A STUDY OF LAND DYNAMICS IN THE SOUTHERN FRINGES OF KOLKATA METROPOLITAN AREA FOR SUSTAINABLE PLANNING

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DOCTOR OF PHILOSOPHY

BY

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UNDER THE GUIDANCE OF

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CERTIFICATE FROM THE SUPERVISOR

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Abstract

Rush for the urban amenities compel the cities to change their land dynamics through repeated cycles of land infill, redevelopment, land fragmentation and expansion along their fringes due to lower land values, bigger land parcels and proximity with the city core. In the developed parts of the cities land use gradually gets even more complex, with upward land value and dearth of sufficient space. In the undeveloped pockets, redevelopment and infilling of land, and in the city-fringes development of vacant spaces and gradually merging of fringes with the main city ultimately increase the share of built-up areas. The urban land use pattern is thus modified with reduction in waterbodies, farmland and vegetation cover, that trigger land surface temperature. Unless planned a priori, the unplanned addition to the built-up areas, mostly by private players, pose difficulty in introducing adequate urban infrastructures at a later stage, suffocating with insufficient corridors and space. Again, unless the sprawl dynamics is understood, governance and control cannot be planned.

The planners can resort to remote sensing, digital image processing and geographical information system (GIS) tools to predict the land use/ land cover for a horizon year and plan for the future with periodic reviews and updates.

In 2017, Kolkata Municipal Corporation (KMC), a part of Kolkata Metropolitan Area (KMA), the oldest urban agglomeration in India, possessed less than 4% land dedicated towards roads, a very basic infrastructure, against recommended 10-12%, forming an interesting study area. KMC spread over 205 sq. km, forms the nerve centre of socio-economic and political life of the state of West Bengal, India, while Kolkata Metropolitan Area (KMA) covers 1,876 sq. km. KMC has a negative population growth rate in her core areas (loosely termed as the 'inner' wards, Ward 1 through 100, existent since 1965) while the trend in the periphery (the so-called 'outer' Wards 101 through 144) is just the reverse, undergoing active residential infilling and population growth. Since the fringes of KMA are growing at rapid pace, it is proposed to review three study areas which manifest high, intermediate and nascent states of urbanisation, identify their problems and plan accordingly for a horizon year, fifteen years hence in 2040. Year 2040 has been chosen assuming 2041 would be a census year to which the results of this research could be corroborated.

In this research KMC Ward 109, the Baruipur Municipality and the KMC Ward 144 are proposed as the three study areas showing advanced, intermediate and initial strides of urban development. They are expected to showcase different types of urban problems, from which recommendations could be drawn that may be paid heed while planning for any fringe area within KMA or similar other areas for a sustainable future. With KMC Ward 109 brimming with built-up areas, Baruipur Municipality, in the south of KMA, has started transforming into a residential hotspot; however, the pace of transformation has been medium since the proposal to develop Baruipur as an administrative hub has been stalled after takeoff. In KMC Ward 144 urban transformation is at its early stage after its inclusion into KMC in 2012.

In this research Gaussian Maximum Likelihood, Multi-Layer Perceptron Neural Network (MLPNN) and Markov Chain (MC) models have been selected to classify the images, generate transition potential maps and predict growth after necessary validation. ArcGIS and IDRISI Selva have been used for LULC change analysis, urban sprawl and future growth prediction, while FRAGSTATS has been used for allied statistical analysis of the study areas for their fragmentation. IDRISI Selva has helped to identify the driving factors, natural and anthropogenic, responsible for the LU changes and predict the scenario for year 2040 along with accuracy assessment at different steps of prediction. The modelling has achieved above 90% accuracy in forecasting land use location changes.

The impact of LU changes on modification in employment pattern land value and land surface temperature have been premeditated. While waterbodies are getting transformed to vacant lands, it has been noticed that the built-up areas are replacing pockets of land use like vacant, agricultural and vegetation land. Gradually the fragmented landscape is aggregated into urban patches accountable for urban expansion.

The share of land use classes has been compared with the Government of India planning guidelines that requires to be bridged. To this end certain recommendations have been proposed to make such changes sustainable and humanitarian.

Key words: Land use, Land fragmentation, Urban sprawl, Urban growth modelling, Change allocation, Recommendations.

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Abbreviation

1. ABM - Agent Based Modeling
2. AHP - Analytical Hierarchical Process
3. ANN - Artificial Neural Network
4. BUAV - Base unit area value
5. CA - Cellular Automata
6. CA-MC - Cellular-Automata-Markov Chain
7. CBD - Central Business District
8. CMDA – Calcutta Metropolitan Development Authority
9. DEM – Digital Elevation Model
10. EM Bypass – Eastern Metropolitan Bypass
11. EKW - East Kolkata Wetland
12. GIS - Geographical Information Systems
13. GPS - Ground Positioning System
14. KMA - Kolkata Metropolitan Area
15. KMC – Kolkata Municipal Corporation
16. KMDA - Kolkata Metropolitan Development Authority
17. LCM - Land Change Modeler
18. LST - Land Surface Temperature
19. LU - Land Use
20. LULC - Land Use Land Cover
21. MCA - Multi-Criteria Analysis
22. MCM - Markov Chain Model
23. MLP - Multilayer Perceptron
24. MLPNN - Multi-Layer Perceptron Neural Network Model
25. MVC - Municipal Valuation Committee
26. RS - Remote Sensing
27. UDPFI - Urban Development Plans Formulation and Implementation
28. URDPFI - Urban and Regional Development Plans Formulation and Implementation
29. UHI - Urban Heat Island
30. USGS - United States Geological Survey
31. UTM – Universal Transverse Mercator
32. WGS – World Geodatic System

Chapter I

INTRODUCTION

1.1 Introduction

With passage of time, the cities usually grow along with corresponding growth of urban population, associated demand for proportionate urban facilities and space requirement to accommodate the same. Thus, new peripheral areas evolve through the transformation of rural neighbourhoods of a city, which eventually merge with the city and newer urban fringes are defined with passage of time. The inducted peripheries have tremendous growth potential due to lower land value and availability of larger land parcels the only deterrent being connectivity with the mainstream transportation network, which is established gradually and the land value shoots up. Proper prediction of their future growth and planning them for adequate service facilities for some horizon year is very important, but often overlooked.

Kolkata Metropolitan Area (KMA) (Figs. 1.1a and 1.1b), currently spread over an area of 1,886.67 sq. km, is the third most populous city in the Eastern India, behind Mumbai and Delhi, the thirteenth most populous and eighth largest urban agglomeration city in the world, with a population of approximately 14.11 million according to the Census of India 2011 report. It includes 4 Municipal Corporations (Kolkata, Howrah, Bidhannagar, and Chandannagore), 37 Municipalities and 23 Panchayat Samitis. In 2009, 35.26 sq.km have been added to KMA of which Baruipur covers 4.92 sq.km and the rest is being contributed by Haringhata. The KMA is the most important urban region in the state of West Bengal accounting for 51 per cent of its urban population (Shaw 2015).

The Kolkata Municipal Corporation (KMC) with 200.71 sq. km[1] of area as of 1 September 2012, when the last three Wards (142 through 144[2]) have been added to the KMC, is the largest of the four municipalities, and the oldest urban local body within the core of KMA having been founded in 1726. Wards 101 through 141 have been added in 1984 to Wards 1 through 100, the oldest of the KMC wards. While being the oldest, KMC has only a meagre share of roads, the most basic infrastructure necessary to access all urban facilities. A parking policy document published by the Kolkata Municipal Corporation (KMC) in 2017[3], reveals that during that time

[1] https://www.keiip.in/about-us.html#:~:text=KMC%20is%20responsible%20for%20the,are%20grouped%20into%2016%20boroughs.
[2] https://www.kmcgov.in/KMCPortal/outside_jsp/Incorporation_erstwhile_Joka.jsp
[3] https://www.kmcgov.in/KMCPortal/downloads/Car_Parking_Policy_05_05_2017.pdf

the share of road space in KMC was less than 4%, while the Urban and Regional Development Plans Formulation and Implementation guidelines (URDPFI, 2014) endorses an allotment of 10-12% of the total space for roads. Thus, the case of Kolkata (KMA and KMC) is an interesting research problem from the perspective of sustainable planning and development.

