

Modelling Spatio-Temporal Urban Land Cover Growth Dynamics Using Remote Sensing and GIS Techniques: A Case Study of Khulna City

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Abstract

The primary objective of this paper is to predict and analyze the future urban growth of Khulna City using the Landsat satellite images of 1989, 1999 and 2009. Khulna City Corporation (KCC) and its surrounding impact areas have been selected as the study area. At the beginning, a fisher supervised classification method has been applied to prepare the base maps with five broad land cover classes. In the next stage, three different models have been implemented to simulate the land cover map of Khulna City of 2009. These are named as 'Stochastic Markov (St_Markov)' model, 'Cellular Automata Markov (CA_Markov)' model and 'Multi Layer Perceptron Markov (MLP_Markov)' model. Then the best-fitted model has been selected based on various Kappa statistics values. This is how the 'Multi Layer Perceptron Markov (MLP_Markov)' model has been qualified as the most suitable model for this research. Later, using the MLP_Markov model, the land cover map of 2019 has been predicted. The MLP_Markov model shows that 33.33% of the total study area will be converted into built up area in 2019.

Introduction

Khulna, the 3rd largest city and the 2nd port entry of Bangladesh has been developed largely in an unplanned manner. Other than infrastructure, services and major institutions, most of the city's establishments are developed in an unplanned fashion by private initiatives (Master Plan, Khulna City, 2002:4).

Although the history of Khulna City extends over more than a century, its growth and development took place in the recent decades, particularly in the post partition (1947) and post liberation (1971) periods. In 1991, the population of Khulna City Corporation (KCC) was 6, 63,000. As per the 2007 estimation, the population of KCC area increased to 1,400,689 (Urban Strategy, Khulna City, 2002:31).

The increasing population pressure makes adverse impacts on Khulna city, like unplanned urban growth, extensive urban poverty, water logging, growth of urban slums and squatters, traffic jam, environmental pollution and other socio-economic problems. In the process of urbanization, the physical characteristics of the city are gradually changing as plots and open spaces have been transformed into building areas, low land and water bodies into reclaimed built-up lands etc. If this situation continues then Khulna would soon become an urban slum with the least livable situation for the city dwellers (Urban Strategy, Khulna City, 2002:42).

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In the above context, the main objective of this research is to forecast the future urban growth of the selected study area within greater Khulna City.

Applications and Prospects of Remote Sensing in Urban Planning

Remote Sensing (RS) and Geographic Information System (GIS) techniques are being widely used to assess natural resources and monitor environmental changes. It is possible to analyze land use/ land cover change dynamics using time series of remotely sensed data and linking it with socio-economic or bio-physical data using GIS. The incorporation of GIS and RS can help analyzing this kind of research in variety of ways, like land cover mapping, detecting and monitoring land cover change over time, identifying land use attributes and land cover change hot spots etc (Lambin, 2001). With the advancement of technology, reduction in data cost, availability of historic spatio-temporal data and high resolution satellite images, GIS and RS techniques are now very useful for conducting researches, like land cover change detection analysis and predicting the future scenario (Das, 2009).

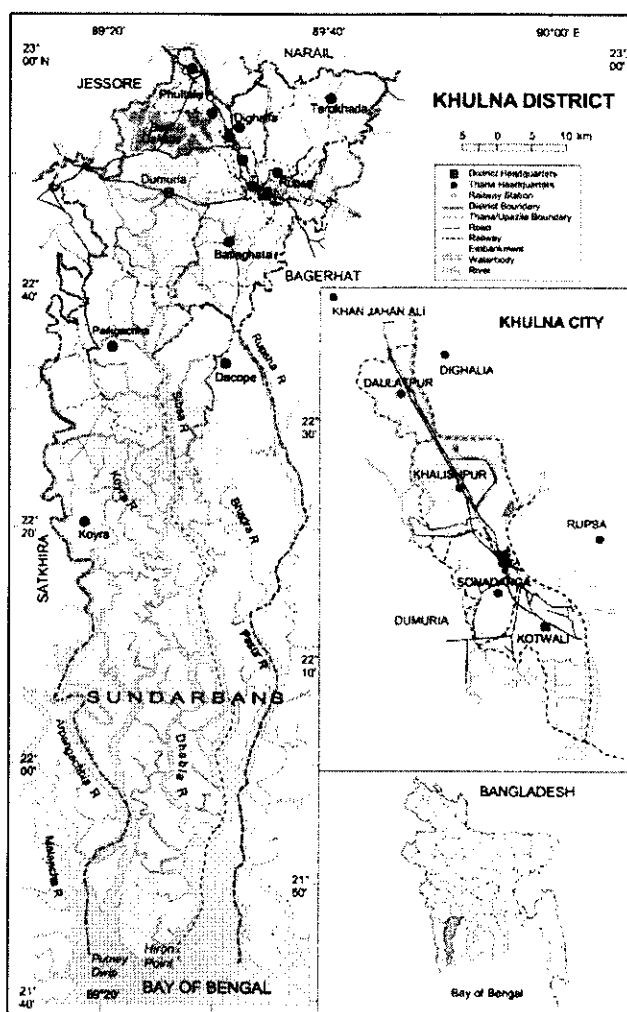
Information on land use and land cover is required in many aspects of land use planning and policy development, as a prerequisite for monitoring and modeling land use and environmental change, and as a basis for land use statistics at all levels (Billah and Rahman, 2004). RS can provide frequent land cover of an area which can be a useful tool to monitor urban land use pattern and change for physical planning of an urban area. The use of satellite image is popular worldwide, but its application is limited in Bangladesh. RS technology has already been proved as a time saving and economic technology than any other method of spatial purpose map preparation and spatial data collection. Data related to land space is an important and basic tool to urban planners. Remote sensing can provide required data in short time with a reasonable accuracy. Planners may use this data to monitor urban growth pattern, urban sprawl, land management, urban structural change and to find out potential land for development (Billah and Rahman, 2004).

Everything on earth is changing with time. Land cover map can be a powerful tool to compare the changes of an area over time. It is impossible to cover a large area in short time through manual survey, but with remote sensing it is an easier task.

