified into four broad LULC classes such as i) built-up area (Industrial area, residential, commercial and transportation network); (b) agriculture Land (green lands, agricultural lands, and vegetations); (c) water Bodies (coastal rivers, reservoirs, canals, and streams; (d) bare Land (Fallow soil, sand, and vacant soil) for the year of 1999, 2009, and 2019 based on the SVM algorithm in ENVI 5.

Around 35 samples were collected in order to produce LULC maps for each LULC class. The accuracies of maps were evaluated through 180 ground truths from available field data and Google Earth images. These 180 pixels were chosen through a random sampling process. The overall accuracy (1), user accuracy (2), producer accuracy (3), and kappa statistics (4) were calculated for accuracy assessment, which is one of the best quantitative measures for image classification accuracy.

$$\text{Overall Accuracy} = \frac{\text{Total number of corrected classified pixels (diagonal)}}{\text{total number of reference pixels}} * 100 \tag{1}$$

$$\text{User Accuracy} = \frac{\text{number of correctly classified pixels in each category (diagonal)}}{\text{total number of reference pixels in each category (row total)}} * 100 \tag{2}$$

$$\text{Producer Accuracy} = \frac{\text{number of correctly classified pixels in each category (diagonal)}}{\text{total number of reference pixels in each category (column total)}} * 100 \tag{3}$$

$$\text{Kappa Coefficient (T)} = \frac{\text{Total number of Sample} * \text{Total Number of Corrected Sample} - \sum(\text{col.tot} * \text{row tot})}{(\text{Total number of Sample})^2 - \sum(\text{col.tot} * \text{row tot})} * 100 \tag{4}$$

Simulation of future LULC changes

Because of its reputed precision, the CA model was used to forecast future patterns of LULC in many studies. Cellular Automata (CA) model was used to predict future LULC changes in the year 2029 in the study area. MOLUSCE plugin in QGIS was used to generate the future pattern in the study area. The prediction was based on two types of variables- dependent variables and independent variables. Here dependent variables were the past pattern of LULC changes estimated from 1999 through 2019 Landsat images and independent variables were distances to road, elevation, and slope. Euclidian distance function and Digital Elevation-Shuttle Radar Topography Mission (SRTM) have been used in ArcMap 10.6 to calculate dependent variables. Using a random sampling technique and setting a maximum iteration of 1000 cells (3×3 neighborhood pixels), these dependent variables help to generate the transition potential matrix as inputs.

Validation of the simulated LULC images

CA model was applied to predict future LULC changes for the year 2029 after modeling the transition potential matrix using the logistic regression method. The CA model was applied by using MOLUSCE plugin in QGIS software. This must be checked using current databases to ensure that the model is accurate in forecasting LULC change for a given predicted year. The CA model was therefore validated for its accuracy to predict the 2017 LULC changes, which was then compared to the same year's estimated LULC from Landsat data. Besides, the IDRISI Taiga software was used to validate the model by generating multiple Kappa (K) parameters: K-location, K-no, K-location strata, K-standard used to assess the model accuracy. The validation module of the QGIS- MOLUSCE tool was also used to measure the overall Kappa coefficients, and accuracy percentage between the LULC classified and predicted map of 2019.

III. Result and Discussion

Analysis of LULC change (1999 – 2019)

The pattern of shifts in LULC classes estimated from Landsat images for the years 1999 to 2019 using the SVM algorithm is shown in Fig. 2. For 1999, 2009, and 2019, respectively, Table 2, the total classification accuracy resulted as 90.25%, 89.36%, and 91.45%. The results of the accuracy find that validation rates are higher than 85% for all years, which shows clear consensus (Estoque & Murayama, 2015; Wang et al., 2017).