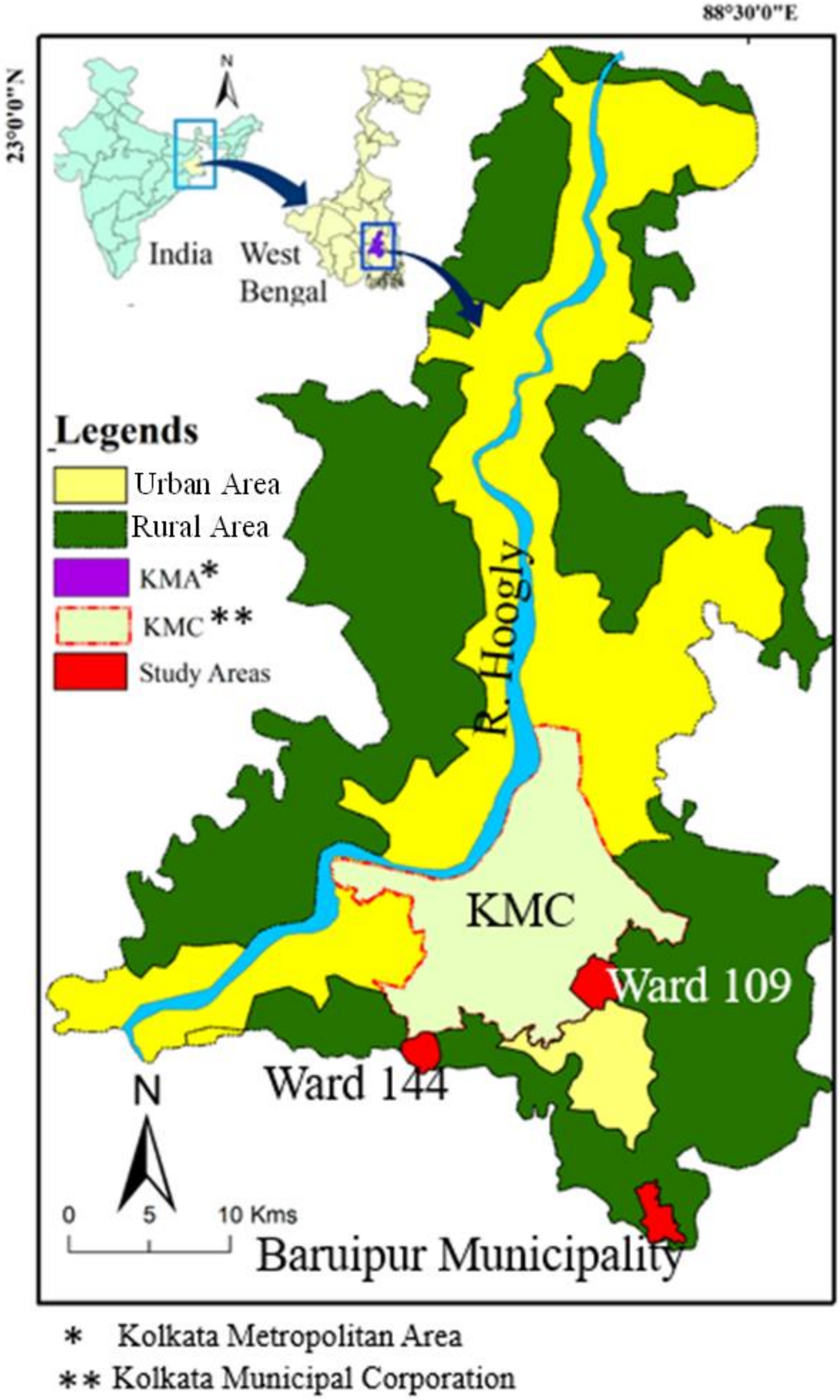
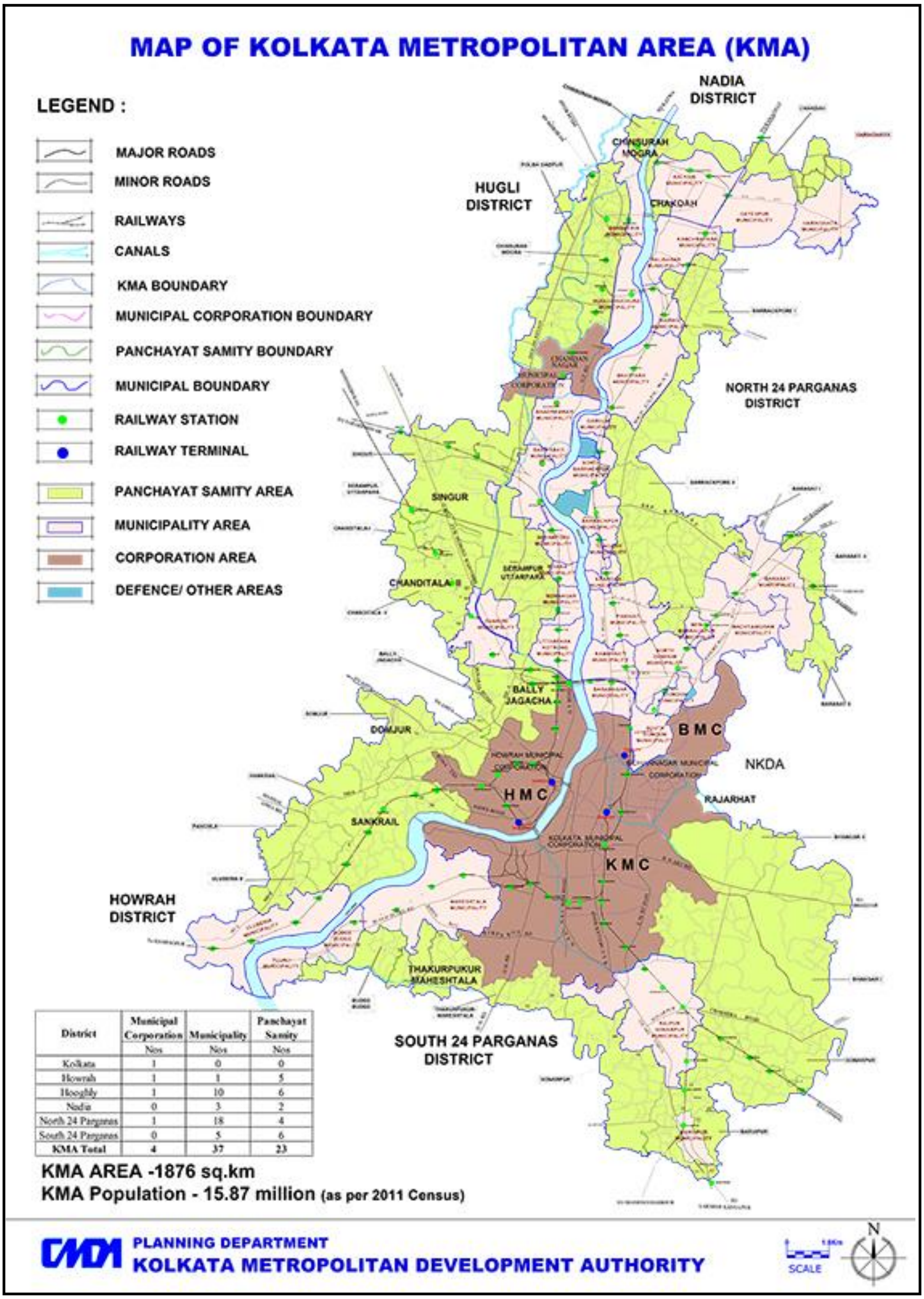


Fig. 1.1a: The locations of Kolkata Metropolitan Area and Municipal Corporation within India



District	Municipal Corporation	Municipality	Panchayat Samity
	Nos	Nos	Nos
Kolkata	1	0	0
Howrah	1	1	5
Hooghly	1	10	6
Nadia	0	3	2
North 24 Parganas	1	18	4
South 24 Parganas	0	5	6
KMA Total	**4**	**37**	**23**

Fig. 1.1b: The locations of Kolkata Metropolitan Area and Kolkata Municipal Corporation (Source: https://kmda.wb.gov.in/page/cms/map_of_kma_c1fed8)

1.2 Review of Literatures on Spatio-Temporal Changes around KMA

According to the 2001 Census, KMA holds 14.77 million[4] people within 1851.41 sq. km, total urban population of West Bengal being 22.5 million. With more cities evolving, there is a steady fall in the ratio of urban population in KMA to that in West Bengal, being 59% in 2001, 64% in 1991 and 69% in 1981. Yet 59 % is a big share. During the 2011 census, population in KMA has dropped to 14.11 million while the area increased to 1,886.67 sq. km, whereby per capita space allocation has increased. The density of population of KMA is nearly 8000 people per sq. km, highest among the Indian metropolises. Again, looking into KMC, Table 1.1a reveals that after a spike in population due to East Pakistan infiltration during the census years around Indian independence, specifically 1941 and 1951, the decadal growth rate has gradually receded and became negative in KMC in 2011, the last published census year.

Table 1.1a: Population trend in Kolkata Municipal Corporation (KMC)

Year	Population	Growth rate (%)	Year	Population	Growth rate (%)
1901	1009853	-	1961	3351250	+13.35
1911	1117966	+10.71	1971	3727020	+11.21
1921	1158497	+3.63	1981	4126846	+10.73
1931	1289461	+11.30	1991	4399819	+6.61
1941	2352399	+82.43	2001	4572876	+3.93
1951	2956475	+25.68	2011	4496694	-1.67

(**Source**: Census of India, 2001, 2011)

Again, until 1983, Kolkata Municipal Corporation (KMC) had only 100 wards, which may presently be visualized to form a set of 'inner wards', while in 1984 Wards 101 through 141 were inducted into KMC. In 2012 three more wards have been inducted into KMC from Joka I and II Gram Panchayats making the count reach 144. Wards 101 through 144 form an outer cluster of wards. Table 1.1b reviews the split-up growth trend for the inner and the outer wards.

