POPULATION GEOGRAPHY
ISSN 0256-5331 Volume 47(1) June 2025

Multilayer Perceptron Neural Network and Markov Chain Model for Urban Growth Prediction – A Micro Level Case Study

Ruma Pal, Arup Guha Niyogi, and Jayita Guha Niyogi

To cite this article: Pal, R., Niyogi, Arup G. & Niyogi, J. G. (2025). Multilayer perceptron neural network and Markov chain model for urban growth prediction: A micro-level case study. *Population Geography*, 47(1), 29–46.

Abstract

Accurate and reliable forecasting facilitates effective long-term planning and enhanced management. This goal has led to the application of a Multilayer Perceptron Neural Network and Markov Chain model to forecast the future scenario of Ward 109, Kolkata Metropolitan Corporation in West Bengal. This peri-urban area underwent rapid urbanisation in less than 30 years, using vectorised maps created from historical Google Earth images and ground truth data. Following change detection, predictions for 2021 have been made using ten variables. Following validation, a 2040 urban growth simulation was created to corroborate the scenario with census-population data, which is anticipated to be released in 2041. Additionally, population projections for 2021 have been made, showing a fourfold increase. According to National-level planning guidelines, in India, Ward 109 already has a population density comparable to that of a medium to large city; however, the authority's urban structure and amenities are disproportionate to the population. A gap has formed between the population and the resources available in relation to demand and supply. This paper will be helpful in formulating schemes to minimise the gap between government guidelines and the real-world scenario for sustainable development.

***Keywords*:** urban growth prediction, multilayer perceptron neural network model, population projection

Introduction

Unplanned urban growth definitely affects natural resources and the quality of human life (Devendran & Lakshmanan, 2018). Unrestricted urban growth leads to urban sprawl, which demands increased infrastructure and basic services for

Article:
Received: 03.07.24 Reviewed: 26.09.24 Accepted: 08.11.24

expanding areas, posing a threat to the environment (Garouani et al., 2017).

Machine-learning-based algorithms for land use land cover (LULC) classification, change identification, and urban growth prediction (Jamali, 2021), along with population projection, help planners, environmentalists, and governments endorse optimal arrangements that make the plan more economical and well-structured.

The increased rate of urbanisation makes it extremely challenging and inadequate to monitor changes using conventional surveys (Nath & Acharjee, 2013). Therefore, remote sensing and geographic information systems (GIS) are now the most effective instruments for detecting such changes.

Liu Y (Liu, 2008) reviewed urban development models based on different scales, concepts, and calculations. Cellular automata (CA), introduced by Ulan and Neuman in 1940 (Triantakonstantis & Mountrakis, 2012), are a simulation-based model where a cell evolves through many discrete steps according to a set of rules based on the states of its neighbouring cells (Falah et al., 2020). Though strongest, to overcome the shortcomings of the CA (Vispoel et al., 2022) model, it is integrated with the Markov Chain (Aburas et al., 2016), which is a process consisting of a number of states with transition probabilities (Li & Zhang, 2009) and aim to predict the situation of an object at future times (Dai & An, 2018). A Markovian chain makes predictions using the Land Transformation Model (LTM). An LTM has been presented by Pijanowski (Pijanowski et al., 2002) to predict land use changes using GIS, along with Artificial Neural Networks (ANN). ANN, a method in artificial intelligence (AI), utilises data from remote sensing and GIS, processing it in a manner similar to the human brain. Data are used in interconnected nodes in a layered structure. A Multilayer Perceptron (MLP), also known as a Land Change Modeler (LCM), is a type of neural network that has three or more layers. The input layer receives data, the hidden layers, which serve as the computational engine of the MLP, process the data, and the output layers predict and classify the data (Devendran & Lakshmanan, 2018, 2019; Maithani, 2020; Abirami & Chitra, 2020). GIS has developed driver variables that are responsible for changes. A Multilayer Perceptron Neural Network (MLPNN), trained on training data and reducing error through backpropagation, has been used to generate transition potential maps. These maps represent the potential for transformation of a given Land Use and Land Cover (LULC) category into another. Many researchers used an integrated MLPNN and Markov Chain Model

(MCM) to predict future LULC. This is one of the preferred methods for predicting future land use adopted by scholars (Saeed et al., 2021; Vinayak et al., 2021; Alshahrane & Altuwaijri, 2023). Although MLPNN can handle large and complex datasets, its cost increases, and its accuracy depends on the model's training; efficient training yields efficient prediction, which is crucial for effective planning and improved land management.

The physical expansion of Kolkata, West Bengal, India, occurred in a south-easterly direction (Majumder & Sivaramakrishnan, 2020). From 1991 to 2011, the city core of Kolkata Municipal Corporation (KMC), West Bengal, experienced negative population growth, as reported in the 1991, 2001, and 2011 Censuses of India. In contrast, the outer areas, or peri-urban fringes, gained momentum due to lower land prices and the expansion of arterial roads. Ward 109 of KMC, chosen as a study area, is located at the eastern boundary of KMC. Once unattractive and covered by agricultural and vacant land in the 1980s, it has become a liveable area. The unplanned new construction and amenities in the Ward, following its inclusion in 1984, caused significant stress in the delivery of transportation infrastructure, as well as social and environmental services.

