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# LAND USE CHANGE PREDICTION OF CUMILLA CITY USING GIS AND REMOTE SENSING TECHNIQUE WITH CELLULAR AUTOMATA MARKOV ANALYSIS

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## ABSTRACT

Assessment of urban growth pattern is a priority in transportation and urban planning as land use change and transportation network closely interact with each other. The objectives of this research are to develop a land use prediction model and analyse the future urban growth of Cumilla, a major city in Bangladesh. In the study, ArcGIS has been used as a data processing and Multi Criteria Evaluation (MCE) analysis platform, and mathematical modules like Markov and Cellular Automata Markov (CA Markov) have been run on IDRISI Selva edition. Three major parts of the land use prediction model on this research are 1) Markov analysis; 2) MCE; and 3) CA Markov analysis. Markov analysis predicts future temporal changes in land use classes based on two previous land use images but only determines magnitude of change, not direction. MCE analysis determines areas which are most likely to change based on various user defined criteria. These criteria might be socio-economic, demographic or spatial data and depends on the objective of the research. CA Markov analysis combines the result of Markov and MCE analysis to predict future land use pattern. Also, it overcomes the limitation of Markov analysis and adds direction to the model. First, Landsat images of 2001 and 2011 have been classified as water, trees, agricultural field and urban classes by remote sensing. From these classified imageries, an intermediate prediction of land use of 2018 has been performed through Markov analysis. Markov analysis generates a probability matrix that defines the probability of each land type turning into other types over the year. Multi-criteria evaluation (MCE) analysis has been incorporated in the process, which included factors and constraints like road, railway network, population, slope, waterbody etc. Based on these factors and constraints, most suitable areas for each land class's growth have been determined. MCE generated suitability maps for each land use type. Then, using transition probability matrix of 2018 and suitability images from MCE , CA Markov model have been run to predict final land use of 2018. This prediction of 2018 has been checked with classified land use of 2018 for validation. Afterwards, using the validated model, land use classification of 2030 has been predicted. Analyses shows that urban area will increase by almost 145% in 2030 than 2001 (Urban area was 2405 and will be 5893 hectares in 2001 and 2030 respectively). Result also shows decreased percentage of agricultural field and trees while percentage of waterbody remains almost the same. The Land use prediction model developed for Cumilla in this research can work as a framework for a more robust integrated land use transportation model for the region.

***Keywords:*** *Land use prediction podel, CA markov, Multi-criteria evaluation, Urban growth, GIS.*

## 1. INTRODUCTION

Rapid urban development has exerted heavy pressure on land and resources in and around the cities as well as caused various environmental and socio-economic problems. So, prediction of urban growth and forecasting land use change pattern carry a lot of significance to the planners and policy makers (Kashem, 2008). Developing countries lack comprehensive decision making process and planning regarding urban development. As a result, they are experiencing rapid and unplanned urban sprawl (Kashem & Maniruzzaman, 2008).

Bangladesh possesses few fast growing cities like Dhaka, Chattogram, Cumilla, Bagura, Gazipur etc. Among them Dhaka, the capital of Bangladesh, has already faced a lot of geospatial changes over the decades. Previously, land cover changes and urban expansion of Dhaka between 1975 and 2003 have been analyzed using satellite images and socio-economic data by Dewan and Yamaguchi (2009). Also, Ahmed (2011) has examined spatio-temporal growth dynamics of Dhaka between 1989 to 2009, using remote sensing and GIS techniques.