Table 1.1b: Population trend in KMC Wards 1~100 and 101~141

Census Year	KMC wards 1-100			KMC wards 101-141		
	Population	Area (sq.km)	Population Density	Population	Area (sq.km)	Population Density
1971	3136391		29122.4	-		-
1981	3288148		30.531.5	-		-
1991	3375534	107.697	31.342.9	1006642	78.725	12786.8
2001	3333408		30951.7	1247136		15841.7
2011	3122528		28993.6	1374027		17453.5

(**Source**: Census of India, 2001, 2011)

4 https://kmda.wb.gov.in/eodb/home/download/TGpOd2tZQndrdzRCUzZHMk5rVGpnbkU4WFlZTzdUK2lVM0s3cFpTazgxb3VJdTdMNUlVY2VpUG5MamF4REJybEVJV3FMOHFNVWIwa1p2T2E1c3NOWlE9PQ==#:~:text=of%20industrial%20growth.-,The%20population%20of%20KMA%20is%20projected%20at%2017%20million%20in,and%2021.1%20million%20in%202025.

A closer look into Table 1.1b would reveal that while the population in the inner wards 1 through 100 is truly receding, the population is on the rise in the peripheral wards. The land value in the inner wards is naturally higher while the vacant land parcels are fragmented. It is just the reverse in the outer wards and hence the development has shifted outwards, the accessibility from the city fringes to the employment hubs being well-established through the gradual extension in road, suburban rail, circular rail and metro rail service networks.

Consequently, there are quite a few research publications in recent times dealing with Kolkata Municipal Area, Kolkata Urban Agglomeration, or, a part thereof, some of which are discussed below. The list is, however, only representative, and not exhaustive.

Bhatta (2009) uses satellite images of Kolkata Municipal Corporation (KMC) from 1975 to 2005 for binary classification through a nonparametric parallelepiped classifier to extract the urban (built-up and other impervious areas) and non-urban areas and the outcome has been reproduced in Table 1.2.

Table 1.2: Percentage of built-up area in KMC

	Zones					
Year	**North**	**Central**	**Western**	**Southern**	**Eastern**	**Overall**
1975	80.15	77.89	28.37	11.39	24.81	43.08
1990	84.21	85.61	50.62	58.25	34.44	63.56
2000	86.26	85.63	52.89	63.94	51.33	68.20
2005	87.59	85.63	54.18	70.31	69.33	72.89

Source: Table 3, Bhatta (2009)

Table 1.2 reveals that the northern and central zones are saturated with built-up areas, western part is attaining stagnation, while the Eastern and Southern zones are getting transformed. There are urban sprawls in the Eastern and Southern flanks of Kolkata. Bhatta infers that the city is dispersing though the population was decreasing gradually which corroborates with Table 1.1a and the reasons provided in Table 1.1b is reflected in Table 1.2 too. Very high magnitudes of Shannon entropy obtained in Bhatta (2009) also corroborates the occurrence of sprawl, which in turn, seeks initiative to provide planned urban amenities (Ramachandra et al., 2014).

While working with urban dynamics using temporal remote sensing data for a period of 1973 to 2010 for Kolkata and its buffer area of radius 10km around the Central Business District (CBD), Ramachandra et al. (2014) observes that a basic problem with the unplanned urbanization is urban sprawl by which there are conversions of environment-friendly land uses in the urban–rural fringes into urban areas, however, sans basic facilities and amenities. They resorted to GRASS and FRAGSTATS software with Gaussian maximum likelihood supervised pattern classifier to obtain a density gradient and other statistics in ten concentric circles of 1km annular rings and divided the study area into four regions, north-east, south-west, north-west and south-east. The solution they suggested is to adopt a holistic and integrated regional planning approach.

Majumdar and Sivaramakrishnan, (2015) while studying the sprawl of Kolkata Metropolitan Area (KMA) between 2010 and 2015, opine that the degree of land use change in KMA is low in the city core while being much higher in the city peripheries. The sprawl is in the south-easterly and south-westerly directions on the eastern banks of river Hooghly. The authors have resorted to normalized difference vegetation index (NDVI) to analyse the nature of vegetation cover. They considered four types of land use: vegetation, built-up area, water body and agricultural land.

Once again, Majumdar and Sivaramakrishnan, (2020) while working on the Rajpur-Sonarpur Municipality, the largest municipality within Kolkata Metropolitan Development Authority (KMDA) on the southern fringes of Kolkata that hosted mostly the refugees from the East Pakistan during Indian independence, reported that the Eastern wards of Rajpur-Sonarpur Municipality are too crowded due to better connectivity and people are now settling in the peripheries of the Rajpur-Sonarpur Municipality for affordable land value. Sahana et al., (2018) have analysed urban spatial pattern and trend of urban growth in Kolkata urban agglomeration using urban sprawl matrix during 1990–2000 and 2000–2015.

Mukherjee et al., (2018) have stressed on the necessity to plan for ensuring water security around Kolkata in light of population growth and land use land cover (LULC) changes and conducted supervised classification of KMC between 1980 and 2014 using ERDAS Imagine software and a non-parametrical feature-space classifier for three types of land use: built-up areas, vegetated areas and local water bodies. Concern has been raised against uncontrolled urbanization processes causing LULC changes and insufficient water management practices, which have their resultant combined effects on water insecurity within the KMC area, and challenges the sustainable development goal of providing accessible clean water for all.

Ali and Ahmed, (2019) worked on Kolkata using artificial neural network (ANN) time series model along with autoregressive technique to project monthly solid waste generation for the year of 2030 in Kolkata. They gathered monthly data of 96 months in between 2010 to 2017 for their predictive analysis.

Majumder, (2020) has detected the land use changes in the southern fringes of Kolkata with special emphasis on Sonarpur-Rajpur with remotely sensed data.

Hasnine and Rukhsana, (2023) have studied LULC changes around Kolkata by supervised classification, where LU growth prediction has been done by Markov Chain and Cellular

Automata model and validation has been done by receiver operating characteristic (ROC) and Chi-square analysis.

John et al., (2020) deals with declining groundwater level in the urbanized regions of KMC based on ground investigation and GIS techniques between 1991 and 2010 by assessing post-monsoon groundwater depletion levels by applying the inverse distance weightage (IDW) technique in ArcGIS to find that water levels have receded at Narendrapur, Chitpur, Sinthi, Ballygunge, Park Street and Jadavpur, while increased slightly at Mukundapur and Kalikapur regions.

Das and Sarkar, (2020) reports a spatiotemporal change detection analysis of LULC in the Bhagirathi-Hugli river banks between Nadia and Purba Bardhaman districts of West Bengal, during four time stations between 1989 and 2017 for fragmented land use considering six landscape metrics, and four land use classes. A highly fragmented land use has been reported.

Dinda et al., (2021) has reported loss of urban green space (UGS) in KMC area by studying Landsat data between 1980 and 2018 with an integrated cellular automata-Markov chain (CA-MC) model and predicted LULC for 2025 and 2035. After a detail review of various analysis tools, they assessed the LULC classification by a combination of maximum likelihood classifier, artificial neural network and support vector machine, while the land dynamic factors used to predict future land use have been compiled using the analytical hierarchy process, expert opinion and field survey.

Gupta and Malik, (2021) reports urban sprawl and LULC changes around Kolkata's Salt Lake and neighbouring municipal and panchayat areas. Jamal and Ali (2022) reports LULC change studies of KMC between 1990 and 2020 using ArcGIS and ERDAS Imagine software and classified into four land use classes, built-up are, open space, green space and water bodies, where the urban sprawl is forum along South-West and South-Easterly directions. The work of Mohibul et al., (2022) deals with LULC change of Kolkata Urban Agglomeration (KUA) using an unsupervised classification technique from 1996 to 2008 and 2008 to 2020 for wetland or water bodies, fallow land, impervious surface, scrubs land, and grassland, etc., using ERDAS Imagine software.

Halder et al., (2022) have worked with anthropogenic interventions affecting hydro-geomorphology of KMA posing flooding problem in Kolkata since the road levels have been continuously elevated and essentially residential areas are consequently in lower elevations. They have also shown that the rise in population density is fasted in KMC wards 108 and 109.

Recently Basu et al., (2024) have studied LULC changes in Barasat sub-division in North 24-Pargana district between 1990 and 2024, where they indicate the agricultural land reduced from

60.32% in 1990 to 46.74% in 2024, while the built-up space went up from 5.69% to 30.35% in the same time.

From the above studies it is revealed that green patches and waterbodies are rapidly been converted to built-up areas in multiple places in and around Kolkata, more so in the peripheral wards and municipalities. However, this is a basic phenomenon world-wide, since people in rural areas prefer to congregate in the urban regions to access the benefits of urban infrastructure. United Nations proclaims that "Today, 55% of the world's population lives in urban areas, a proportion that is expected to increase to 68% by 2050"[5]. The rising share of urban population in India in Table 1.3 only endorses this fact explaining the pressure of influx that the cities face.

Table 1.3: Trends of Urbanization in India from 1961 to 2011

Census Year	Urban Population (in millions)	Percentage with respect to total population
1961	78.94	17.97
1971	109.11	19.91
1981	159.46	23.34
1991	217.18	25.72
2001	286.12	27.86
2011	377.10	31.16

Notes: As the 1981 Census was not conducted in Assam, and 1991 Census was not held in Jammu and Kashmir, the population of India includes their projected figures.
Source: Census of India - respective censuses (www.censusindia.gov.in).