There were persuasive examples of two patterns of transition (Fig. 2); first, a Gradual growth of the built-up region and agricultural land and water bodies declined during the period of study. The built-up area was 161.78 km^2 (6.79%) in 1999, which increased to 440.70 km^2 (18.50%) in 2019, with a net change of +7.81%. In the meantime, in 1999, agricultural land was 1221,50 km^2 (51.28%), which slipped to 926.18 km2 (38.88%) in 2019, leading to a net change of -8.27%. Bare land was covering 703.70 km^2 (29.54%) in 1999 began to grow by 889.54 km^2 (37.34%) in 2019, showing a net change of +5.20%. In 1999, water bodies covered an area of 294.24 km^2 (12.39%) and were massively reduced to 125.67 km^2 (5.28%) in 2019, results in a net change of -4.75% (Table 3).

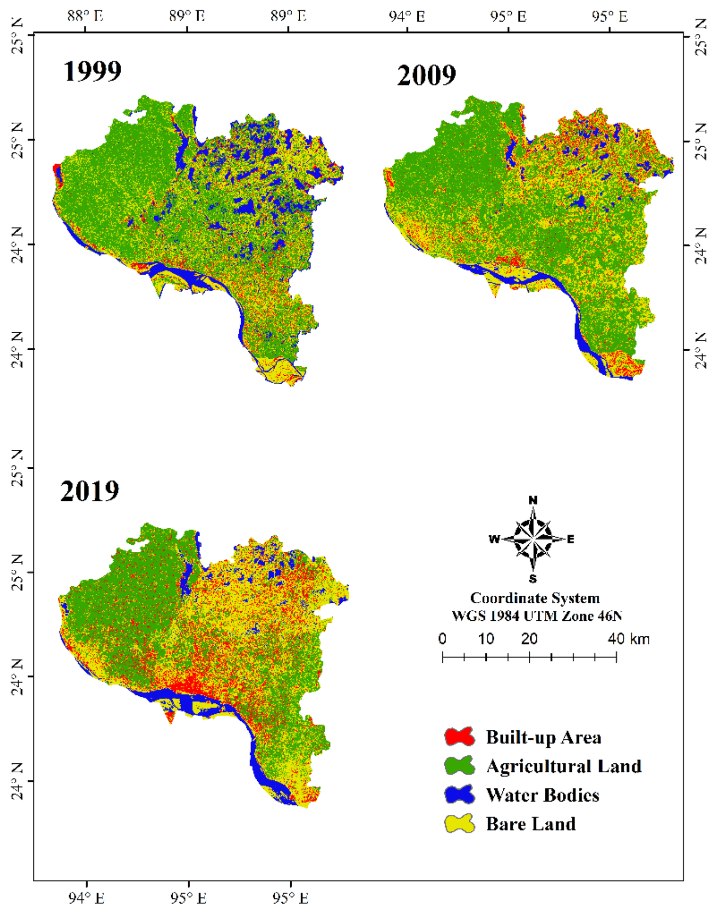

Figure 2: LULC maps of the study area estimated using SVM approach for the year 1999 to 2019

Table 2: Accuracy Assessment of classified LULC maps using Random forest Algorithm

Classified Year	User Accuracy	Producer Accuracy	Overall Accuracy	Kappa Statistics
1999	89.26	91.3	90.25	89.06
2009	91.26	88.57	89.36	90.87
2019	92.03	93.25	91.45	92.36

Table 3: Area distribution in km^2 of LULC classes and net change in percentage

LULC	1999	2009	2019	Net Change (%)
Built-up Area	161.78	270.23	440.70	+7.81
Agricultural Land	1221.50	1108.91	926.18	-8.27
Water Bodies	295.24	206.80	125.67	-4.75
Bare Land	703.70	796.29	889.54	+5.20

Built-up area expansion and degradation of agricultural land

Estimated LULC changes reveal that in the study period, agricultural land and the water body of the study area converted into built-up area and bare land. The most decreasing rate of agricultural land (12.4%) showed how rapid urban expansion and people's growth rate increased in two decades. Besides, an 11.71% increased rate of the built-up area during this study period revealed that urban areas' growth was the main factor behind losing agricultural lands of the study region. Water bodies' decreasing rate was 7.12%, whether bare land increased at a 7.8% rate during 1999-2019 in the study area (Table.4). In the last decade (2009-2019), 17.89% of the study area transformed into bare land, and 6.78% of the study area converted into built-up area, respectively Fig.3. Rapid urban growth is becoming a crucial issue now for humankind. In the study region, population growth and migration drive the built-up area increases, which caused this agricultural land degradation.