Prediction of land use change is a complex process, dependent on many variables. For developing countries, scarcity of detail historical and socio-economic data is also a setback. In such cases, combination of Markov Chain (MC) model and Cellular Automata (CA) model presents the best outcome. Markov Chain model is a probabilistic model which predicts how a land will change from one mutually exclusive state to another (Thomas & Laurence, 2006). It calculates the change between two previous time periods ‘t’ and ‘t-1’. Based on the past change, it predicts future change at time ‘t+1’. The MC model analyzes two historical land cover images and generates a transition probability matrix, a transition area matrix, and some conditional probability images (Eastman, 2006; Takada et al., 2010). Yet, a stochastic Markov model isn’t accurate as it only gives right magnitude of change but not the right direction (Boerner et al. 1996). Cellular Automata (CA) adds direction to the model by incorporating spatial component (Soe & Le, 2006). The combined Markov-CA model overcomes the limitations of markov model. Multi Criteria Evaluation (MCE) analysis adds an element of spatial contiguity, specific decision, and also the knowledge of dynamic distribution in the model (Sang et al., 2011). MCE analysis is also known as suitability analysis. The MCE analysis uses various user-defined criteria, which can either be a factor or a constraint (Eastman 2006), to develop suitability images for each land class.

Based on this method, a model to predict land use change of Cumilla, a major city along the Dhaka-Chattogram highway , has been developed in this study. The Dhaka-Chattogram highway is known as principle economic corridor of Bangladesh, connecting the port city Chattogram to capital city Dhaka. Recently, the highway has been developed into a four lane corridor. In addition, major development works are underway along this route which makes Cumilla a potential study area to analyze future land use change.

Principle objectives of this research are:

1. To develop a land use prediction model for Cumilla
2. To quantify the rate of urban growth of Cumilla

In this study, ArcGIS has been used as a data processing and Multi Criteria Evaluation analysis platform, and IDRISI Selva has been used as a mathematical module. The IDRISI Selva is an integrated GIS and image processing software which facilitates not only format conversion between data sets, map composition, and map display but also provides statistical analysis, time-series analysis, spatial land use analysis, and decision support analysis.

## 2. METHODOLOGY

### 2.1 Study Area

Cumilla district is under Chattogram Division of Bangladesh, having an area of 3146 km$^2$. The district is well connected with the whole country with rail and road network. Focus of this study is the city area of Cumilla, which is along the Dhaka-Chattogram highway. Therefore, 3 upazillas of Cumilla District: Cumilla Adarsha Sadar, Cumilla Sadar Dakshin and Burichang have been selected as Study area (Figure 1). The selected portion of Cumilla District covers a large urban agglomeration and is the central part of Cumilla city in terms of social and economic aspects. As a result, it is undergoing rapid unplanned urbanization.

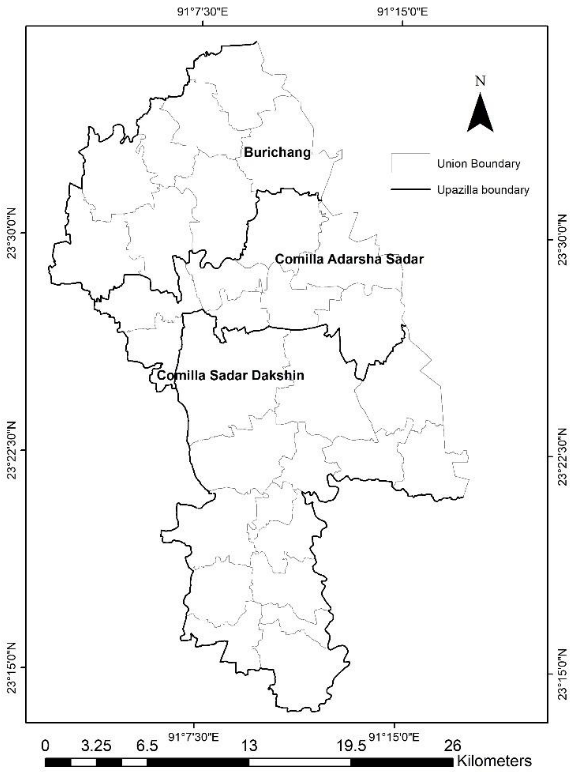



Figure 1: Study Area

### 2.2 Data Collection

Three types of data have been used to develop the model. Data types along with their sources are mentioned below-