1.2.1 Research Gap

The review presented in Article 1.2 shows that recently many studies have been published which deliberates on LULC changes in and around KMA. These are individual researches in their scope dealing with one particular study area. Hence, this research proposes to study multiple such pockets, manifesting rapid, medium and inception level of urban growths at the ward- or municipal level and suggest a holistic sustainable solution addressing all kinds of problems that are noted due to rapid urbanisation at such fringes of KMA.

1.2.2 Selection of Study Area

In this context, this research aims at reviewing three study areas in the fast growing fringes of KMA, one approaching saturation, one growing at rapid pace and one where rapid urbanization is taking pace.

[5] https://www.un.org/sw/desa/68-world-population-projected-live-urban-areas-2050-says-un#:~:text=Today%2C%2055%25%20of%20the%20world's,increase%20to%2068%25%20by%202050.

With reference to Fig. 1.1a, KMC Ward 109, the first of the proposed study areas, lying on either side of the Eastern Metropolitan (EM) Bypass, is on the eastern fringe of KMC and KMA that has come up with residential high-rises, multiple hospital facilities and many associated land uses during the 1990s, however, without there being any a priori future plan with specified infrastructural controls to adhere to. The end result manifests a fragmented LULC change. Ward 109 is an administrative division of KMC, under KMC Borough 12 in south eastern Kolkata, inducted into KMC in 1984. In absence of a master plan, various facilities have come up through private entrepreneurship causing fragmented growth hindering future provision of services, and can provide insights if thoroughly studied. The present KMC Ward 109 was one of such fringe areas of KMA that underwent indiscriminate change in its land and socio-economic character with steep rise in built-up area, with corresponding reduction in forest, vegetation cover, arable land and water bodies. Social changes have forced the small farmers to move away further adjust to urban ways of life within a very short time. In absence of municipal vigils, urban amenities like roads, pipelines for potable water supply and sewerage disposal, facilities for solid waste disposal system, etc., has lacked severely.

With open space within KMC scarce, CMDA (presently KMDA) published a "Concept Development Plan of a New Town at Sonarpur Baruipur Area" in 1995 and reiterated the same in "Vision 2025: Perspective Plan of CMA: 2025" published in 2005 proposing to develop region along the South-bound corridor. This boosted a rapid urban transformation of the-then Baruipur, which forces to select Baruipur as the second study area to the south-eastern fringe of KMA in Fig. 1.1a), that used to ensure the city's food security through supply of fruits and vegetables. There have been land allocations under the governance of West Bengal State Government to develop new infrastructures at Baruipur alongside private acquisitions it being a lucrative land acquisition hotspot.

However, the proposal was abandoned at a later stage, but by then acquisitions by the realtors have taken place that has potentially impaired efficient identification an earmarking of the space necessary for future infrastructural facility developments. Thus, once again planning intervention is essential to ensure right amount of roads, organized open space, etc., in this study area.

Finally, the last of the three proposed study areas would be KMC Ward 144 (Fig. 1.1a), which is actually the last of the wards to be included in the list of KMC in 2012 from the erstwhile Joka Gram Panchayats I and II, located at the south of KMA, where road (National highway, NH-12) and Metro Railway connectivity has now been established and many housing clusters, each hosting a set of towers, are coming up. Conversion from Gram Panchayat to KMC Ward is a clear indication to rural to urban transformation.

It needs quick intervention at KMC Ward 144, if the area has to be developed according to a master plan enriched by the experiences from KMC Ward 109 and Baruipur Municipality as well as other researches involving LULC of Kolkata. Also, some remedial measures can be suggested for Ward 109 and Baruipur to make some degree of amends in ensuring future urban infrastructures from the projected land use land cover at some horizon year.

In this research three study areas have been selected to study a rapid, a medium and an inception level of urban growth at the ward- or municipal level, and come up with a set of proposals addressing all kinds of problems observed in these three types of study areas. They show distinctive pace of growth.

Looking into Table 1.4a, that considers the first study area, KMC Ward 109, the pace of urbanisation is much retarded compared to the second study area at Baruipur Municipality (Table 1.4b), while the pace of urbanization is the fastest in KMC Ward 144 as shown in Table 1.4c. Vide Table 1.4a, the built-up area in Ward 109 has steadily grown over 36 years from a meagre 8.6% to 54.88%. However, in Baruipur Municipality the built-up area rose from 33.59% to 42.73% in only 10 years, while in 12 years, in KMC Ward 144, the built-up area rose from 22.96% to 39.14%. Looking into Table 1.4a, the development in KMC Ward 109 began in 1992. By 2010, Ward 109 was saturating, so people rushed to Baruipur making growth at Baruipur shoot up very fast. The same may be seen if Table 1.4b is compared to Table 1.4c. The growth in KMC Ward 144 started shooting up when the rest of Kolkata is nearly filled in rendering KMC Ward 144 a hotspot for the developers. This explains the logic behind choosing the three study areas.

Table 1.4a: Land use classification for KMC Ward 109 (705.27 ha) over time

Land use classes	1992	2002	2010	2018
Built-up Area	8.60%	21.13%	45.17%	54.88%
Vacant Land	64.37%	61.02%	41.3%7	32.33%
Waterbody	21.11%	16.00%	11.87%	11.08%
Vegetation	5.60%	1.50%	0.68%	0.63%
Stadium and Open Space	0.32%	0.35%	0.90%	1.09%

Table 1.4b: Land use classification for Baruipur Municipality (608.77 ha) over time

Land use classes	2010	2020
Built-up area	33.59%	42.73%
Vegetation	23.32%	19.14%
Vacant land	11.68%	10.80%
Waterbody	6.13%	4.99%
Agricultural land	25.29%	22.34%

Table 1.4c: Land use classification for KMC Ward144 (446.91 ha) over time

Land use classes	2011	2023
Built-up area	21.96%	39.14%
Vacant land	48.71%	39.37%
Vegetation	9.32%	4.40%
Waterbody	8.13%	5.10%
IIM Joka	11.87%	11.87%

The spatio-temporal changes in the vicinity of southern KMA indicate a gradual compact growth. The changeability of landscape from rural to urban built-up area along the outskirts or fringe at the surrounding areas of KMA undergoes social, economic and built environment changes. Changeability of landscape from rural to urban built-up area along the hinterland at the surrounding areas of city undergoes social, economic and built environment changes. The land conversion results serious environmental implications. Rapid population and economic growth in the low capacity rural areas and fragmented local government, result a significant stresses in terms of the delivery of social and environmental services, transportation infrastructure etc. Thus there is a need for researchers and policy makers to substantially predict the growth of urban expansion, plan accordingly at the very of its inception. So that gaps between demand and supply in planning can be avoided. Growing concern for citizens, environmental organizations, governments because of its negative impacts associated with target and achieved sustainable living can be optimally solved and planned by early governance and recommendations with the integration of predictive model. A prospective model is targeted to develop on Ward No. 109 and after validation it will be tried at Baruipur and Ward no. 144 for assess it generalization. So that the model can be implemented for other urban fringe areas.

1.3 Objective and Scope

1.3.1 Objective

It is proposed to study the rapidly growing urban fringes of KMA which are facing varied degrees of urbanisation, mostly under private entrepreneurships, creating infrastructural challenges since private operators do not derive much short time benefit out of the space left for development of future infrastructures. This results in space shortage and alignment crises in absence of any a priory detailed working plans.

The research aims to

- Study the present situation and figure out the spatio-temporal transition in urban hotspots in the study areas.
- Identify the natural and anthropogenic driving variables governing the dynamics of land use changes in the study area.

- Simulate growth for horizon year 2040
- Identify gaps by comparing with the Urban and regional Development Plans Formulation and Implementation (URDPFI) guidelines
- Provide guidelines for future planning to address the identified gaps in the existing cases while abide the URDPFI recommendations in new cases of urban planning

1.3.2 Scope

Since it is not prudent and cost-effective to study the entire fringes of KMA, it is proposed instead, to study only three areas, the KMC Ward 109 on the Eastern fringes by the East Kolkata Wetland, the Baruipur Municipality to the south of KMA, and the KMC Ward 144, since they represent high, medium and nascent paces of urbanisation, respectively, where different sets of problems are expected to show up. Finally, image processing, remote sensing and GIS tools are mobilised to project future land use land cover (LULC), validate the results for their accuracy, and project for a future horizon year to watch the outcome if the present trend of growth continues unabated. The future LULC would reviewed for their flaws to infer a solution guideline for the entire KMA fringes and similar other situations.

The gap between the URDPFI, 2014 recommendations and the existing or future recommendations must be addressed and minimised.

Year 2040 (15 years hence) has been chosen as the horizon year so that the results could be corroborated with the Census reports expected in 2041. Naturally, in the wards/ municipalities where the share of built-up spaces is more, and mostly fragmented, it would be a bigger challenge, while Ward 144 can benefit the most if the proposed intervention is made at the earliest.

The research works mentioned in Article 1.2 further identifies certain analysis tools that are reviewed in the following section to select the software to initiate the present research.