Study Area

The study area for this research is Khulna City Corporation (KCC) and its surrounding impact areas (Figure 1 and Figure 2). Geographically, Khulna lies at 22°49' north latitude and 89°34' east longitudes. Its mean elevation is 7 feet above Mean Sea Level. Khulna is a linear shaped city. Environmentally, Khulna is comparatively in the less risk zone in terms of flood, cyclone and earthquake. However, any rise in the sea level may affect Khulna directly (Urban Strategy, Khulna City, 2002:27). The importance of the city lies in a number of strategic factors. First, the city provides important links to the second seaport of the country, namely *Mongla* port. Secondly, the city has a strong industrial base. Finally, Khulna is the ultimate source of export processing activities on shrimp cultivation, which is virtually the second biggest foreign exchange earner in Bangladesh, after ready-made garments (Urban Strategy, Khulna City, 2002:25).

Within the KCC core area, there are roughly 11,280 acres of land. Nearly 10 percent of these lands are not yet in urban use. This means that about 1100 acres of land are available within KCC for future urban growth (Structure Plan, Khulna City, 2002:59).

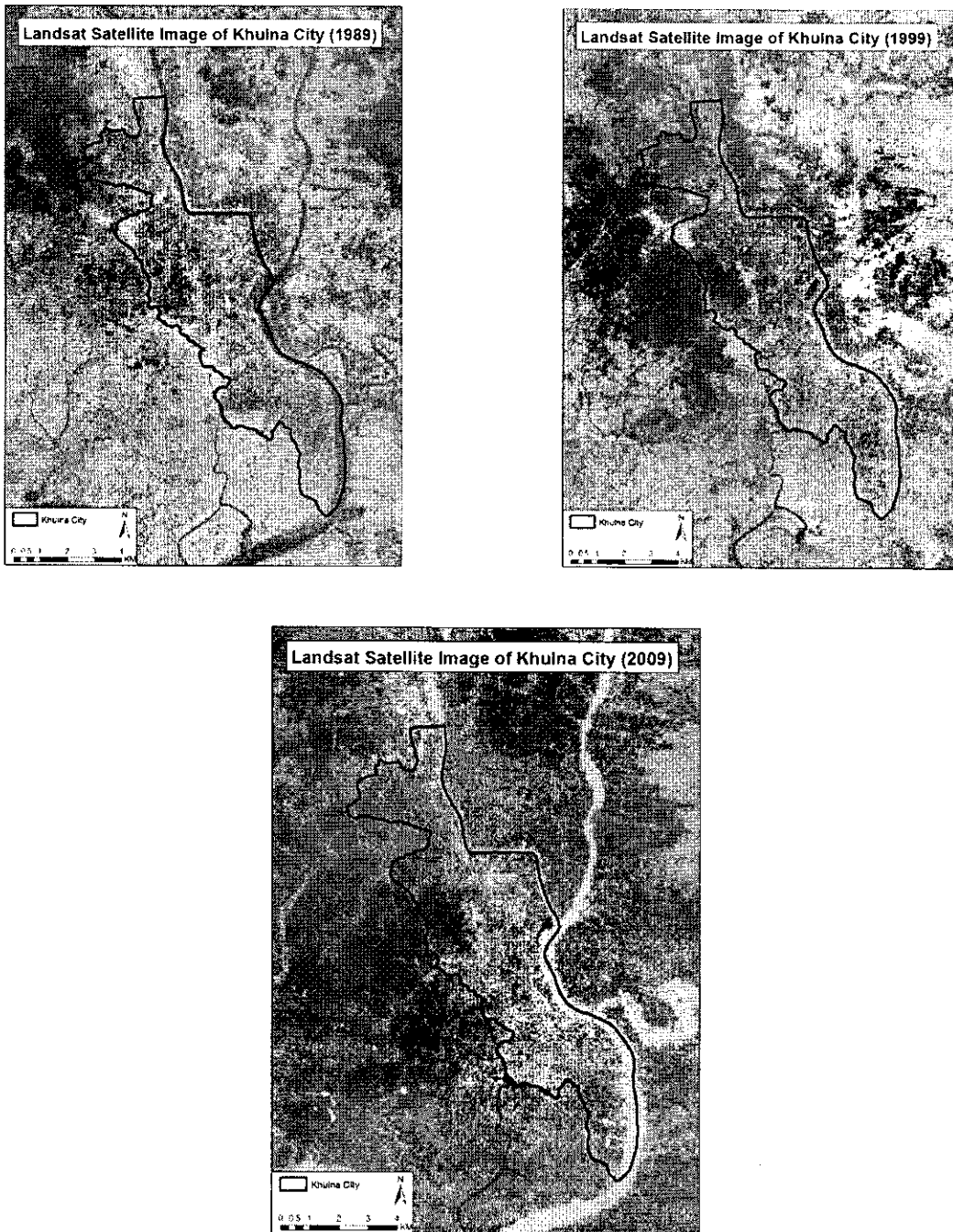


Source: Banglapedia, National Encyclopedia of Bangladesh, 2011.

Fig. 1: Location of Khulna City in Bangladesh.

Base Map Preparation

An in-depth study and analysis of the maps of the study area is made in this research. For the application of different methods to achieve the research objective, the Landsat satellite images (1989, 1999 and 2009) have been collected from the official website of U.S. Geological Survey. Landsat Path 137 Row 44 covers the whole study area. Map Projection of the collected satellite images is Universal Transverse Mercator (UTM) within Zone 46 N– Datum World Geodetic System (WGS) 84 and the pixel size is 30 meters. Five land cover types have been identified for this research (Table 1).



Source: U.S. Geological Survey (USGS), 2010 and Shapefile, Khulna.

Fig. 2: Location of the Study Area (Areas of Khulna City Corporation and Adjoining Fringe Areas) on Landsat Satellite Images of different times. Map prepared by the researcher; Image of Khulna City Corporation (KCC), 2008.

Table 1: Details of the land cover types.

Land Cover Type	Description
Builtup Area	All residential, commercial and industrial areas, villages, settlements and transportation infrastructure.
Water Body	River, permanent open water, lakes, ponds, canals and reservoirs.
Vegetation	Trees, shrub lands and semi natural vegetation: deciduous, coniferous, and mixed forest, palms, orchard, herbs, climbers, gardens, inner-city recreational areas, parks and playgrounds, grassland and vegetable lands.
Low Land	Permanent and seasonal wetlands, low-lying areas, marshy land, rills and gully, swamps, mudflats, all cultivated areas including urban agriculture; crop fields and rice-paddies.
Fallow Land	Fallow land, earth and sand land in-fillings, construction sites, developed land, excavation sites, solid waste landfills, open space, bare and exposed soils.

For the purpose of ground-truthing/ referencing, several base maps of Khulna City have been collected from the Survey of Bangladesh (SoB). Google Earth is another option to get some ideas about the recent land cover pattern. The detail land use map (2009) of has been collected from the Khulna City Corporation (KCC). These reference data have been used for training site selection and accuracy assessment of the final land cover maps.