1. Satellite Images of year 2001, 2011 and 2018: USGS
2. Historic Google Earth Images as Reference Data: Google Earth
3. Socio-economic, demographic and spatial data: Survey of Bangladesh (SoB)

Satellite images have been collected from official website of United States Geological Survey (USGS). Depending on availability, images from Landsat 4-5, 7 and 8 satellites have been downloaded. Landsat 4-5 and 7 images of 2001 and 2011 have 7 spectral bands and Landsat 8 image of 2018 have 8 spectral bands. From these bands, False Color Composite (FCC) of Red, Green and Blue (RGB) bands 4-3-2 has been used in this research. For avoiding the effect of seasonal variation in remote sensing, the images are of the same season (March and April).

### 2.3 Image classification

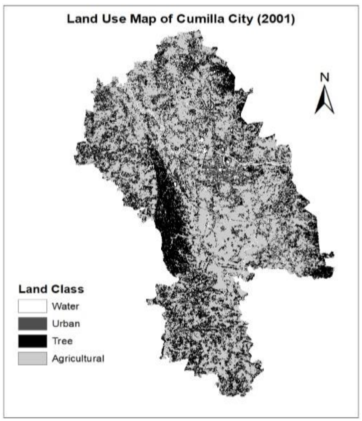
Two basic methods of image classification are used for remote sensing: supervised and unsupervised. For supervised classification, one need to know about the terrain of the concerned area. Therefore, for this research, a supervised classification method has been used. ArcGIS 10.5.3 has been used as remote sensing platform for classification.

Each Landsat images were classified into four land use classes: Water, Trees, Agricultural Field and Urban Area. In RGB 4-3-2 combination, urban areas appear blue, vegetation red, water bodies from dark blue to black, soils with no vegetation from white to brown (Geospatial Data Service Centre, 2008). First, several training sites were developed for each land class. More than one training sites were defined for each class. The vector files of the similar training sites indicated pixels which were used to develop signature files. These signature files consist statistical information about reflectance value of the pixels of each land cover type (Eastman, 2009). After that, Fisher Classifier was used to classify the images based on the signature files. Fisher classifier works best when there are very few unknown areas in an image and representative training sites are available (Eastman, 2009). In this research the satellite images have been classified into four land classes as shown in the Table 1 below-

Table 1: Details of the land Cover Classes

| Land Cover Classes | Description |
|---|---|
| **Water** | River, permanent open water, lakes, ponds, canals and reservoirs. |
| **Trees** | Trees, shrub lands and semi natural vegetation, deciduous, coniferous and mixed forest, palms, orchard, herbs, climbers. |
| **Agricultural Field** | Agricultural field, Fallow land, earth and sand land in-fillings, open space, bare and exposed soils, grasslands and vegetable lands. |
| **Urban** | All residential, commercial and industrial areas, villages, settlements and transportation infrastructure. |

The final stage of image classification process is accuracy assessment. For accuracy assessment, random points were chosen from the classified images. Land class of each point was added to its attribute. Next, the points were placed on google earth historic images i.e. points from classified 2001 Landsat images were placed on 2001 google earth image of that area. The land class type from google earth was given input as another attribute in these points and compared with the previous attributes. The accuracy for 2001, 2011 and 2018 images were found 86%, 87% and 91% respectively. Classified Land Use images of 2001 and 2011 are shown in Figure 2.