This work predicts the land use of Ward 109 for the year 2040 based on the land use data of 2002 and 2010. In the first step, a prediction for 2018 has been made. The result has been compared with the LULC map of the real-world situation. Following the accuracy assessment, a map for 2040 has been predicted, along with a population projection for 2021.

Following India's independence, rapid urban growth created a need for developing infrastructure and other essential services. Hence, the Urban Development Plan Formulation and Implementation (URDPFI) guidelines were prepared in 1996 (UDPFI, 1996), modified as needed, and implemented at the regional level (URDPFI, 2014, 2016). It classified urban centres according to their population (small, medium, large cities, metro cities) and provided guidelines for the proposed land use structure under different land use categories. After predicting future land uses in Ward 109, population projections helped compare the parameters with those of URDPFI. This paper can be implemented in other likely areas, and sustainable planning can be developed holistically. Several studies have already been conducted to understand urban dynamics and forecast futuristic urban growth. This study differs from others in that it has examined the spatiotemporal dynamics of a peri-urban area, predicted land use changes, and sought to identify the gap between national guidelines and the actual scenario for KMC Ward 109.

Materials and Methods

In Step I, the study area, KMC Ward 109, has been identified. Step II shows urban growth prediction and comparison with the actual scenario. In step III, the predicted map was accurately assessed against the actual scenario. Lastly, Step IV involves comparing the guidelines of URDPFI with the ground-level situation in KMC Ward 109.

The Eastern Metropolitan Bypass (EM Bypass), connecting north Kolkata and south Kolkata, divides Ward 109 into east and west, passing through the north and south of the Ward (Fig. 1). Both sides of this road have become focal points of development. The vicinity of the EM Bypass, its connection to the City of Kolkata, and the suburban railway's connectivity attracted people to KMC Ward 109, as the situation prompted them to move outward from the city core. Hence, the real estate boom and later hospital-centric developments led to unplanned urban growth in this area.

Rapid urbanisation at the ward level created first-level development along both sides of the EM Bypass. However, it hindered growth at the interior level, resulting in congested traffic movement, roadside parking, the absence of footpaths, and disproportionate multi-storied houses to the road width, as well as effluent sewerage, a scarce potable water supply, and waterlogging. This individual ward-level study, showing development in one part and deterioration in the other,

will help other municipalities keep provisions for providing facilities in their boundary areas before problems start to arise. The driving forces incorporated into the study, responsible for LULC changes in such a boundary Ward, will provide an estimation of the future scenario, which involves the exhaustion of natural resources.

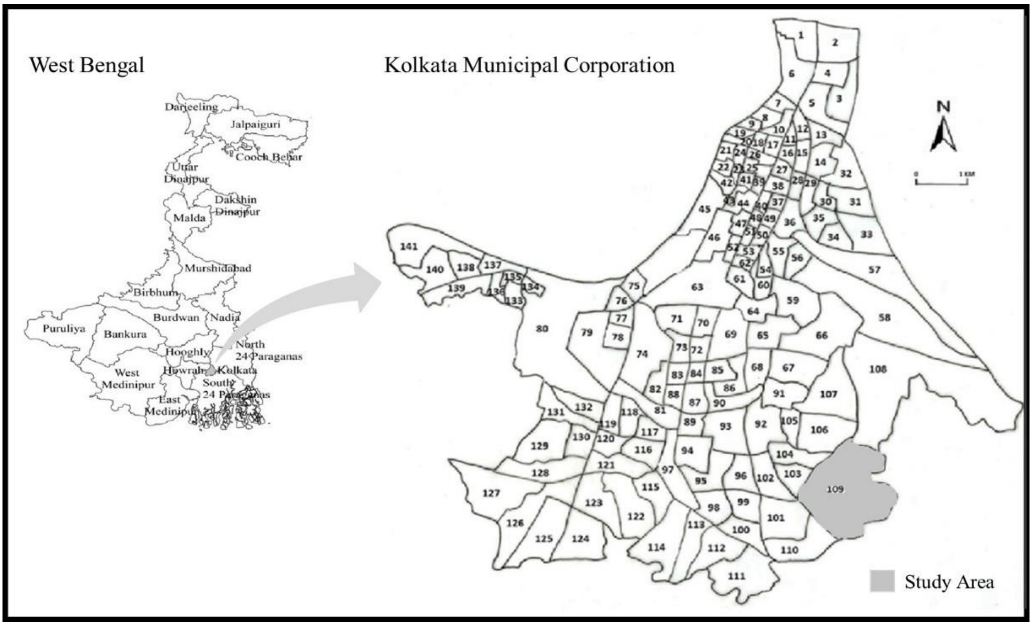
The Calcutta Municipal Corporation Act of 1980 came into effect in January 1984. As KMC expanded its boundaries, wards 100 to 141 came under its jurisdiction. Thus, Ward 109 came under the authority of KMC. This Ward is located in the south-eastern part of KMC (Fig. 1) and is positioned approximately between 22°30’N and 22°28’N, and 88°23’E and 88°25’E, covering an area of 7.05 sq. km. East Kolkata Wetland (EKW), located in the eastern part of Kolkata – a Ramsar site - absorbs contaminants drained from Kolkata (Mondal et al., 2022), situated in the eastern and northeastern part of the Ward.