1.4 Review of Methods of Analysis and Prediction for Future

Remote sensing (RS) methods can be integrated with geographical information systems (GIS) to design sustainable LU allocation model. Cellular automaton (CA) models hold strong footprints in understanding the temporal evolution of urban land uses. Agent Based Modelling (ABM) involves the interactions of autonomous agents with multi-criteria analysis (MCA). Artificial Neural Network (ANN), a machine learning (ML) tool, consists of three or more interconnected layers. A Multilayer Perceptron (MLP) neural network is a feedforward artificial neural network that can perform a variety of tasks, including image recognition and transition prediction, useful in LULC change modelling. Statistical technique FRAGSTATS can be used to quantify the landscape distribution pattern.

1.4.1 Remote Sensing (RS) and Geographical Information System (GIS)

Remote sensing images can be analysed, manipulated and managed in a geographical information system to classify satellite images according to their LU classes using a land change modeller. In the pixel-based classification, each pixel is compared to the corresponding pixel from one date to another without considering their neighbourhood (Adam et al., 2016). In object-based image classification (OBIC), the remotely sensed imagery is classified according to the image objects instead of pixels. Thus, it is a two-step process that initially involves segmentation, where the image is divided into discrete objects or features by grouping pixels that are similar based on their spectral properties, shape, texture, and spatial relationship and finally classifying the objects, similar land cover types, in the present case.

Land use classification and land cover change detection studies have been conducted by Anderson et al., (1976) Lepers et al., (2005) Bhatta (2009), Taha (2014), and Basu et al., (2024) making use of with RS technique. LU classification maps, the basis of every analytical studies done with the satellite imageries, can be prepared by ERDAS IMAGINE (Lynch et al., 2020; Biswas et al., 2020, Nimbarte, Sainis and Balamwar, (2022). Dupuy et al., (2012) and Simwanda and Muryama, (2017) have employed the eCognition software for such a classification. Ramchandra et al., (2014), have studied the rate of land use change with the help of geoinformatics. Integrated RS and GIS methods have been used in land use/land cover (LULC) changes by Yang et al., (2003) Mundiya and Aniya, (2005) Deng et al. (2009) Sahalu (2014) and Ghosh, (2016) to refer a few. Data and maps generated and analysed by RS and GIS are further used in studies for urban growth prediction. Simwanda and Muryama, (2017) worked with RS and GIS for LU classification and have faced some pixel mixing problem.

A very common problem with the remotely sensed images while mapping the LULC is facing spectral confusion, whereby misclassification of pixels might happen. Manual digitization might be the best solution for this pixel-mixing problem (Lea, 2024).

1.4.2 Cellular Automata (CA)

Von Neumann and Ullam proposed the CA model during the 1940s. In a CA model, the study area is divided into cells using grid lines, usually square in shape for ease of partitioning them, each of which then keep evolving through a number of discrete time steps according to a set of rules based on the states of its neighbouring cells in the immediate previous step.

Wolfram (1984) was the first to use a one-dimensional CA. A two-dimensional CA model can be visualized as a sheet of graph paper where the smallest square area may be assumed as a cell. Each cell has two possible states, black (on) and white (off). Neighbourhood cells imply adjacent cells. There are two types of neighbourhood cells, the von Neumann neighbourhood (4 orthogonally adjacent cells surrounding the cell due for an update) and Moore neighbourhood (along with the 4 orthogonal cells, 4 cells placed diagonally giving 8 cells in aggregate surrounding the cell whose state is being inspected to be calculated having $2^9 = 512$ or 2^9). For each possible pattern, the rule would state whether the centre cell will be black or white on the next time instant.

Another neighbourhood type is the extended von Neumann neighbourhood which includes two closest cells in each orthogonal direction, there being eight such cells once again. In Fig. 1.2a, the grey cells are the von Neumann neighbourhood for the black cell. In Fig. 1.2b, the grey cells are the Moore neighbourhood for the black cell. In Fig. 1.2c, the grey cells are the extended von Neumann neighbourhood for the black cells

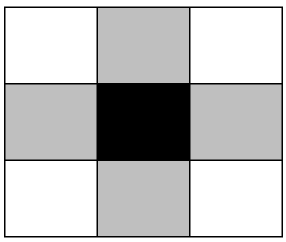


Fig. 1.2a: The von Neumann neighbour-hood for the black cell

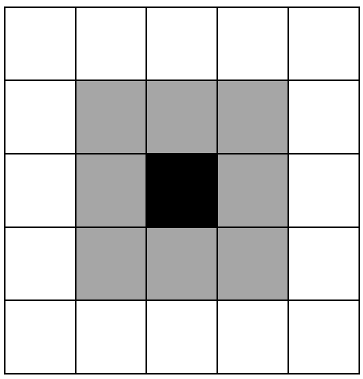


Fig. 1.2b: The Moore neighbourhood for the black cell

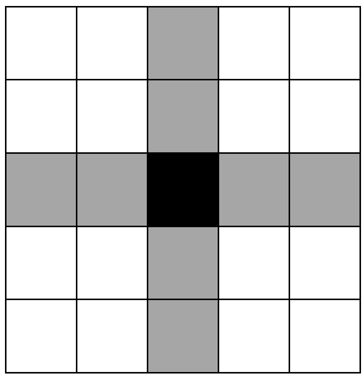


Fig. 1.2c: The extended von Neumann neighbourhood for the black cell

In CA the study area is divided into an array of cells and their transformation is decided by the transition rules set from the complexity of real world situation to simulate the pattern and process of urban growth.

Li, and Yeh, (2000) have discussed on implementation of CA being integrated with GIS to help the planners to understand better simulation in urban land use changes. Sietchiping (2000), Almeida et al., (2003), Shan et al., (2008), Ab Ghani (2011), Falah et al. (2020), and Zhang, et al., (2023) have worked on simulation for urban LU change coupled with other models, namely, Markov chain, SLEUTH, and Analytical Hierarchical Process (AHP).

Spatial and temporal heterogeneity and complexity of urban expansion create difficulty in use of CA model in urban growth prediction.

1.4.3 SLEUTH

The SLEUTH model uses five coefficients, namely, dispersion coefficient, breed coefficient, spread coefficient, slope coefficient and road gravity coefficient, to control the four growth rules, i.e., spontaneous, diffusive, organic and road-influenced, so as to simulate the urban growth at some later time instant. Also, vide Silva and Clarke, (2002) "besides the urban layers (that for statistical purposes need to number at least four), the model requires at least two transportation layers of different years (in each road layer it is also possible to define a road hierarchy), a single layer contains percent topographic slope, one layer with areas excluded from urbanization (the model allows classification in the layer by probability of exclusion), and a hillshade layer for use only as a background with the graphical version of the model". Different urban growth curves such as linear, S-shaped, exponential are represented denoting different urban growth rates (Hua et al., 2014). Spontaneous, diffusive, organic and road influenced growth are identified. Diffusion factor, breed coefficient, spread coefficient, road gravity factor and slope resistance factor are the controlling factors influencing the behaviour of the system (Clarke et al. 1996). Jantz et al., (2003) Oguez (2004), and Gandhi and Suresh, (2012) have worked with SLEUTH model to find out the controlling factors of growth and quantify the urban LU changes. Kumar and Agarwal, (2022) have calibrated LU changing factors to predict LULC of Prayagraj city with SLEUTH. Saxena and Jat, (2019) worked on Pushkar town, India, with SLEUTH capturing heterogenous urban growth with this model.

SLEUTH have been successfully used for global urban growth prediction purposes (Zhou, et al., 2019). Though SLEUTH is a very good tool for future prediction, but spatial accuracy and scale sensitivity must be considered carefully. It is not successful to predict the growth at pixel level (Jantz, Goetz and Shelley, 2003). Time consuming calibration process is another problem with SLEUTH.

1.4.4 Markov Chain, GEOMOD and MOLAND

Markov chain is a technique of estimation of probability of changes from its original state to any final state after a sequence of discrete or continuous time steps. Combining cellular automata spatial rule and Markov transition rule (i.e., the probability of transitioning to a specific state in a Markov chain depends only on the current state and the time interval) the prediction are made. The transition rule controls the transformation of a cell from one state to another state over a specific time period depending on the state of neighbourhood cells. For setting the transition rules, global restriction condition (distances to road and railway, etc.) local restriction condition (influence radius of a cell), geographical influence of an object (wherein, the influence decreases with increasing distance from the object) and other values (supplementary value reflecting urban land use better) are considered. After setting the transition rule, one can simulate the probability of changes in land use pattern. The simulation parameters can be calibrated by testing and analysing the simulated and real world land use images. The calibration finishes when the simulated value of each land use equals to the real value (Huang et al., 2015). Spatial pattern of changes by CA model and quantitative forecast of LU changes by Markov model have been done by several researchers (Sang et al., 2011, Jafari et al., 2016, Omar et al., 2014, and Baqa et al., 2021). Very recently, Baqa et al., (2021) have used CA-Markov model for Karachi, Pakistan, while have analysed Al-Hassa Oasis of Saudy Arabia, and Azabdaftari and Sunar, (2024) applied the same for Istanbul, Turkey, for urban growth predictions. Selmy et al., (2023) have used the CA-Markov model to detect, analyse and predict LULC changes in the arid regions of Egypt (Sohag Governorate) which help land policy-makers.