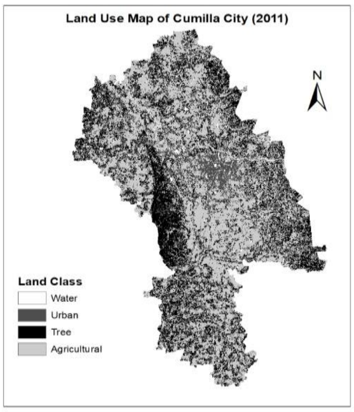




Figure 2: Classified Images of 2001 and 2011 of Cumilla City

### 2.4 Markov Analysis

Markov Analysis is a stochastic process that predicts future land use change at time 't+1' based on the change between two previous land use at time 't' and 't-1' respectively. In this research, Markov model has been run on IDRISI Selva 17.0 edition. Land use images of 2001 and 2011 were used as base years to predict land use change in year 2030. But first for validation purpose, land use map of 2018 was predicted with Markov model. Markov analysis produces a transition matrix (Table 2), a transition area matrix, and a set of conditional probability images for each land class. The transition matrix shows the probability at which one category will change into other categories in future. Table 3 shows the number of cells that will transform into other land types over time.

Table 2: Markov Probability of Changing Land Cover Types

| | **Waterbody** | **Trees** | **Agricultural Field** | **Urban** |
|---|---|---|---|---|
| **Waterbody** | 0.4629 | 0.2912 | 0.0897 | 0.1562 |
| **Trees** | 0.0291 | 0.4887 | 0.4011 | 0.0811 |
| **Agricultural Field** | 0.0378 | 0.2269 | 0.6980 | 0.0374 |
| **Urban** | 0.0902 | 0.1873 | 0.1732 | 0.5529 |

Table 3: Expected Cell Transition to Different Land Classes

| | **Waterbody** | **Trees** | **Agricultural Field** | **Urban** |
|---|---|---|---|---|
| **Waterbody** | 15852 | 99973 | 3073 | 5350 |
| **Trees** | 5109 | 85954 | 70545 | 14264 |
| **Agricultural Field** | 13283 | 79727 | 245284 | 13134 |
| **Urban** | 4363 | 8891 | 8382 | 26755 |

### 2.5 Multi Criteria Evaluation (MCE) Analysis

Performing a Cellular Automata-Markov (CA Markov) analysis requires suitability images. Suitability image of a land class shows which areas are suitable for that particular land class's future growth. In this way, suitability images add direction to CA Markov analysis. Suitability images are developed through Multi Criteria Evaluation analysis. In this study, ArcGIS has been used as MCE analysis platform.

Each land class requires a separate suitability image. And for that, MCE analysis had to be performed separately for each land class. It uses various user-defined criteria which can either be a factor or a constraint. A factor facilitates growth while a constraint impedes development. Road and rail network, waterbodies, slope, population density and urban developed sites were used as various criteria for MCE analysis. The factors were assigned with weighted values based on various literature review and authors' judgement. The constrains were assigned as Null value which restricted any growth in those regions. Table 4 shows weighted values for developing Urban suitability image.

Table 4: Weighted Value of Criteria Assigned to Urban Suitability Analysis

| **Factor/Constraint** | **Criteria** | **Weighted Value (%)** |
|---|---|---|
| Factor | Distance from Road | 15% |
| | Distance from existing Urban Area | 25% |
| | Slope | 10% |
| | Population | 20% |

| | | |
|---|---|---|
| | Classified base map of 2011 | 30% |
| Constraint | Water Body | Null value |
| | Road Network | Null value |
| | Rail Network | Null value |

Figure 3 presents the suitability image for each land class. The higher the value (from 0 to 6), higher the chance of that cell to turn into that land class.