To classify the images, a 'Supervised Classification' method has been used (Eastman, 2009). At the beginning, the training sites are developed based on the collected reference data and ancillary information. After developing signature files for all the land cover types, the images have been classified using a hard classifier called 'Fisher Classifier'. Fisher performs linear discrimination analysis (Eastman, 2009). Then a 3×3 mode filter has been applied to generalize the fisher classified land cover images. This post-processing operation replaces the isolated pixels to the most common neighbouring class. Finally, the generalized images are reclassified to produce the final version of land cover maps for different years (Figure 3).

Accuracy Assessment

The next stage of image classification process is accuracy assessment. For each classified image 250 reference pixels have been generated using stratified random distribution process. Then the collected base maps have been used to find the land cover types of the reference points. The overall accuracies for 1989, 1999 and 2009 are found 85.89%, 87.56% and 92.78% respectively, with kappa statistics of 0.8021, 0.8398 and 0.8649. It is typical that most land cover classification images are 85% accurate (Eastman, 2009). Therefore, it can be stated that the classification accuracy achieved here is above the satisfactory level.

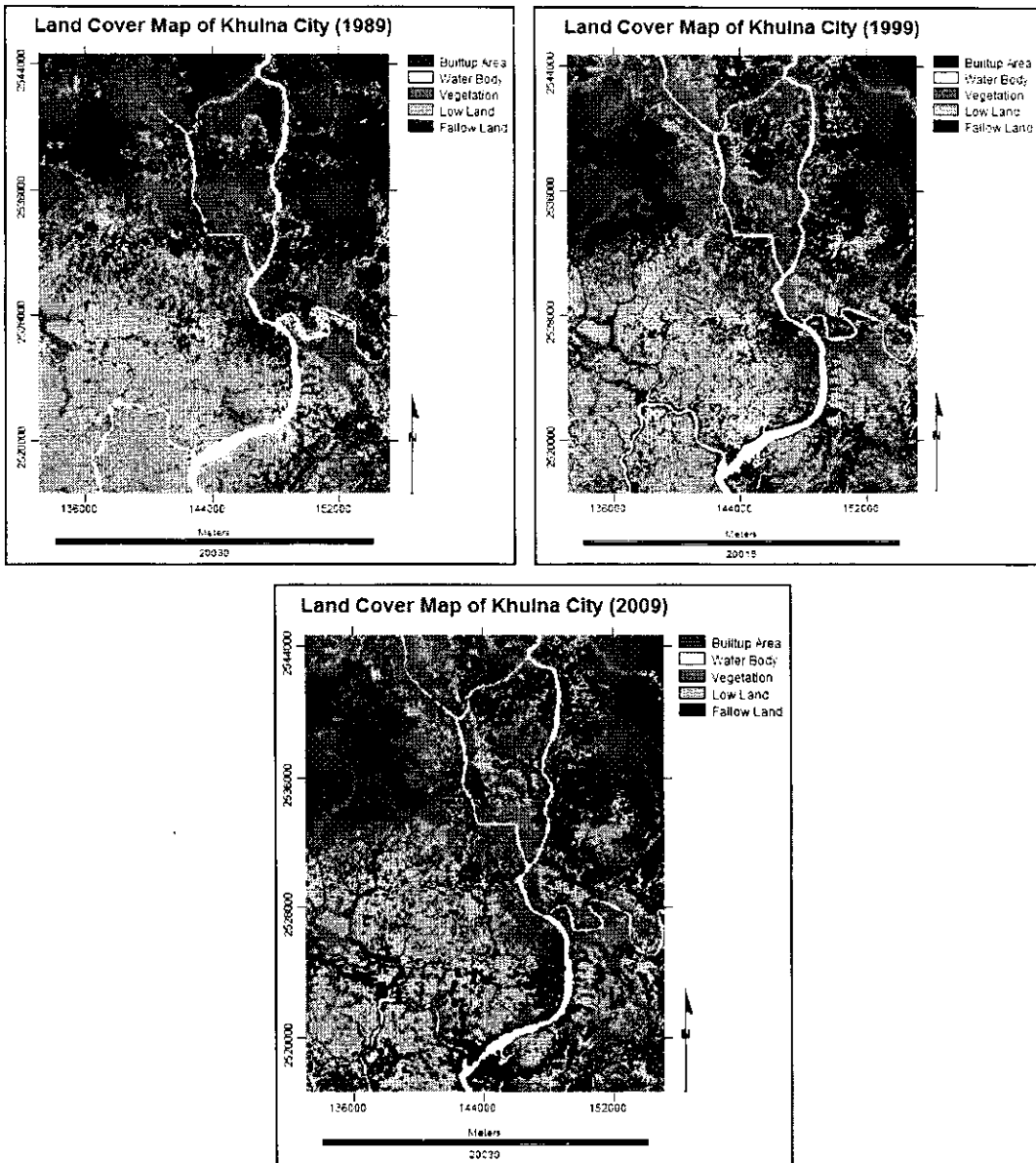


Fig. 3: Final land cover maps of the Study Area.

Methods, Results and Discussion

Stochastic Markov Model

The first model that has been implemented is given the name as 'Stochastic Markov Model (St_Markov), because this model combines both the stochastic processes as well Markov chain analysis techniques (Basharin *et al*, 2004). This kind of predictive land cover change modelling is suitable when the past trend of land cover changing pattern is known (Eastman, 2009). A Markov chain is a stochastic process (based on probabilities)

with discrete state space and discrete or continuous parameter space (Balzter, 2000). In this random process, the state of a system s at time $(t+1)$ depends only on the state of the system at time t , not on the previous states. Here the past and future are independent (Eastman, 2009). At the beginning, Markov chain produces a transition matrix (Table 2), a transition areas matrix (Table 3) and a set of conditional probability images by analyzing two qualitative land cover images (Figure 4) from two different dates 1989 and 1999 (Eastman, 2009).

Table 2: Markov probability of changing among Land Cover Types (1989-1999).

	Builtup Area	Water Body	Vegetation	Low Land	Fallow Land
Builtup Area	0.3194	0.0242	0.0870	0.4383	0.1312
Water Body	0.3010	0.6129	0.0228	0.0531	0.0103
Vegetation	0.0545	0.0019	0.6699	0.2341	0.0395
Low Land	0.2504	0.0128	0.1254	0.5134	0.0979
Fallow Land	0.1834	0.0010	0.0877	0.2250	0.5028

Table 3: Cells expected to transition to different classes (1989-1999).