Ramchandra et al., (2013) used GEOMOD for modeling the spatial pattern of urbanization, which uses a hybrid approach, combining cellular automata, Markov chains, and machine learning algorithms to simulate land use/land cover changes. It requires the land use derived data to be classified into two groups: urban and non-urban. According to Ramchandra et al., (2013) CA-Markov is neighbourhood- and rule-dependent and shows exaggerated output. GEOMOD has given better results but it has a capability of work with only two land use classes. It works on a binary map (Aithal et al., 2018) and done using IDRISI TAIGA software. Soffianian and Nadoushan, (2010) used GEOMOD for Arak, Iran, Novin and Khosravi, (2017) the same for Bojnourd city, while Cruze-Bello et al., (2023) applied the model for Mexico City to simulate urban growth and study the effects.

CA-Markov model does not consider socio-economic factors, to convert a land, which, if incorporated, is likely to produce more accurate results (Subedi et al., 2013).

MOLAND (Monitoring land use/cover dynamics) is also a constrained cellular automata model whose inputs requires various referenced digital data: land use, accessibility, suitability, zoning and socio-economic. The model generates maps showing predicted land use development and indicators (Engelen, 2007). In this model each cell is earmarked with the dominant land use activity it manifests. The competing tries to achieve the best location on the basis of the influence of neighbourhood cells, accessibility to the infrastructure, physical suitability and zoning regulation. Barranco et al., (2014) have applied MOLAND for many European cities.

According to Nilsson et al., (2013), MOLAND does not predict future scenario too well at cell level but the prediction at neighbourhood level is quite good. The weight of each factor would be adopted by the experts and characteristics of the region.

1.4.5 Analytic Hierarchy Process (AHP)

AHP, proposed by Saaty (1980), can work with multi-criteria decision making projects using hierarchical structure. This method is useful in deciding the weights of the influencing factors. Land suitability analysis can be done after weighing the criteria according to their importance. Thereafter, all criteria maps could be overlaid using suitability indices. The suitability map is determined by multi-criteria evaluation and multi-objective land allocation. After deciding the factors affecting the land use of the area, pair wise comparison decides their weights and by overlaying, the suitability maps are prepared (Patil et al., 2012: Aburas et al., 2015).

Patil et al., (2012) have used AHP to generate land use suitability for residential purposes. They have used landscape characteristics response model (LCRM), socio-economic response model (SERM), environmental response model (ERM), geophysical response model (GRM) and utility response model (URM) in Pimpri-Chinchwad-Municipal Corporation (PCMC) area, Maharashtra, India. They have applied Saaty's nine-point weighing scale and made pairwise comparison matrix to show relative preference among the factors. AHP has been used by multiple researchers, namely Mohammadi et al., (2013), Mosadeghi, et al., (2015), Mawjoud, and Jamel, (2016), and Falah et al., (2020) to predict the urban growth by determining the factors affecting urban growth and putting weightage. Thapa and Murayama, (2010) have used AHP to determine the factors of urban growth in the Kathmandu valley, Nepal. Sahin et al., (2024) have worked for Turkey to identify suitable areas for urban development integrating AHP with GIS.

Limitation of AHP regarding its "subjectivity and uncertainty" have been studied by Li et al. (2018) and they have introduced a coefficient of variation for better evaluation of the method. The output of AHP depend on the inputs chosen by the decision makers. It does not provide sufficient guidance in structuring the problems to be solved, forming the levels of hierarchy. As the level of hierarchy increases, the difficulty of synthesizing weightage also comes up.

1.4.6 Agent Based Modelling (ABM)

This is a new trend for forecasting land use changes integrating with CA models and is giving a better result in predicting future urban sprawl (Sudhira et al., 2004). This model involves the interactions of autonomous agents with multi-criteria analysis. Group of agents identified on their behaviour. Based on rule interactions of agents create suitability map or score to the land parcel which are incorporated into GIS following two phases, namely, land selection and land conversion. Agent based model finds out the future change on the basis of interaction within neighbourhood and potential growth parcels. Fuzzy logic and AHP are used to find the factors influencing the land use changes. Agents' suitability scores are taken as inputs in ABM (Bharath et al., 2016). Agents can be static or mobile and can represent the external drivers responsible for changes. Agents' behaviour is determined by the rules taken and behaviour of other agents (Karah et al., 2024). CA-based transition and agent based state transition built feedback loop and deliver output.

Gaube and Remesch, (2013) have worked with ABM for urban planning of Vienna with interaction between household and spatial units and, population estimation along with socio-ecological system. Gonzalez-Mendez et al., (2021) have conducted urban planning with ABM relating physical environment and human needs. Guo, et al., (2024) worked on Wuhan, China for "population–land simulation" and Zare et. al., (2024) worked on Sydney with ABM for chalking the development of decision-making process and sustainability. Shuvo and Janssen, (2013) have worked on Dhaka city, Bangladesh to find out the settlement growth with CA-generated suitability score. Gonzalez-Mendez et al., (2021) have conducted urban planning with ABM relating physical environment and human needs. Rohit (2022) has researched on growth potential of Hyderabad (Zone-1) by using ABM. Every parcel with suitability score and vector attributes are contributed towards future growth potential of any area.

Though many researchers have worked with ABM, its complex system composed of heterogeneous agents Crooks et al., (2008), which made ABM questionable for its applicability.

1.4.7 Artificial Neural Network (ANN) and Multi-Layer Perceptron Neural Network Model (MLPNN)

ANN is a kind of machine learning model that functions like human brains. It consists of artificial neurons called units which are arranged in three layers, namely, the input layer (receives data), the hidden layer(s) (analyses data) and the output layer (produces results), and a very important application of artificial intelligence (Wu and Feng, 2017). This model has successfully been used for climate change (Zhang, 2018) and urban growth prediction for five major Greek cities (Tsagkis et al., 2023).

Pijanowski et al., (2002) have presented a land transformation model (LTM) with ANN to forecast and understand the pattern of land use changes. The output of ANN shows the chances of change in a cell. Maithani (2009) has worked with ANN for Saharanpur city, India, to demonstrate the relationships between "urban growth potential and the site attributes". Integration of ANN with CA has a powerful ability for modelling the behaviour and pattern of urban land use changes and can become one of the tools for urban planning (Xu et al., 2014).

Xu, et al., (2020) has used an ABM-ANN model since it shows more accurate results than ANN based CA model. MLPNN is a modern feedforward ANN model, trained with backpropagation method. It consists of at least layers with one or more hidden layers of nonlinearly-activating nodes sandwiched between an initial input layer and a terminal output layer. Layers are fully connected. Backpropagation, used for training the neural network, is a gradient estimation method in network parameter updating. Deciding the time steps (discrete or continuous) and number of iterations for urban growth are also very important determinants as accuracy of the model depends on iterations. The simulation will not be the same in all the cases. Few time steps will not show the spatial details in simulation process, necessitating increment in number of steps to yield accurate simulation results.

MLPNN has been used by researchers for urban growth prediction (Hakim, et al., 2021; Kim et al., 2022; Dousari et al., 2023, Dolui and Chakraborty, 2023, and Mithun et al., 2022). Halder et al., (2024) worked with MLPNN Land Change Modeler (LCM) module of TerrSet software to forecast built up area in Durgapur Municipal Corporation. Saha, et al., (2022) worked with MLPNN Markov chain model for Siliguri Municipal Corporation built up up area forecasting to manage the unplanned growth problem.

Though greater computational burden (Jack, 1996) is a real problem with ANN but MLPNN is considered one of the most efficient forecasting technique for urban growth prediction.

1.4.8 Statistical Method – FRAGSTATS

To compute landscape metrics for categorical maps, FRAGSTATS may be adopted. It is an open source software. The statistical analyses by FRAGSTATS quantifies the landscape distribution pattern. Parameters related to class area, patch mosaic and landscape help researchers to know about the composition of the land (McGarigal and Marks, 1995). Deng et al., (2009) used FRAGSTATS' spatial metrics to assess the LU change pattern. Ramchandra et al., (2012), worked with temporal remote sensing data and FRAGSTATS, to understand the urban dynamics based on landscape metrics for Bengaluru. They have performed vegetation cover analysis, land use analysis, and density gradient analysis and used FRAGSTATS to develop landscape metrics including patch area, percentage of landscape, largest patch index, and number of urban patches, patch density, perimeter-area fractal dimension, and landscape division index, etc., to explore the pattern of urbanisation. Once again, Ramchandra et al., (2014) have studied Kolkata and its 10 km buffer area and its land fragmentation through FRAGSTATS.

Taha (2014) has also used FRAGSTATS software on classified images to assess the land cover changes in Al-Monib Island and analyses the spatial metrics which were derived from the images. Mehta et al., (2022) have recently worked with FRAGSTATS for the area around

Greater Gir Landscape, Gujarat, for fragmentation assessment of the forest area which help in conservation and expansion of the forest area. Cheng et al., (2024) and Noviani et al., (2023) have worked with FRAGSTATS for urban growth pattern. However, Masoudi et al., (2024) while with metrics have highlighted that metrics depend on the resolution of the image. Das and Sarkar, (2021) have conducted statistical analysis for a part of Bhagirathi-Hugli river basin of Nadia and Purba Bardhaman district to assess health of the river. Mustaqum and Islam, (2023) have done LU classification, where analysis where LU quantification of Murshidabad district, West Bengal, through FRAGSTATS has helped in socioeconomic development and preserving ecological system to nurture local biodiversity.