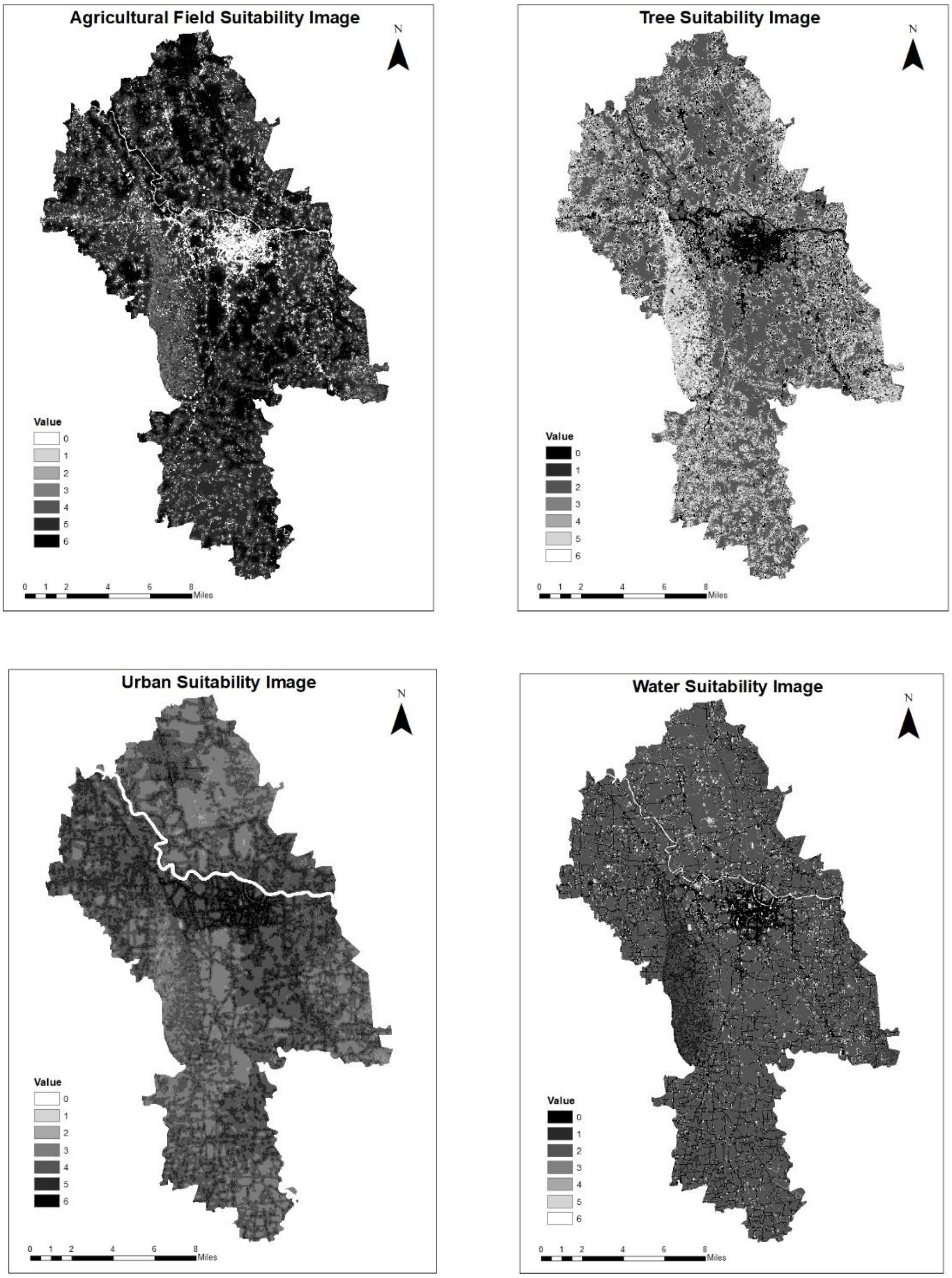



Figure 3: Suitability Map of different Classes (Higher Value indicates Higher Suitability)

### 2.6 Model Validation

For model validation, first Markov analysis was used for predicting 2018 land use which generated a transitional probability matrix for year 2018 specifiaclly. After that, suitability images were developed by MCE analysis. Then, CA Markov module was run with the transitional probability matrix of 2018 and four suitability images. CA Markov module also needs a basis land cover image which is the later land use images of the two base images (in this case image of 2011). From this predicted land use image of 2018 was obtained. The predicted image was compared with the classified Landsat image of 2018. The comparison is presented in Table 5 which shows that the model is validated.