The Calcutta Municipal Corporation Act of 1980 came into effect in January 1984. As KMC expanded its boundaries, wards 100 to 141 came under its jurisdiction. Thus, Ward 109 came under the authority of KMC. This Ward is located in the south-eastern part of KMC (Fig. 1) and is positioned approximately between 22°30’N and

22°28'N, and 88°23'E and 88°25'E, covering an area of 7.05 sq. km. East Kolkata Wetland (EKW), located in the eastern part of Kolkata, a Ramsar site, absorbs contaminants drained from Kolkata (Mondal et al., 2022), situated in the northeastern part of the Ward. Dhapa, a waste dumping ground of the KMC (Ali et al., 2019), provides livelihoods to a significant number of local families through garbage farming and aquaculture (Roy, 2021), and is approximately 11 km away by road from the specified Ward.

Figure 1

Location map, Ward 109, Kolkata Municipal Corporation

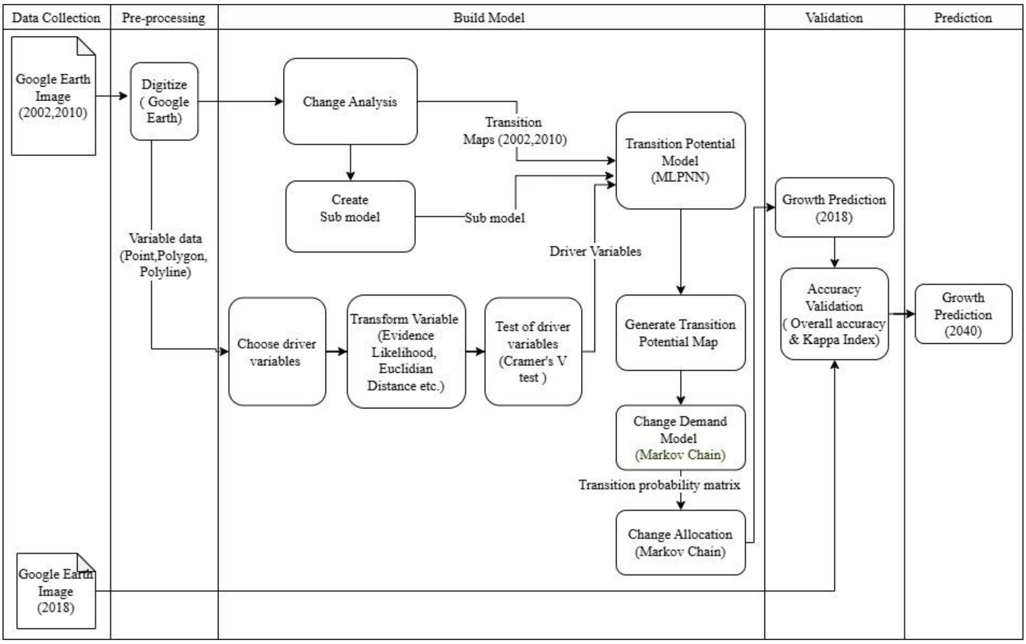


For land planning, the LCM is a method for predicting changes in land use. It maps future change scenarios using historical land cover change maps and empirically models the relationship between land cover transitions and explanatory variables (Eastman & Toledano, 2017).

The growth prediction computation consists of five stages, as depicted in Figure 2: data collection, pre-processing, transition potential and changes demand modelling, building the model, validation, and prediction.

Figure 2

Proposed Methodology for Growth Prediction



As shown in Figure 2, images of two base years are selected for the study area during the data collection stage. To enhance the accuracy of predictions, multitemporal land-use maps for 2002 and 2010 have been developed from Google Earth images. Five land use classes have been identified: Built-up Area, Vacant Land, Vegetation, Waterbody, stadium, and Open Space. CartoDEM has been downloaded from the National Remote Sensing Centre, BHUVAN website (bhuvan.nrsc.gov.in) to generate the slope map.

A Digital Elevation Model (DEM) map has been extracted from Cartosat satellite data. A slope map generated from a digital elevation model (DEM) in ArcGIS shows the rate of elevation change for each cell. Roads and railway lines in polyline features, rail stations, hospitals, and nearest working places as point features, as well as built-up areas, water bodies, and other land use classes as polygon features, have been digitised in Google Earth and converted from a KML file to a .shp file in ArcGIS. Euclidean distance maps for the variables calculate Euclidean distance from the centre of the source cell to the centre of the closest cell of the variables, which are generated in ArcGIS. Maps are exported to an ASCII file and imported into IDRISI 17.0 SELVA Edition. However, time is required for this kind of extensive work to ensure proper planning and prediction.

The growth prediction begins with transition maps, which display the changes in land cover over time between two different years, generated by the change analysis process in IDRISI Selva. Sub-models are created from the transition maps. The driver variables (Eastman, 2012) need to be selected based on prior experience and data availability, then transformed and tested repeatedly before being imported into the sub-model structure. The Euclidean distance of each variable has been computed and extracted from the point or polyline features of the digitised images. For the chosen variables, transformation using the evidence likelihood method (Eastman, 2009), which evaluates the strength of the association of variables with the hypothesis, has been found to yield better outcomes. Each variable is tested using Cramer's V test (Cramer, 1946; Eastman, 2009), which represents the association between the variable and the distribution of land covers in the future land cover map to select useful driver variables. This test has been incorporated into the transition sub-model evaluation structure. Once the transition sub-model structure is formed, it is executed using the MLPNN procedure. The model is tuned, built, and run to generate transition potential maps that represent the pressures on each land use for potential changes.