Table 4: Transformation rate of different LULC classes

	1999-2019			
Area (km2)	Water Body	Built-Up Area	Agricultural Land	Bare Land
Area change to	20.36	331.45	29.56	529.46
Area converted from	190.28	26.34	708.25	321.84
Transformation rate (%)	7.01	0.79	25.21	10.34
Increasing rate (%)	0	11.71	0	7.8
Decreasing rate (%)	-7.12	0	-12.4	0

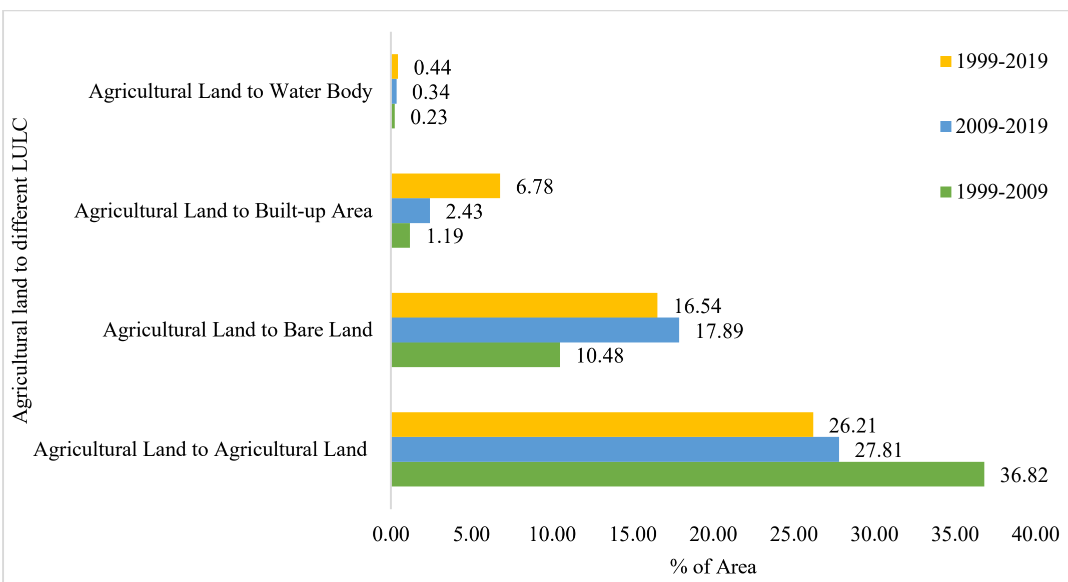

Figure 3: Agricultural Land transformation to different LULC classes

Simulation of LULC maps for the year 2029

LULC classes significantly changed during the study period (1999-2019) in the area (Fig. 4), and it was, therefore, essential to simulate the future LULC shifts. Moreover, future sustainable urban planning framework can be made from this prediction. For this reason, the validated cellular automata (CA) model was used for the simulation of LULC changes in the study area in 2029. The model was first validated by using 2019 estimated and simulated LULC changes. In the IDRISI Selva Land change module, the kappa parameters, i.e., K-location, K-no, K-location strata, and K-standard values, were 0.85, 0.82, 0.81, and 0.80. respectively Table 5. The model validation results showed that the overall Kappa value was 0.8, and %-correctness was 85.45.

Table 5: Predicted LULC model validation in IDRISI Selva and QGIS

Prediction Year	CA model validation for LULC prediction using two modules					
	Kappa Parameters of IDRISI Selva Land Change module				QGIS-MULUSCE Plugin module	
2019	K-location	K-no	K-location Strata	K-standard	%-correctness	Overall Kappa Value
	0.85	0.82	0.81	0.80	85.45	0.8