1.5 Study of Land Surface Temperature (LST)

Land use land cover (LULC) changes have direct and indirect effects on various facets of the environment. Urban Heat Island (UHI) occurs when an area experiences a much warmer condition compared to its nearby surroundings. Generally, city areas do have warmer temperature compared to adjoining rural areas. Solecki et al., (2004) have examined the UHI effect at Camden, New Jersey, using meteorological station data and tried to mitigate the situation. Mallick et al., (2008) have worked on land surface temperature (LST) in Delhi. Different standardized LST can be seen in different land uses. Buyadi et al., (2014) worked on the cooling effect of the park by measuring the temperature difference between inside and outside the park. They found that the cooling effects of parks depended on their composition. Urban green spaces could reduce the high radiant temperature of the surrounding developed areas. Ramrez-Aguuilar et al., (2019) have worked on the relationship of thermal, demographic and urban form data of Bogota, Colombia, and found a relationship between UHI and population size.

Allaka et al., (2019), studied the effect of rapid urbanisation on the increase of LST in Kolkata by using Radiative Transfer Equation (RTE) on LANDSAT images in between 2000 to 2017.

Das and Angadi, (2020) deals with land surface temperature (LST) changes along with LULC changes along with unplanned urban growth between 1990 and 2016 in Barrackpore subdivision in the North-Eastern fringes of Kolkata. They have used multi-spectral satellite data from Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) data for the months of January, April, and November. They have made use of indices like normalized difference vegetation index (NDVI), normalized difference built-up index (NDBI), normalized difference moisture index (NDMI), and normalized difference water index (NDWI) to correlate LST and different land-use classes.

Maity and Srivastava, (2020) studied LST using NDVI for Kolkata Urban Agglomeration (KMA), West Bengal, India. They summer season and LST has a negative relationship and winter season has vice versa.

Biswas and Ghosh, (2022) studied spatiotemporal distinction of LST in Kolkata and its suburban area in response to LULC changes. They calculated several indices, namely, Normalized difference built-up index (NDBI), Normalized difference vegetation index (NDVI), Modified normalized difference water index (MNDWI) at pixel level and overlaid to find out the correlation between indices and LST. They found mean LST is comparatively high in the core region than the surrounding. LST is relatively high over built up area, agricultural land without crop and open land and low on water bodies and forested area.

Bera et al., (2022) worked on LST in KMC relating to different surface categories during different seasons using regression analysis and hierarchical partitioning analysis. They recognised that LST is influenced by surface materials, landscape composition, socio-economic parameters, topographic parameter, and pollutant parameter.

Mahata et al., (2024) worked on impact of land cover changes on LST over the periphery of KMC and performed hotspot analysis for the period of 1991-2021.They found impervious surface contributes higher for higher LST. They used Getis-Ord Gi* index for hot spot and cold spot analysis. Urban Heat island (UHI) has also been studied and tried to find the significance of green space in extenuating UHI.

Saha et al., (2024) tried to find out relationship in between LST and biophysical indicators (NDVI, NDBI, NDWI) of Kolkata city by using R programming in GAM model.

1.6 Selection of Software

The references mentioned in this review are representative only and by no means exhaustive. All of the works have used remote sensing and GIS combined with multiple statistical and analytical tools. It is understood by now that accurate data requirement over a wide span of time, appropriate land use maps and related information are the prerequisites for a good result. Extensive application of numerical tools like cellular automata, Markov chain model, SLEUTH model and MOLAND model have been used to predict the future urban sprawl. All methods have their own strengths and weaknesses that would influence the outcome. For example, the CA model can simulate changes only in a binary form (change between two categories) while the CA-Markov model can simulate change among several categories.

MLPNN can work with several connected layers having complex data pattern. Feedforward propagation passes the input data one layer to another after computation whereas backpropagation is an algorithm which trains neural networks adjusting weights and biases to minimise distance between prediction and actual scenario. MLPNN is a very efficient forecasting method since it considers physical, socio-economic and environmental independent variables, probability transition maps and integrating with Markov-CA model express better result.

Thus, it is proposed to couple the MLPNN and Markov Chain algorithms in remote sensing and GIS platforms (ERDAS Imagine 2014, ArcGIS 10.2) to define an efficient set of forecasting skillset that may be implemented for the present research. Finally, FRAGSTATS could be applied to provide a statistical account of the degree of land use fragmentation. A (Gaussian) Maximum Likelihood Supervised Classification, which has been observed to have produced satisfactory Kappa coefficients (Lillesand et al., 2015) during the analyses to follow, is proposed for classifying the images. It is proposed to use the 'Land Change Modeler for Ecological Sustainability' of IDRISI 17.0 (the Selva edition), for the growth predictions for the future horizon year, 2040, in the present study. The horizon year is 15 years hence from 2025, and the results could be matched with the Census reports of India, expected in 2041.

A predictive model combining data from various sources predicts urban growth pattern for the horizon year which helps to allocate resources and enhance infrastructure planning. By analysing historical data and current trends, the model predicts where a city would expand, where population densities will shift, when water bodies will be engulfed, or open spaces would be occupied, or greeneries be removed. These insights would help the planners to assign resources more effectively ensuring that infrastructure would keep pace with demand. Areas overcrowded or underserved along with population growth and economic factors can be marked with satellite imageries, Geographical Information System (GIS), population growth and economic indicators and can be planned accordingly. Reducing water bodies, greeneries impact environment and ecosystems. Predictive modelling aids in disaster management with proper immediate and long term planning. Renewable resources can be better distributed by preventing waste and promoting equitable distribution. Provision for employment, health, education, potable water, sanitation, sewerage, controlled land value can be prioritized for the deprived areas and gap can be removed in between underserved and privileged ones. So predictive modelling ensures sustainable urban development for generations to come.

1.7 Organisation of the Thesis

The thesis is distributed over six chapters followed by a list of references. Chapter 1 introduces the problem, and reviews recent researches on LULC changes in and around Kolkata Metropolitan Area or certain pockets inside KMA for problem identification. The research gaps, study area, objective and scope of research have been delineated. The methodology has been planned in Chapter 2. Chapter 3 introduces the study areas in some detail. Chapter 4 presents the analysis of the three study areas in full detail beginning with collection of Google Earth and Landsat images, subsetting the study areas, spatio-temporal change, and growth prediction by transition potential and change allocation. The outcomes from Chapter 4 are discussed in Chapter 5, followed by conclusions and recommendations in Chapter 6.

Chapter 2

METHODOLOGY

2.1 Introduction

In Chapter 1 some recent works on the study of changes in LULC and LST around Kolkata has been reported along with a review of the software used by various researchers. From these, the objective and scope of work for this research have been delineated along with identification of three study areas in the form of KMC Ward 109, the Baruipur Municipality and the KMC Ward 144, all within KMA, arranged in the ascending order of non-built-up area they hold. Ward 109 is on the east and the remaining two to the south of KMC. Baruipur is located outside the KMC and Ward 144 in the fringe of KMC. Certain analysis tools have been proposed. It is proposed to compare the present state of the three study areas with the Urban and Regional Development Plans Formulation and Implementation (URDPFI, 2014) recommendations to detect the gap in between guidelines and ground reality. If this gap proliferates without being managed or planned, the situation in the proposed horizon year, 2040, will proliferate, calling for a holistic and sustainable remediation, thus defining the scope of this research.

2.2 The Proposed Methodology for Growth Prediction

To predict the growth for the horizon year, 2040, for the three study areas the methodology is graphically presented in Fig. 2.1 and narrated as well in the following:

Step 1: Identification of the Study Area

Since the built-up areas in KMA is expanding due south-west of KMA along the Diamond Harbour Road (a part of National Highway 12, NH-12[1]), and due south-east along the E. M. bypass and the State Highway 1 (SH-1[2]), three areas along these roads have been selected which manifest three stages of urbanisation in the fringes of KMA, maximal at KMC Ward 109, intermediate at the Baruipur Municipality, and the least in KMC Ward 144 (Fig. 1.1a). Being representatives of very heavily built-up, intermediate and nascent

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[1] NH-12 initiates from NH-27 at Dalkhola in Uttar Dinajpur district, continues through Karandighi, Raiganj, Malda, Berhampore, Beldanga, Bethuadahari, Krishnanagar, Ranaghat, Barasat, Dankuni, Santragachi, Behala, Joka, Diamond Harbour, and Kakdwip to terminate at Bakkhali.
Source: https://en.wikipedia.org/wiki/National_Highway_12_(India)

[2] Starting from Bangaon, SH 1 connects Chakdaha, Madanpur, Kalyani, Halisahar, Naihati, Ichapore, Barrackpore, Kolkata, Jadavpur, Garia, Rajpur Sonarpur, Baruipur and Jaynagar Majilpur to end at Kulpi.
Source: https://en.wikipedia.org/wiki/State_Highway_1_(West_Bengal)

growth zones, they are expected to highlight all kinds of infrastructural shortfalls which should be addressed while planning for future.