	Builtup Area	Water Body	Vegetation	Low Land	Fallow Land
Builtup Area	41895	3170	11414	57490	17209
Water Body	8086	16467	612	1425	276
Vegetation	7373	253	90614	31667	5349
Low Land	63411	3253	31757	129982	24793
Fallow Land	25843	148	12363	31711	70862

The matrix of transition probabilities (Table 2) shows the probability that each land cover category will change to other categories in 2009. Table 3 presents the number of cells (30 m \times 30 m) that will be transformed over time from one land cover type to other types. Markov Chain Analysis also produces related conditional probability images (Figure 4) with the help of transition probability matrices. Each conditional probability image shows the possibility of transitioning to another land cover class. It is clear that the Markovian conditional probability of being builtup area ranges upto 0.32 (Figure 4). It indicates that most areas will convert into builtup areas. This probabilistic prediction is dependent upon the past trend of the last ten years (1989-1999).

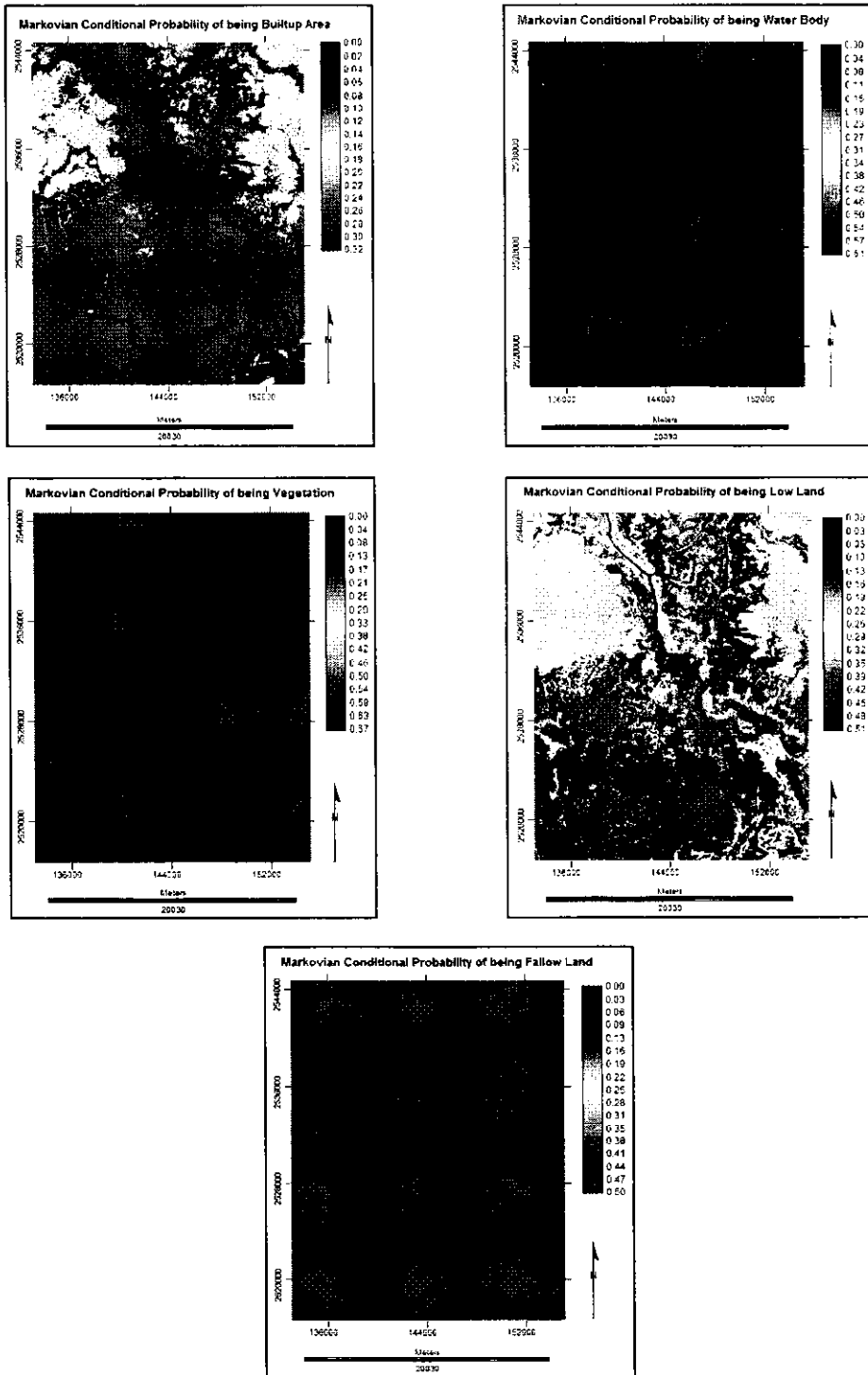


Fig. 4: Markovian conditional probability images, 1989-1999.

The next step is to make one map for future prediction aggregating all the Markovian conditional probability images. This prediction is performed by a stochastic choice decision model which creates a stochastic land cover map by evaluating and aggregating the conditional probabilities in which each land cover can exist at each pixel location against a rectilinear random distribution of probabilities (Eastman, 2009). The Stochastic Markov predicted land cover map of 2009 is shown in Figure 5.