The "change demand model" (Eastman, 2009) uses transition potential maps (Eastman, 2012) for the prediction year. The model utilises MCM to calculate the probability of transitioning from one category of LU to another, referred to as the transition probability matrix (Eastman, 2009). The change allocation module uses transition potential maps and a transition probability matrix to generate the prediction maps (Eastman, 2009) for a recent prediction year for which actual images are available.

The predicted results are compared with the actual image, and an accuracy assessment is performed by computing the overall accuracy and the kappa index (Liu & Mason, 2016).

Once the accuracy is established at 91%, a prediction for the year 2040 has been made to compare it with the census population, which is expected to be released in 2041.

Population projection is a way of estimating the population for future dates. Based on past and present decadal data collected from the Census of India (1991, 2001, 2011), the population of 2021 has been forecasted. The arithmetic increase method, geometric increase method, incremental increase method, and declining growth method are the methods used for estimating future population growth.

The arithmetic increase method follows the formula:

$$P_n = P_0 + nc \tag{1}$$

Where the prospective population P_n after n decades, P_0 is the last known population, and c is the rate of population growth.

In the Geometrical increase method, the formula is

$$P_n = P_0 \left(1 + \frac{r}{100}\right)^n \tag{2}$$

Where population P_n after n decades, P_0 is the latest known population, $and\, r$ is the geometric mean.

In the Incremental increase method, the population after the nth decade

$$P_n = P_0 + nc + \frac{n(n+1)}{2}x \qquad (3)$$

Where, estimated population P_n after n decades, P_0 is the last known population, c is the average increase, and x is the incremental increase.

In the Declining growth method, the formula is

$$P_n = P_0 + \frac{r-r_1}{100} * P_0 \qquad (4)$$

Where, estimated population P_n after n decades, P_0 is the last known population, r is the percentage increase of the population, r_1 is a decrease in the percentage of the population

the average of the arithmetic increase, geometric increase, incremental increase, and declining growth methods has been taken as the projected population for Ward 109, KMC, for the year 2021 to avoid the biases inherent in the results of any single method,

Planners and policymakers can utilise this study to inform land use changes that support sustainable development.

Discussion and Results

Two digitised base year maps for the years 2002 and 2010, developed in Google Earth and processed in ArcGIS 10.2, have been exported to IDRISI Selva 17.0, which uses an MLPNN-based (Jensen, 2015) land change modeller (LCM) and Markov chain algorithms (Eastman, 2009).

The land use distribution of KMC Ward 109 for the years 2002 and 2010 reveals that, within 8 years, the built-up area more than doubled, while the vegetation area decreased by over twice (Table 1). Accessibility to the city and the expansion of metro railways are the root causes of the growth in the built-up area.

Table 1
Land Use Distribution in KMC Ward 109 (in per cent)

Classes	2002	2010
Built-up Area	21.13	45.17
Vacant Land	61.02	41.37
Waterbody	16.00	11.87
Vegetation	1.50	0.68
Stadium and Open Space	0.35	0.90

The conversion of vacant land, vegetation, and water bodies into built-up areas. Transitioning the water body to vacant land is also the first step in the expansion of the built-up area. The depletion of vegetated land to built-up areas and vacant landmarks is a change in the land character of the Ward. 7.28 ha of waterbody has been transformed into a built-up area, and more alarmingly, another 21.01 ha of waterbody has been converted to vacant land, highlighting a lack of governance. The intrusion of new urban areas and the introduction of high rises often require the demolition of older construction sites. Hence, built-up areas are often found to change to vacant land LU (11.39 ha in the transition matrix (Table 2).

Furthermore, sub-models derived from transitions identify the potential of five land use (LU) classes: built-up areas, vacant land, vegetation, water bodies, stadiums and open spaces. These sub-models are later grouped to drive the underlying determinants of prediction (Table 3).

Table 2

Land Use Transition Matrix in KMC Ward 109 (in hectares)

		Land cover (LC) in 2010 (ha)				
	Classes	Built-up area	Stadium and open space	Vacant land	Vegetation	Waterbody
LC in 2002 (ha)	Built-up area	**136.82**	00.68	11.39	0	0
	Stadium and open space	0	**2.30**	0	2.3	0
	Vacant land	173.32	2.93	**250.48**	3.3	0.43
	Vegetation	1.2	0	8.80	**0.48**	0
	Waterbody	7.28	0.37	21.01	0.92	**83.24**

Table 3

Sub-models Generated From Transition Maps

Sub-model	Changes from	Changes to
Change_to_built	Vacant land, Vegetation, Waterbody	Built-up area
Change_to_vacant	Built-up area, Vegetation, Waterbody	Vacant land
Change to_veg	Waterbody, Vacant land	Vegetation
Change_to stad	Waterbody, Vacant land, Built-up area	Stadium and open space

Table 4

The Driver Variables for Growth Prediction for KMC Ward 109

No.	Variable Category	Variable	Distance method	Evidence Likelihood	Cramer's V test
1	Socio-economic	Distance to built-up area	Euclidian distance	Yes	0.4001
2		Distance to schools	--do--	Yes	0.1180*
3		Distance to workplaces	--do--	Yes	0.1700
4		Distance to hospitals and health services	--do--	Yes	0.1330
5	Utilities	Distance to roads	--do--		0.2027
6		Distance to the railway	--do--	Yes	0.1300

7		Distance to railway stations	--do--		0.1800
8	Physical area	Digital Elevation Model (DEM)	No	No	0.1805*
9		Slope in per cent	No	No	0.0552
10	Environmental	Distance to water body	--do--	Yes	0.4505
11		Distance to vegetation	--do--	Yes	0.4541
12		Distance to vacant land	--do--	Yes	0.4683
* These variables are not included in the Transition Sub-model structure.					