Table 5: Statistical Comparison between Classified and Simulated Map

| **Land Cover Type** | **Classified Map (2018)** | | **Simulated Map (2018)** | | **Change in Area (%)** |
|---|---|---|---|---|---|
| | **Area (km$^2$)** | **%** | **Area (km$^2$)** | **%** | |
| **Water body** | 28.417 | 5.17745 | 32.4656 | 5.92087 | 0.74% |
| **Trees** | 171.339 | 31.2172 | 167.404 | 30.5301 | 0.7% |
| **Agricultural Land** | 295.752 | 53.8847 | 294.791 | 53.7621 | 0.12% |
| **Urban** | 53.3528 | 9.72064 | 53.0436 | 9.67375 | 0.05% |

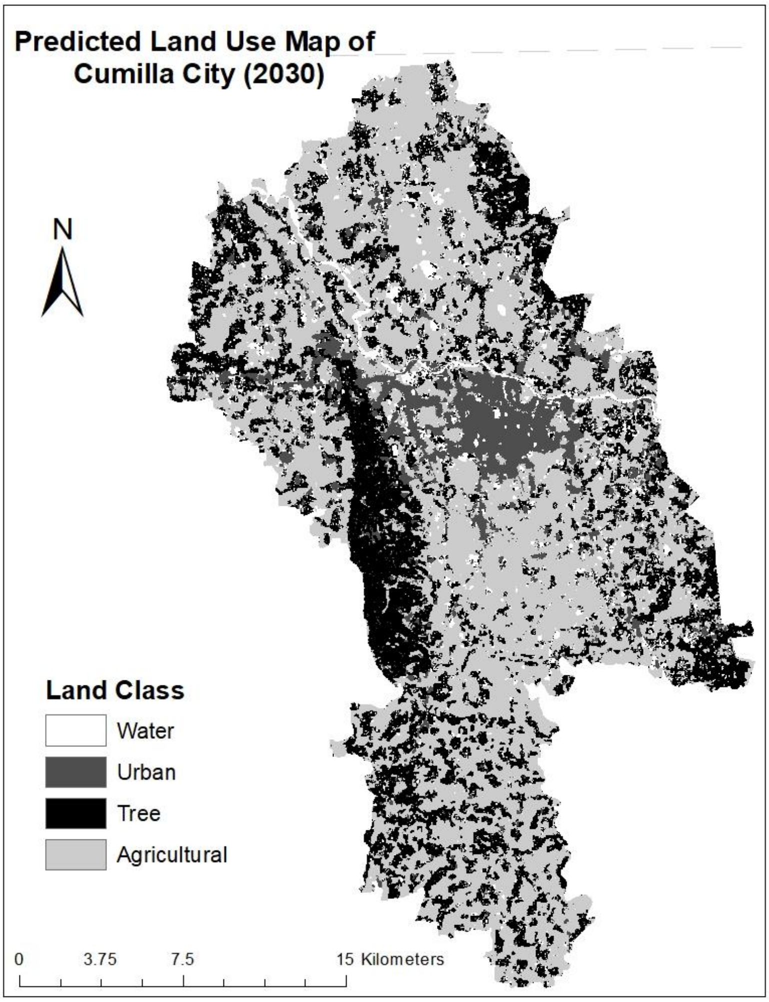



Figure 4: Predicted Land Use Map of 2030 of Cumilla City

### 2.7 Final Prediction

With the validated model, land use of 2030 was predicted for Cumilla city. First, Makrov analysis was performed to obtain a transition probability matrix for 2030. Suitability images for each classes remained same. Afterwards, CA Markov analysis was done with the transition probability matrix of 2030, suitability images, and basis year image of 2011. Figure 4 shows the predicted image of 2030.

## 3. RESULT ANALYSIS

Figure 5 represents the area (hectare) under each land class type of predicted 2030 land use map. Area under Urban Class in 2030 is 5893 ha, which was 2405 ha in 2001. So, there is an 145% increase in Urban land class type.