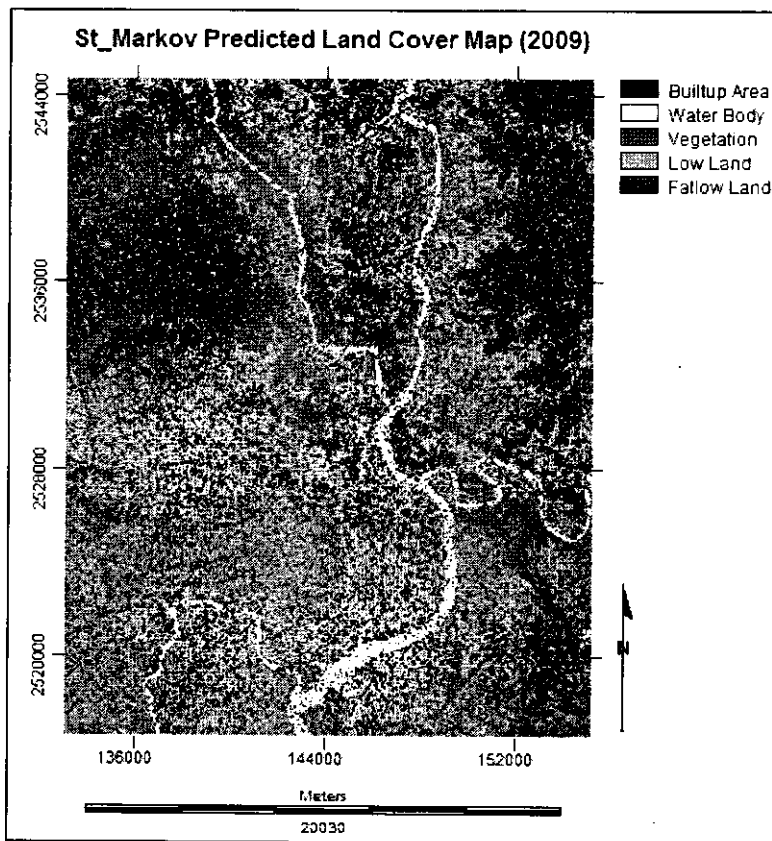


Fig. 5: St_Markov predicted land cover map of Khulna City, 2009.

Cellular Automata Markov Model

The second model that has been implemented is named as 'Cellular Automata Markov Model (CA_Markov). CA_Markov combines the concepts of Markov Chain, Cellular Automata (Maerivoet, 2005), Multi-Criteria Evaluation (Malczewski, 2004) and Multi-Objective Land Allocation (Eastman, 2009). CA_Markov is useful for modelling the state of several categories of a cell based on a matrix of Markov transition areas; transitional suitability images and a user defined contiguity filter. A Markov model applies contiguity rule like a pixel near to an urban area is most likely to be changed into urban area (Eastman, 2009). In this research, a 3×3 mean contiguity filter has been used (Figure 6) for modelling purpose.

0	1	0
1	1	1
0	1	0

Fig. 6: The 3 × 3 Mean Contiguity Filter for CA_Markov Modelling.

The next step is to prepare suitability maps for the land cover types. The basic assumption used for preparing suitability images is “the pixel closer to an existing land cover type has the higher suitability”. It means a pixel completely within vegetation has the highest suitability value (255) and pixels far from existing vegetation pixels will have less suitability values. The farthest pixels from vegetation will show the lowest suitability values. Here the suitability decreases with distance. Therefore, a simple linear distance decay function is appropriate for this basic assumption. The land cover maps have been standardized (Figure 7) to the same continuous suitability scale (0-255) using fuzzy set membership analysis process (Eastman, 2009).

At the end, the Markov transition area matrix (Table 3), all the suitability images (Figure 4), the 3×3 CA contiguity filter (Figure 6) and the base map of Khulna city (1999) have been used to predict the land cover map of 2009. The CA_Markov predicted final land cover image (2009) of Khulna city is illustrated in Figure 8.

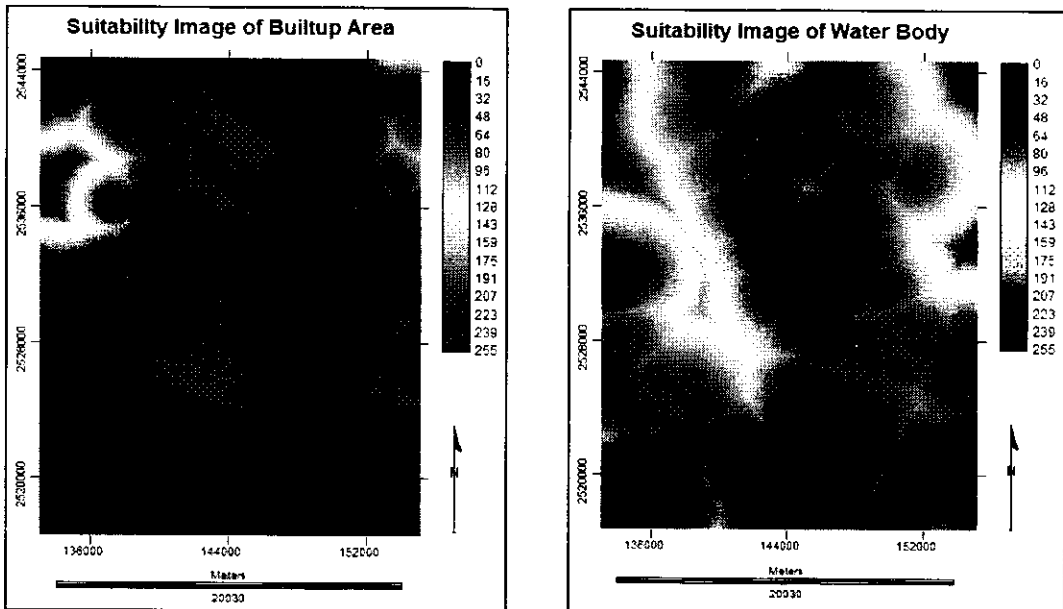


Fig. 7: Suitability images of each land cover type, 1999 (Continued).