The driver variables have been considered based on similar research works, including stakeholder interviews and the ease of data availability. Twelve variables are selected (Table 4) and quantified for Euclidean distances, transformed using evidence likelihood and tested with Cramer's V before being included in the transition potential model structure. Cramer's V values of 0.15 or larger indicate that the potential explanatory value of the variable is acceptable, and those exceeding 0.4 are considered good (Hasan et al., 2020). The maps generated by the evidence likelihood transformation method are also tested before being included in the model.

Transition potential maps are generated for each sub-model and each land transition. They are used by the 'change demand model' to predict changes for the prediction year. The Markov Chain Model (MCM) produces the probability of transition from one category to another. MCM generates a transition probability matrix, which is used by the 'Change Allocation Model' to derive changes for the prediction year and generate prediction maps.

The prediction map for 2018 has been generated (Fig. 3) and validated against the actual image through accuracy assessment in Table 5. The actual map for 2018 was generated through digitisation from Google Earth, and an accuracy assessment was performed using GPS real-world data and Google Earth.

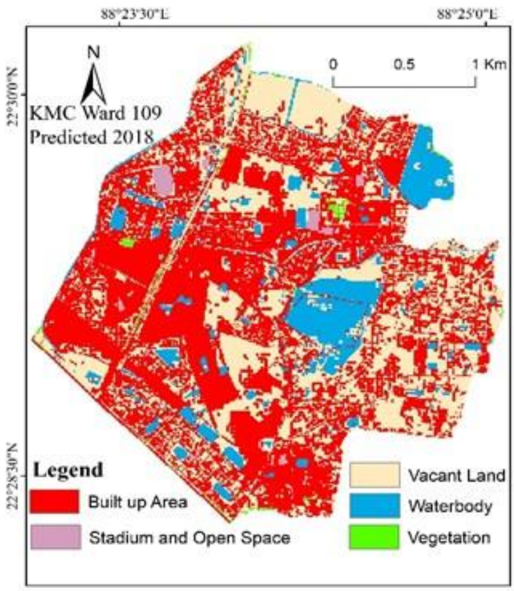
The accuracy assessment in Table 5 shows an overall accuracy of 95% and a kappa index of 0.93, which is acceptable for further simulation. Likewise, accuracy in individual categories yields satisfactory results, as indicated by 'User's accuracy' and 'Producer's accuracy'. The Kappa index also shows a high degree of accuracy.

Figure 3

Predicted LU of 2018 and Actual LU for 2018(in ha and per cent) for KMC Ward 109

Predicted

Actual



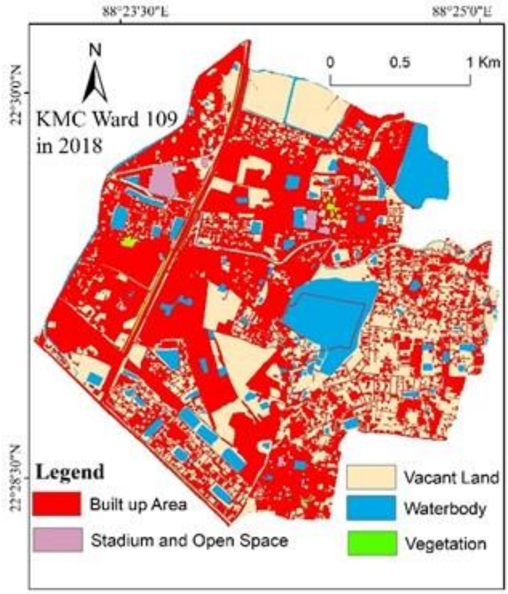


Table 5

Accuracy Assessment for the Predicted Map of 2018 for KMC Ward 109

		Reference data						
		Built-up area	Vacant land	Water body	Vegetation	Stadium and Open Space	Total	User's accuracy
Classified data	Built-up area	**101**	4	0	1	0	106	95%
	Vacant land	1	**33**	1	0	0	35	94%
	Waterbody	0	0	**33**	0	0	33	100%
	Vegetation	0	0	2	**14**	0	16	88%
	Stadium and Open Space	0	1	0	0	**14**	15	93%
	Total	102	38	36	15	14	205	
	Producer's accuracy	99%	87%	92%	93%	100%		

$$Overall\ accuracy\ = 195/205\ = 95\%$$

$$Kappa\ Index = \frac{205*(101+33+14+14+195)-\{106*102\ +35*38+33*36+16*15+14*15)\}}{205^2-\{(27*23)+(22*24)+(22*24)+(15*13)+(16*14)\}} = 0.93$$