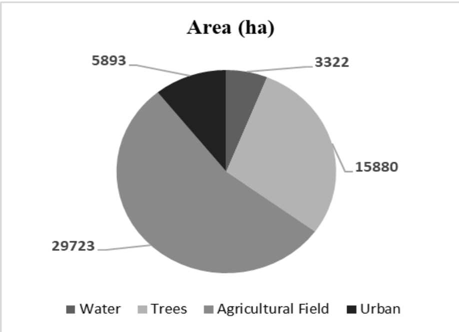



Figure 4: Area Occupied by Different Land Cover Type in 2030

Area occupied by water land class (3322 ha) will stay almost the same as 2001 (54.23% in 2030 and 54.45% in 2001) while there is a loss of area in tree and agricultural field land classes. A comparison of different land classes over the year is presented in Figure 5.

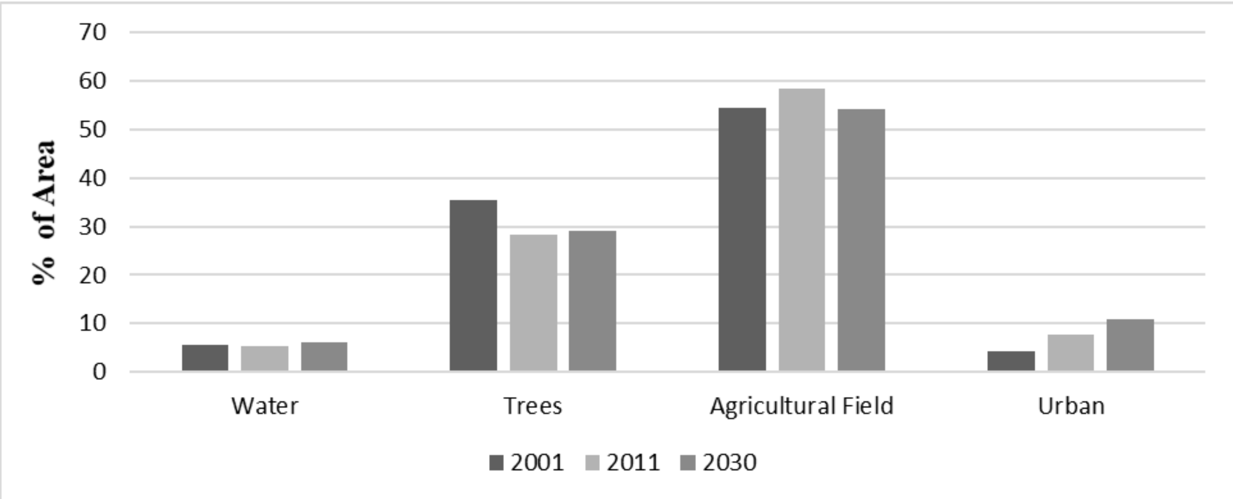



Figure 5: Comparison between Various Land Classes for year 2001, 2011 and 2030

## 4. DISCUSSION

Land Use Prediction model developed though this study shows a growing pattern of Cumilla city. There will be an almost 145% rise in urban area in 2030 compared to 2001. Meanwhile, other land classes will be losing their parts. This depicts the widely seen picture of rapid urban development around the world. However, the model has some limitations. Satellite data has been collected from free sources, therefore, contains a coarse resolution of 30m×30m cell size. It might have affected the accuracy of remote sensing. Also, various socio-economic and spatial data for specific area like Cumilla are rarely available. So, the authors had to limit themselves in choosing criteria for MCE analysis depending on available data. MCE analysis is a crucial part of land use prediction. In case of availability of sufficient data, this analysis could be done more precisely by adding more criteria.

However, this model is one of the first land use prediction models developed for a crucial city like Cumilla. In future, this model might be used as a framework model in developing a robust land use prediction model for the region. Overcoming the constraints might help to develop a complete integrated land use and transportation planning tool for engineers, planners and policy makers to help them make befitting decisions.

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