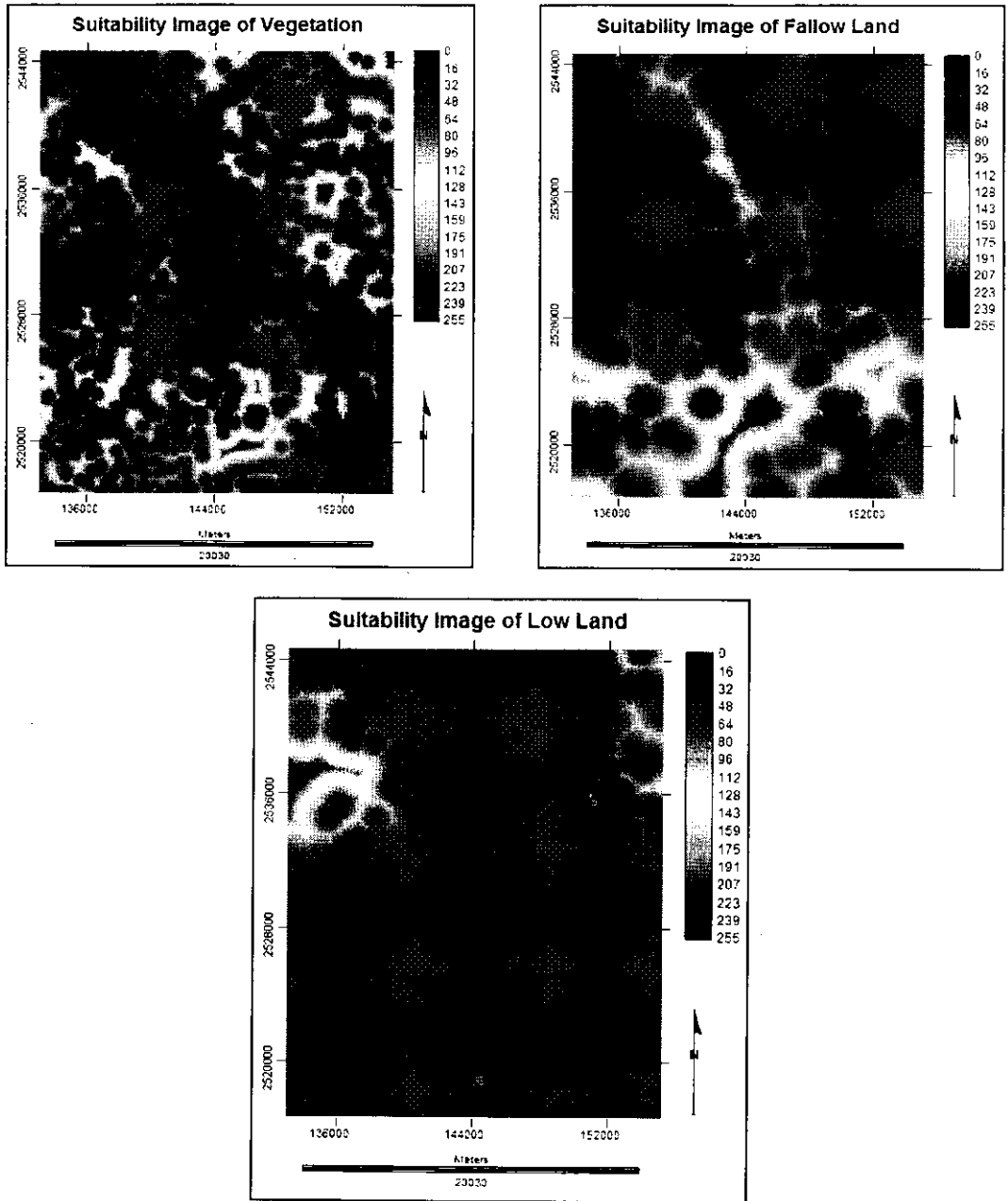


Fig. 7: Suitability images of each land cover type, 1999.

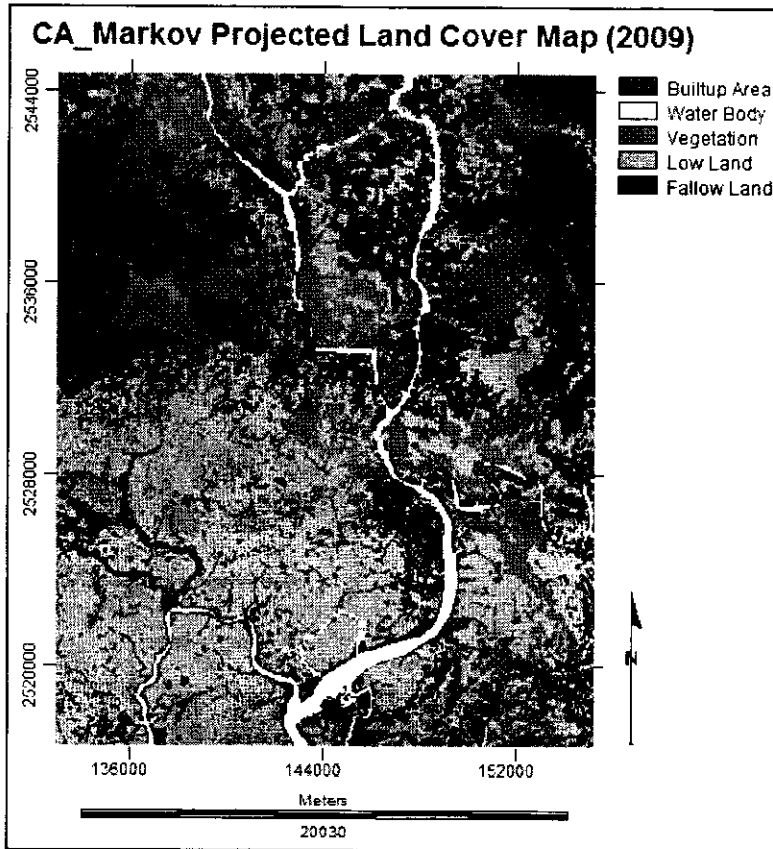


Fig. 8: CA_Markov projected land cover map of Khulna City, 2009.

Multi Layer Perceptron Markov Model

The term 'Artificial Neural Network (ANN)' has been inspired by human biological nervous system (Karul and Soyupak, 2006). In a typical ANN model, simple nodes are connected together to form a network of nodes. Some of these nodes are called input nodes; some are output nodes and in between there are hidden nodes (Atkinson and Tatnall, 1997). Multi Layer Perceptron (MLP) is a feed-forward Neural Network with one or more layers between input and output layers. The great advantage of using MLP perceptron neural network is that it gives the opportunity to model several or even all the transitions at once (Eastman, 2009). The basic concept of modelling with MLP neural network adopted in this research is to consider the change in builtup area over the years. In general, it means other land cover types are primarily contributing to increase the builtup area. At this stage, the issue of which variables affect the change to builtup area (1989-1999) has been considered. Therefore, only the transitions from 'water body to built-up area', 'vegetation to built-up area', 'low land to builtup area' and 'fallow land to builtup area' have been considered for model simulation. These four transitions have been termed as "All" here. Figure 9 exhibits the transition from all to builtup area.

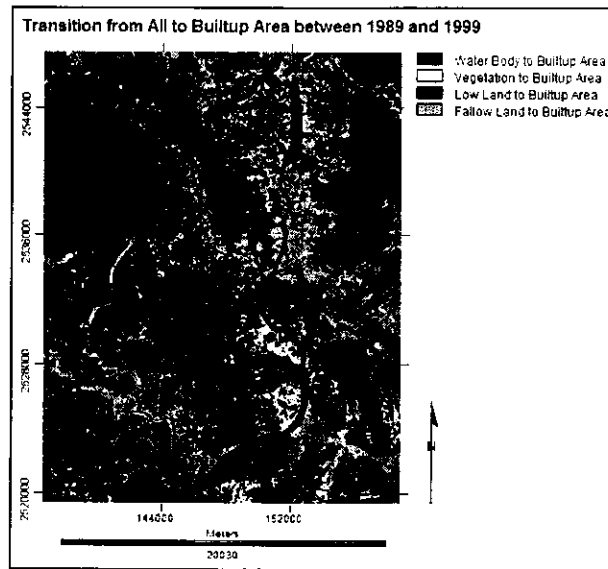


Fig. 9: Transition from all to built up area, 1989-1999.