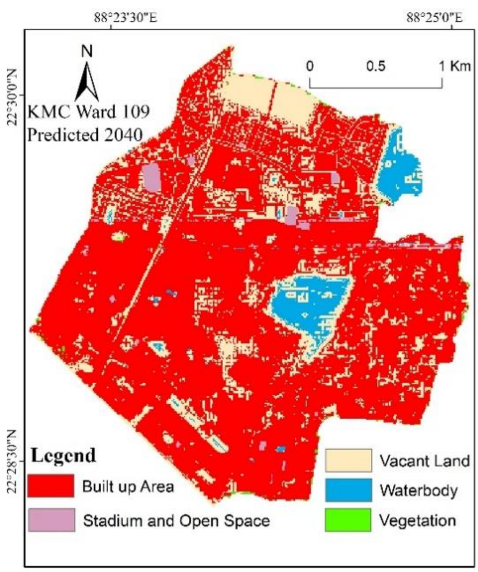
Accuracy assessment (Table 5) shows the model's acceptability. Hence, after validation, forecasting was done for the year 2040 (Fig. 4).

The predicted map of 2040 in Fig. 4 shows an increase in built-up area, with large patches of water bodies drying up. Hence, in 2040, other significant patches might also be challenged if not intervened upon now. Increasing built-up area from 21.13% in 2002 (Table 1) to 74.63% in 2040 (Fig 2) and diminishing vacant land (61.02% in 2002 to 19.56% in 2040), waterbody (16% in 2002 to 5.13% in 2040) and vegetation (1.50% in 2002 to 0.38% in 2040) will heavily affect the environment, necessitating immediate vigilance and planning. The conversion of vegetation and water bodies to built-up areas during urban expansion can still be stopped by proper governance.

In the arithmetic increase method, geometric increase method, incremental increase method, and decreasing rate of growth method, the projected population for Ward 109 in 2021 is 85,215, 107,476, 97,857, and 117,512, respectively. For the year 2021, the projected population, which is the average of all the said methods, will be 102015 (Fig. 5).

Figure 4

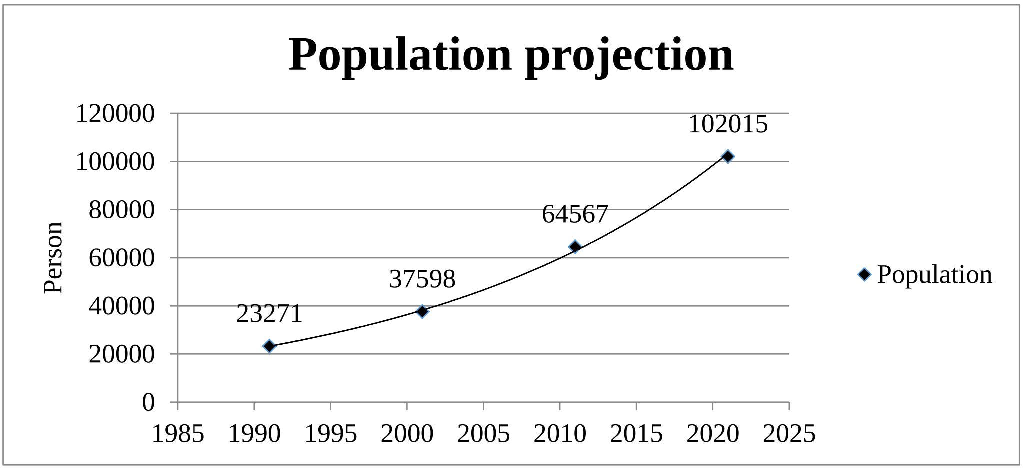
Predicted Land Use of 2040 for KMC Ward 109



Land uses	2040	
Vegetation	2.7 ha	0.38%
Built-up Area	526.73 ha	74.63%
Waterbody	27.9 ha	5.13%
Stadium and other open spaces	10.08 ha	1.73%
Vacant Land	137.93 ha	19.56%
Total	705.34 ha	100%

Figure 5

Population projection for the KMC Ward 109



The Ministry of Urban Affairs and Employment, Government of India, published Urban Development Plan Formulations and Implementation in 1996. It has established advanced guidelines for making cities and towns sustainable by generating sufficient resources with the assistance of State Town and Country Planning departments, urban development authorities, urban local bodies, planning schools, and various research institutions.

The paper compares the real-world situation with the guidelines for 2021, which would help to develop sustainable planning for other likely areas. Table 6 presents the guidelines of URDPFI (Government of India, 2014), which do not prescribe a minimum quantity for agricultural and water bodies.

According to URDPFI (Table 6), KMC Ward 109 could be considered a small town for 1991, with a population of 23,271, although it had 32.99 persons per hectare (pph), which falls below the specified range of 75-125 pph. In 2011, it approached a medium-sized city with a population of 64567. However, the density was 91.55 persons per hour (pph), against the stipulated range of 100-150 pph, and was projected to increase to 102,015 persons with a density of 144.65 pph in 2021. It can be considered a full-fledged, medium-sized town.