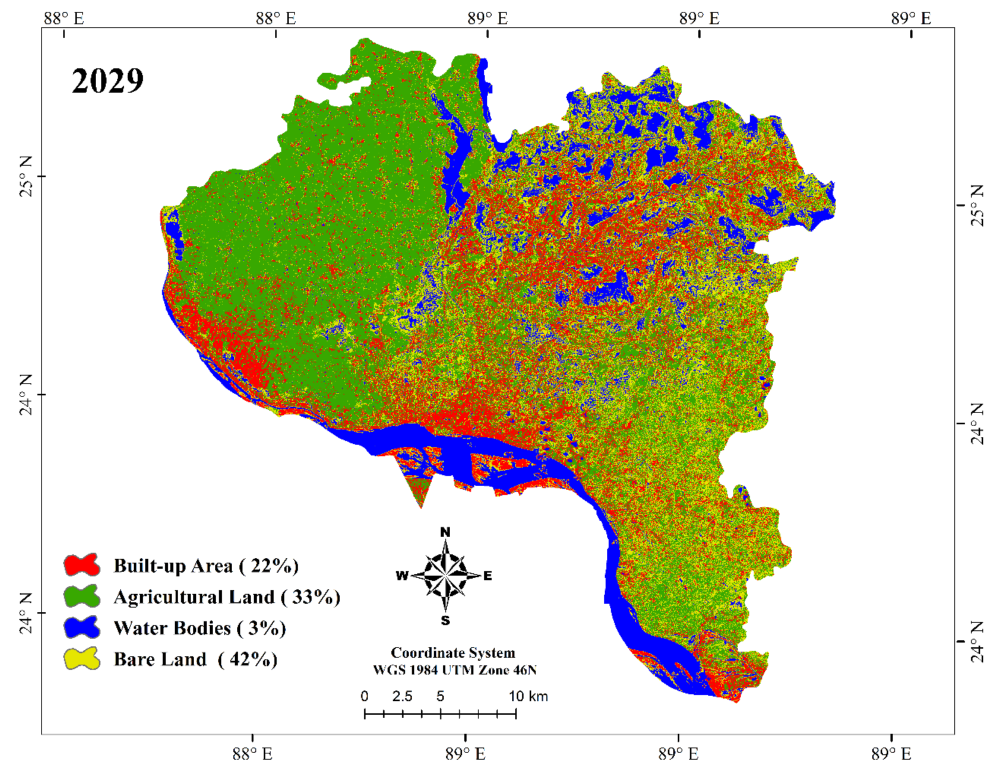

Figure 4: LULC predicted map for the study area in 2029

The prediction result revealed that if the changes rates remain constant in the future, then the urban area will increase by 3.35% from 2019 through 2029. The prediction of the decreasing rate of agricultural land will be 5.93% till 2029 from now. 7.23% of the agricultural land will be transformed into the built-up area by 2029 (Table 6). The increasing rate from 2009 to the predicted year (2029) shows 10.51% in the urban area. From 2009 to 2029, the decreasing rate of agricultural land will be 13.60% if these changes in LULC classes remain the same.

Table 6: Increasing and decreasing trend of the urban area and agricultural land

Increasing and decreasing trend	Change in a different year (%)		
	1999-2029	2009-2029	2019-2029
Increasing rate of urban area	15.06	10.51	3.35
Decreasing rate of agricultural land	-18.33	-13.60	-5.93
Transformation of agricultural land to built-up area	-9.77	-8.45	-7.23

IV. Conclusion

The study analysis showed that over the last two decades, Rajshahi had experienced changes at the fastest rate in terms of all LULC classes. The most remarkable changes found in agricultural land degradation in the study area. The most increasing rate in the built-up area showed how rapidly urban areas expanded in Rajshahi. Population growth and migration are driving this rate increase in the study area.

The CA-ANN model predicted future simulation of LULC class distribution in the study area of the year 2029 showed that the declining trend of agricultural land will continue, and it will be decreased by 18.33%. The tremendous bare land increasing rate also remarkable in this study. It will be one of the causes for making warmer conditions in the study area. Already the world is sick of global warming. For a thorough analysis, the expected impacts of such changes should be addressed, and land use management policies should be planned with this topic in mind. The adoption of sustainable environmental planning and management system would have been vital to guarantee a better environmental scenario. A robust and well-designed system policy on land use in Rajshahi will enable reducing human migration from rural to urban areas and make balances for the climate.

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