It is logical that new areas will be converted to built-up area, where there are existing builtup areas. Therefore, six driver variables have been selected for MLP_Markov modelling. These are: distance from all to built-up area, distance from water body, distance from vegetation, distance from low land, distance from fallow land and empirical likelihood image.

The empirical likelihood transformation is an effective means of incorporating categorical variables into the analysis (Figure 10). It has been produced by determining the relative frequency of different land cover types occurred within areas of transition (1989 to 1999). The numbers (legend) indicate the likelihood of changing into built-up area. The higher the value the likeliness of the pixel to change into the built-up cover type is more.

Now it is important to test the potential explanatory power of each variable. The quantitative measures of the variables have been tested through Cramer's V (Cramér, 1999). It is suggested that the variables that have a Cramer's V of about 0.15 or higher are useful while those with values of 0.4 or higher are good (Eastman, 2009).

After getting satisfactory Cramer's V values for all the driving variables, now the turn is to run MLP neural network model. For each principal transition, particular weights have to be obtained. The MLP running statistics gives a very high accuracy rate of 93.45%. The RMS error curve has been found smooth and descent after running MLP neural network. Based on these running statistics, the transition potential maps have been produced. These maps depict for each location, the potential it has for each of the modelled transitions (Eastman, 2009).

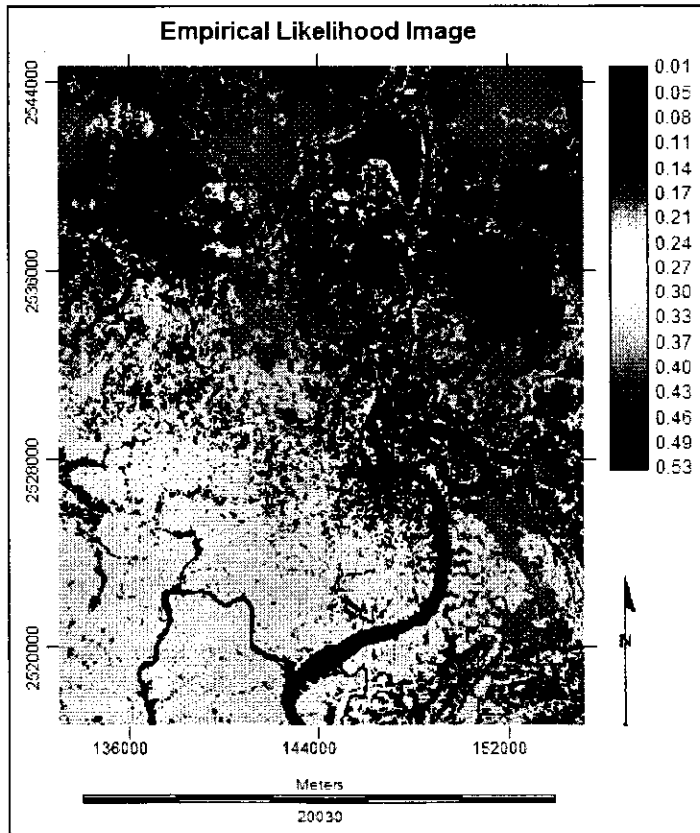


Fig. 10: Empirical likelihood image, 1989-1999.

Using this kind of MLP neural network analysis, it is possible to determine the weights of the transitions (1989-1999) that will be included in the matrix of probabilities of Markov Chain for future prediction. The transition probabilities are shown in Table 4. Based on all these information from MLP neural network, the final land cover map of 2009 (Figure 11) has been simulated through Markov chain analysis. The whole procedure for predicting the land cover map by this way has been termed as ‘MLP_Markov’ model.

Table 4: Transition probabilities (Neural Network Weights) for Markov Chain.

	Builtup Area	Water Body	Vegetation	Low Land	Fallow Land
Builtup Area	0.3757	0.0222	0.0798	0.4020	0.1203
Water Body	0.2169	0.7211	0.0164	0.0382	0.0074
Vegetation	0.0350	0.0012	0.7882	0.1503	0.0254
Low Land	0.2038	0.0105	0.1021	0.6040	0.0797
Fallow Land	0.1507	0.0009	0.0721	0.1849	0.5916

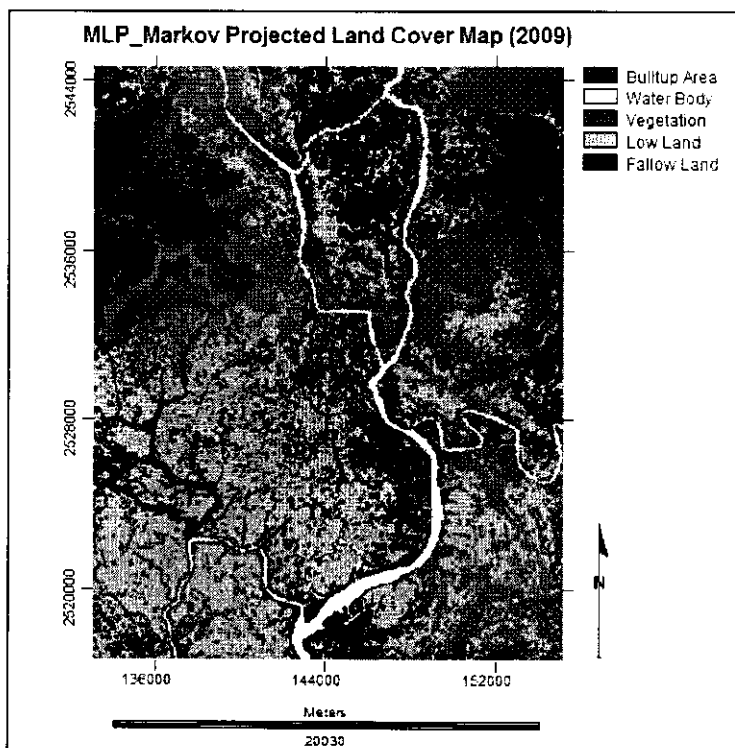


Fig. 11: MLP_Markov projected land cover map of Khulna City, 2009.