KMC Ward 109 has a higher density of residential areas (Table 7), at 45.54% (321.19 ha), derived from Google Earth imagery and real-world locations. The facilities and vicinity attract people, and thus, the residential areas are spreading wider. A ground survey reveals high rises in many areas. The residents of these high-rises primarily rely on water from the borewell. Large housing complexes often have their water treatment plants, but standalone flats typically do not. A few congested slum areas are also present, and no layout plan is available for the residential zone. Sufficient light and air in the buildings, as well as soil water outlets, are lacking, along with protection from noise, dust, and local hazards, in these slums. Although URDPFI has suggested that there should be 4-5% commercial and 10-12% industrial land use in Ward 109, the actual figures are 3% and 0.1%. Government, semi-government, and government-owned land, as well as land for educational and research purposes, medical and health facilities, and social, cultural, and religious purposes, all fall under the public and semi-public land use category. Any large city should have 12-14% of its land designated as public and semi-public, but Ward 109 has only 2.0% of its land allocated for this purpose. As the said Ward is part of a large city, it has very low public and semi-public land. Lands for recreational purposes are also very low, which should be noted in future planning.

Table 6
According to URDPFI, the Land Use Structure of any Urban Centre

Proposed LU structure of Urban Centres by URDPFI				
	Percentage of developed area			
Land use category	Small town	Medium town	Large cities	Metro cities
Population	5k to 50k	50k-5 lakh	5 to 50 lakh	10 lakh -1 crore
Density (persons per hectare)	75-125	100-150	125-175	125-175
Residential	45-50	40-45	35-40	35-40
Commercial	2-3	3-4	4-5	4-5
Industrial	8-10	8-10	10-12	12-14
Public and Semi-Public	6-8	10-12	12-14	14-16
Recreational	12-14	18-20	18-20	20-25
Transport and Communication	10-12	12-14	12-14	15-18
Agriculture and Water bodies	balance	balance	balance	balance

Source: Urban and regional development plans formulation and implementation guidelines, URDPFI, Vol 1, 2014, Tables 5.1 and 5.2

Table 7
LU Structure of KMC Ward 109 in 2021

Ward 109					
LU Category	%	ha	LU Category	%	ha
Residential	45.54	321.19	Transport and Communication	12.29	86.71
Commercial	3.32	23.4	Agriculture	3.11	22
Industrial	0.12	0.83	Water bodies	3.97	28
Public and Semi-Public	2.13	15	Vacant land	29.07	205.01
Recreational	0.45	3.2	Total	100	705.34

The above discussion indicates that comparing the URDPFI Guidelines, 2014, reveals that built-up areas are increasing disproportionately, leaving a smaller share of vegetation, agricultural land, and waterbodies, thereby widening the gap between the provided and proposed percentages. Hence, stringent controls should be implemented to prevent unplanned growth by 2040. In the days to come, the impact of urbanisation will be aggravated if the crisis and demand are not addressed with adequate infrastructural support, considering the driving forces.

Conclusion

This paper aims to assess the problems of rapid urbanisation in a peripheral area of KMC. Attempts have been made to generate land use changes, analyse the changes, and predict future LULC if the process continues uncontrolled till the horizon year 2040. Comparison with the government guidelines urges for meticulous planning at the micro level, following certain guidelines and recommendations of the URDPFI guidelines, 2014, stated by the Ministry of Urban Development, Government of India and implement them in phases, conserve the allocated spaces for the future use, and monitor the changes regularly and redress any untoward shift.

References

Abirami, S. & Chitra, P. (2020). Energy-efficient edge-based real-time healthcare support system. *Advances in Computers*, 117(1), 339–368). https://doi.org/10.1016/bs.adcom.2019.09.007

Aburas, M. M., Ho, Y., Ashaari, Z.H., & Ramli, M. F. (2017). Improving the capability of an integrated CA-Markov model to simulate spatio-temporal urban growth trends using an analytical hierarchy process and frequency ratio. *International Journal of Applied Earth Observation and Geoinformation, 59*, 65–78, http://dx.doi.org/10.1016/j.jag.2017.03.006

Alshahrane, A. S., & Altuwaijri, H. A. (2023). Multilayer perceptron for the future urban growth of the Kharj region in 2040, *Sustainability*, 15 (9), 7037, https://doi.org/10.3390/su15097037

Census of India. (1991). *West Bengal, District Census Handbook*. District Kolkata series 20.

Census of India. (2001). West Bengal, District census handbook. *District Kolkata series 20*.

Census of India. (2011). West Bengal, District census handbook. *District Kolkata series 20*.

Cramer, H. (1946). Mathematical methods of statistics. *Princeton University Press*. http://www.new.dli.ernet.in/handle/2015/223699

Dai, J. and L. An (2018). Time Geography. In Huang, B. (Ed.), *Comprehensive Geographic*

Information Systems, Vol. 1, pp. 303–312. Oxford: Elsevier. http://dx.doi.org/10.1016/B978-0-12-409548-9.09625-1

Devendran, A. A. & Lakshmanan, G. (2018). Urban growth prediction using a neural network coupled with an agent-based Cellular Automata model for Sriperumbudur Taluk, Tamil Nadu, India. *The Egyptian Journal of Remote Sensing and Space Sciences*, 21(3), 353–362. https://doi.org/10.1016/j.ejrs.2017.12.004

Devendran, A. A. & Lakshmanan, G. (2019). Analysis and prediction of urban growth using a neural network-coupled agent-based cellular automata model for the Chennai Metropolitan Area, Tamil Nadu, India. *Journal of the Indian Society of Remote Sensing*, 47(9),1515–1526. https://doi.org/10.1007/s12524-019-01003-8

Eastman, J. R. (2012). IDRISI Selva Tutorial, *IDRISI Production, Clark Labs-Clark University, Worcester,* 45.

Eastman, J. R. & Toledano, J. (2017). A short presentation of the land change modeler (LCM). *Geomatic Approaches for Modeling Land Change Scenarios*.

DOI:10.1007/978-3-319-60801-3_36

Eastman, R. (2009). IDRISI Taiga guide to GIS and image processing, *Clark University, Worcester, MA*.

Falah, N. Karomo, A. & Harandi, A. T. (2020). Urban growth modeling using cellular automata model and AHP (case study: Qazvin city), *Modeling earth systems and environment*. 6, 235–248, https://doi.org/10.1007/s40808-019-00674-z.

Garouani, A. E. Mulla, D. J. Garouani, S. E. & Knight, J. (2017). Analysis of urban growth and sprawl from remote sensing data: Case of Fez, Morocco, *International Journal of Sustainable Built Environment*, xxx, xxx-xxx, http://dx.doi.org/10.1016/j.ijsbe.2017.02.003

Government of India. (2014, 2016). Urban and Regional Development Plan Formulation and Implementation (URDPFI) Guidelines, Volume 1. Town and Country Planning. Ministry of Urban Development. http://moud.gov.in

Jamali, A. (2021). Improving land use land cover mapping of a neural network with three optimisers of multi-verse optimiser, genetic algorithm and derivative-free function. *The Egyptian Journal of Remote Sensing and Space Sciences, 24, 373–390. https://doi.org/10.1016/j.ejrs.2020.07.001*

Li, W. & Zhang, C. *(2009). International Encyclopedia of Human Geography*. (2nd ed.). Elsevier.

Liu, Y. (2008*). Modelling urban development with geographical* *information systems and cellular* automata. CRC Press, pp. 8–10. DOI:10.1201/9781420059908

Maithani, S. (2020). A neural network based urban growth Model of an Indian city, *J. Indian Soc. Remote Sensing,* 37, 363–376, DOI: 10.1007/s12524-009-0041-7.

Majumder, S., & Sivaramakrishnan, L. (2020). Mapping of urban growth dynamics in Kolkata Metropolitan Area: A geospatial approach. In S. Bandyopadhyay, C. R. Pathak, T. P. Dentinho (Eds.), *Urbanisation and Regional Sustainability in South Asia* (pp. 9–24). Springer International Publishing. https://doi.org/10.1007/978-3-030-23796-7_2

Mondal, B. K., Kumari, S. Ghosh, A., & Mishra, P. K. (2022). Transformation and risk assessment of East Kolkata Wetlands (India) using fuzzy MCDM method and geospatial technology. *Geography and Sustainability*, 3, 191–203.

Nath, B., & Acharjee, S. (2013). Urban municipal growth and land use change monitoring using high resolution satellite imageries and secondary data: A geospatial study on Kolkata Municipal Corporation, India. Studies in Surveying and Mapping Science, 1 (3), 43–54.

Pijanowski, B. C. Brown, D. G. Shellito, B. A. & Manik, G. A. (2002). Using neural networks and GIS to forecast land use changes: A land transformation model. *Computers Environment and Urban Systems*, 26(6), 553-75.
DOI:10.1016/S0198-9715(01)00015-1

Roy, S. (2021). Sustainable approach in yield: Urban agriculture in Kolkata dumping ground. *Online International Interdisciplinary Research Journal*, 11(2), ISSN 2249-9598, www.oiirij. o r g.

Saeed, A. Mallick, J. Balha, A. Bindajam, A. Sigh, C. K. & Hoa, P. V. (2021). Spatial and decadal prediction of land use/land cover using multilayer perceptron-neural network (MLP-NN) algorithm for a semi-arid region of Asir, Saudi Arabia, *Earth Science Informatics*, 14, 1547–1562.
https://doi.org/10.1007/s12145-021-00633-2

Triantakonstantis, D. & Mountrakis, G. (2012). Urban growth prediction: A review of computational models and human perceptions. *Journal of Geographic Information System*, 4, 555–87.

Urban Development Plans Formulation and Implementation Guidelines. (1996). Ministry of Urban Affairs & Employment, Government of India, New Delhi, *Centre for Research, Documentation & Trading, 1, ITPI, India*.

Vinayak, B. Lee, H. S. & Gedem, S. (2021). Prediction of land use and land cover changes in Mumbai city, India, using remote sensing data and a multilayer perceptron neural network-based Markov chain model. *Sustainability*, 13, 471.
https://doi.org/10.3390/su13020471

Vispoel, M. Daly, A.J. & Baetens, J. M. (2022). Progress, gaps and obstacles in the classification of cellular automata, *Physica D*, 432, 133074. https://doi.org/10.1016/j.physd.2021.133074

Authors

Ruma Pal

Research Scholar, Jadavpur University rumapal@rediffmail.com

Arup Guha Niyogi

Prof., Dept. of Civil Engineering,

Jadavpur University,
arupguha.niyogi@
jadavpuruniversity. in

Jayita Guha Niyogi
Prof., Dept. of Architecture,
Jadavpur University,
jayitaguha.niyogi@
jadavpuruniversity.in.