Model Validation and Selection

Model validation refers to comparing the simulated and reference maps. Now the task is to select the most suitable model. The selection has been performed based on the overall kappa statistics (Pontius, 2000). The assumption is like- the higher the overall kappa values, the better the model.

Table 5: Overall Kappa Statistics (2009).

	St_Markov	CA_Markov	MLP_Markov
Kno	0.3401	0.8176	0.9363
Klocation	0.3462	0.9306	0.9320
Khisto	0.8671	0.9021	0.9744
Kappa	0.3000	0.8065	0.9320

After analyzing Table 5, it can be concluded that MLP_Markov model is showing the highest values of different types of kappa coefficients among the three models. Therefore, the MLP_Markov model has been selected for predicting the land cover map of Khulna City for the year of 2019.

Simulating the Land Cover Map of 2019

The base maps of 1999 and 2009 have been used to predict the land cover map of 2019 (Figure 12). The procedure followed here is the same as stated in the MLP_Markov modelling (section 4.3).

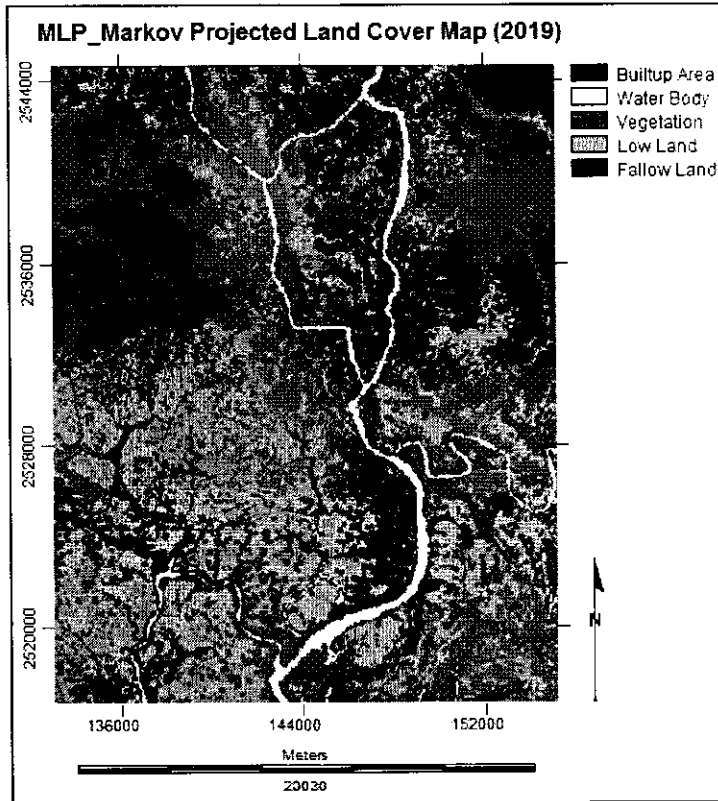


Fig. 12: MLP_Markov projected land cover map of Khulna City, 2019.

Analysis of the Final Predicted Map (2019)

The predicted map of 2019 reveals that 33.33% of the total area will be occupied by the 'built up area' cover type (Figure 13). On the other hand, 'fallow land' and 'low land' cover types are going to decrease in a notable way (respectively from 25% to 16% and 38% to 28%). Moreover, changes in 'water body' and 'vegetation' cover types are negligible.

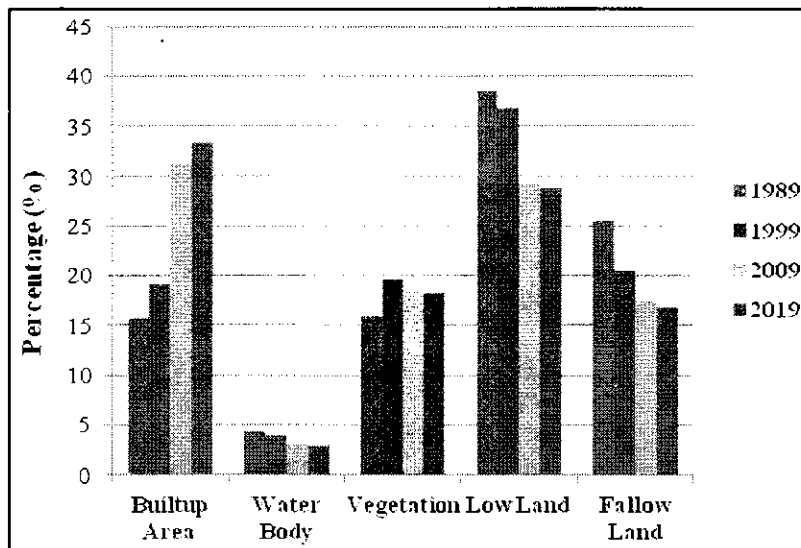


Fig. 13: Percentages of presence of land cover types over the years, 1989-2019.

Conclusions

Urbanization is a complex and dynamic system. Numerous physical, social, economic and environmental factors impact on shaping the urban form of a city. Considering all these driving and influencing factors, it is a difficult and hectic job to predict the future of any city or urban area. Despite all kinds of limitations, it can be concluded that the accuracy results of the supervised classified images, Kappa co-efficient values for model validation and the overall predictive results have been found exceeding the agreeable levels.

Emergence of GIS and Remote Sensing technology as an efficient tool for detailed survey, mapping, modelling, monitoring and analysis in a developing country like Bangladesh has paramount importance. The traditional plan making process that involves extensive surveying is expensive and time consuming. This kind of research to forecast the future is not only time and money saving, but also effective. Therefore, there is an urgent need for long term planning and management strategy in order to make an appropriate use of this technology for the sustainable development of the country. Awareness among the policy makers, different professionals and academicians needs to be increased for sustainable use of this modern technology in the current and future planning practices.

Acknowledgments

I would like to thank Dr. Raquib Ahmed, Director, Institute of Environmental Science, Rajshahi University, Bangladesh for his thoughtful suggestions and enduring guidance at different stages of this research. I would also like to express gratitude to Dr. Pedro Latorre Carmona, Dr. Mário Caetano, Dr. Edzer Pebesma, Dr. Nilanchal Patel and Dr. Filiberto Pla Bañón for their support and comments regarding necessary corrections.

Finally I would also like to thank the European Commission and Erasmus Mundus Consortium (Universitat Jaume I, Castellón, Spain; Westfälische Wilhelms-Universität, Münster, Germany and Universidade Nova de Lisboa, Portugal) for providing me the funding and other research opportunities.

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