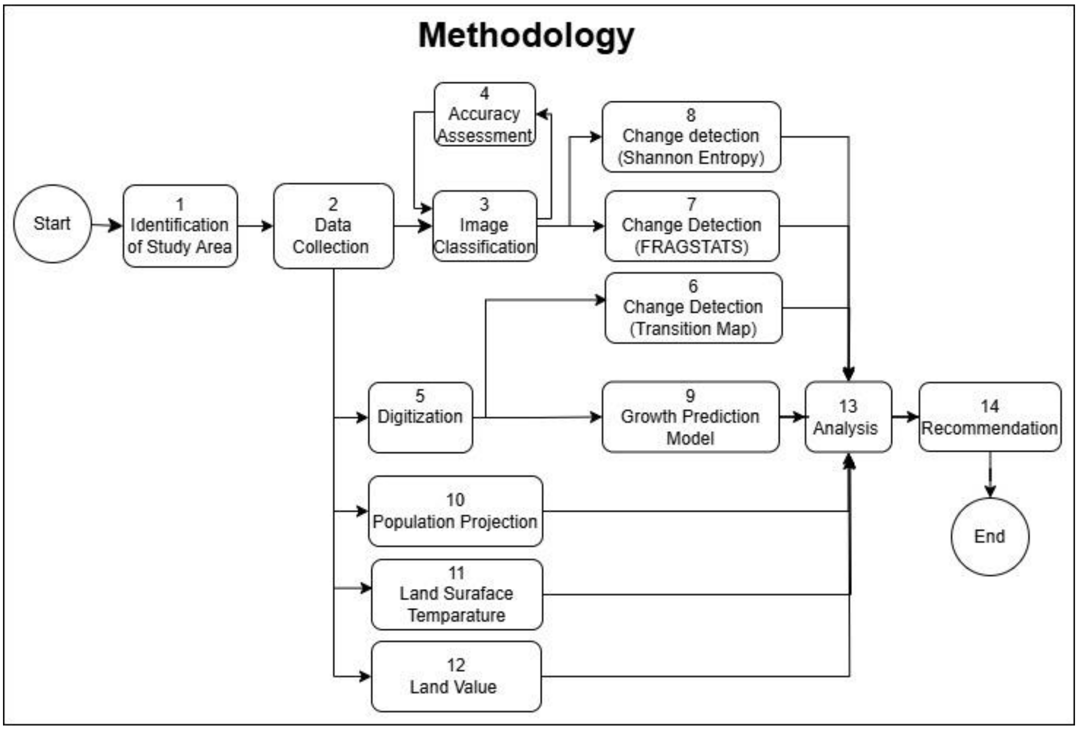

Fig 2.1: Proposed methodology

Step 2: Data Collection

Primary data

I. A Garmin GPS will be used to collect spatial data and converted to a $.shp$ file to train the ArcGIS 10.2 software to identify LU classes having specific pixel and colour tones.

II. Ground truth verification would follow the classification to verify the situations like water bodies, high rises, open space, roads and slum dwelling, etc.

Secondary data

I. Google map images of the study areas will be collected for the historic and present time instants, to be processed in ArcGIS (Ver. 10.2) and IDRISI SELVA (Ver.11.7)

II. Landsat 5TM, Landsat 8 and Landsat 9 images will be collected as inputs from the U. S. Geological Survey (USGS) Earth Explorer[3] website to generate the LULC classification maps and identify the LULC changes, land fragmentation and sprawling.

III. LU maps will be collected from the KMC/municipality offices to extract digitized maps of the three study areas.

IV. The population statistics will be collected from the Census data of 1991, 2001, and 2011.

[3] (http://earthexplorer.usgs.gov)

Step 3: Image Classification

Images will be classified by the Gaussian Maximum Likelihood Classification (Lillesand et al., 2015) algorithm, later found to have provided satisfactory Kappa statistic (Liu and Mason 2016, p. 100) during analysis, to obtain land use changes, urban sprawling and land fragmentation. The GPS survey data would help in ground truth verification and accuracy assessment.

Step 4: Accuracy Assessment

Accuracy assessment will be done for all classified images following Congalton and Green (2019), Liu and Mason (2016) and Lillesand et al. (2015). For historical imageries, sample points are randomly generated in ArcGIS covering every LU category. Stratified random sampling is preferred for point generation since it generates minimum number of samples from each category. LU classes of those points will be extracted and opened in Google Earth. These points are compared pixel by pixel. The accuracy is obtained by computing overall accuracy (Congalton, 2001, p 326), user's accuracy (Story and Congalton, 1986), producer's accuracy (Congalton, 2001, p 326) and kappa index (Congalton, 2001, Rwanga and Ndambuki, 2017). The minimum level of accepted accuracy should be 85% (Anderson et al, 1976). The formulae for accuracy assessment are provided in an appendix at the end of Chapter 2 (Ref. Appendix A2.1, Eqs. A2.1~4, p.27).

Step 5: Digitization

Google Earth images of each study areas will be digitised in ArcMap 10.2 (conversion of geographic data from images to digital or vector format) to identify LULC classes of intended year which helps to avoid misclassification of pixel in classified image (Step 4). The digitised map will be exported to ArcGIS as a $.kml$ file and later converted to a $.shp$ file.

Step 6: Change Detection

It is a technique by which changes in land use/ land covers are detected by using remote sensing imageries over time. In the change analysis [4] technique the digitised maps of base years are compared and transition are quantified for each LULC classes. IDRISI Selva software is used for this.

[4] Change analysis is the evaluation of quantitative changes in land use land cover (LULC) between two maps at two time stations for the study area in the form of net change, persistence, and the specific transition of land cover information (Hasan et al., 2020). A transition map or change map depicts changes from all land categories to a specific land category or all land category, essential for understanding the changes in modelling.

Step 7: Statistical Analysis by FRAGSTATS

Statistical analyses at patch level, class level and landscape level will be conducted using an open source software FRAGSTATS[5] to measure the character of spatial urban growth of the study areas. Classified images (Step 3) in GeoTIFF format are fed in FRAGSTATS to compute metrics at three levels, the patch metrics, class metrics, and landscape metrics[6]. CORE and NCORE indices would explain the patch level metrics, Class area (CA), Percentage of landscape (PLAND), Number of Patches (NP), Largest Patch Index (LPI) and Total Edge (TE) will be used in class level metrics, while Splitting Index (SPLIT), Largest Patch Index (LPI), Number of Patches (NP), Total Edge (TE), and Patch Density (PD) will be used at the landscape level to identify land fragmentation and land dominance.

Step 8: Shannon's Entropy

Degree of concentration or dispersion of built-up area and pattern of urban sprawling will be determined using Shannon Entropy (Yeh and Li, 2001, and Li and Yeh, 2004). Classified images (Step 3) will be fed to ArcGIS to compute the entropy. The study area will be divided into zones or fishnets (area of rectangular cells) and built up area will be extracted and entropy and relative entropy values will be calculated for every zones/fishnets [Appendix A2.2, Eqs. A2.5 and A2.6, p.27].

Step 9: Growth Prediction Model

A growth prediction model identifies the relationship between spatio-temporal changes and fluctuations in socio-economic, physical and environmental variables of any study area and predicts LULC for future years. Images[7] of two base years for each study area will be used for the change analysis and creation of change maps. These maps will be grouped and sub-models will be developed. Based on review of similar study all influencing variables will be selected, transformed using utility (e.g., evidence likelihood transformation'[8]) and will be tested for potential explanatory power using Cramer's V tests[9]. The sub model structure will be built with 'multi-layer perceptron neural network'[10] (MLPNN) as modelling algorithm, selected driver variables, change maps of base years. The sub models will be run repeatedly with different variables, number of iterations and number of hidden nodes until accuracy rate

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[5] https://www.fragstats.org/index.php/downloads
[6] https://www.fragstats.org/index.php/documentation and https://info.undp.org/docs/pdc/Documents/ECU/MetricasFragstats-English.pdf
[7] Base year's images are training data which is used for model building.
[8] Evidence Likelihood Transformation is a very effective means of incorporating categorical or continuous variables (binned to 256 class) into analysis by transforming them through likelihood function.
[9] Cramer's V indicates that the potential explanatory value of two variables showing association between them.
[10] Jensen 2015, p.448

80% is achieved. The final model will be used to generate transitional potential maps[11] for the projected year[12]. Markov Chain (MC) will be used for change prediction and transition matrix[13] is generated which is used for change allocation and prediction map for projected year is generated. The accuracy assessment will be done between predicted and actual map of projected year with overall accuracy, user's accuracy, producer accuracy and kappa index. After satisfactory accuracy assessment for the projected year, the simulation for the horizon year[14] will be undertaken. Land Change Modeller (LCM) module of IDRISI Selva 17.0 will be used for this purpose and the detailed steps along with inputs and output are explained in Table 2.1.

Step 10: Population Projection and other analyses

On the basis of past and present decadal data collected from the Census of India (1991, 2001, 2011), population of 2021 will be forecasted by the average of arithmetical increase method, geometrical increase method, incremental increase method, and declining growth method (Garg 1977). Average of these four will be adopted here for further use. Work participation as a socioeconomic aspect as an effect of urbanisation will be studied. (Ref. A2.3, p.28)

Step 11: Land Surface Temperature (LST)

Land surface temperature is the radiative skin temperature over land. Thus, the three study areas with three different proportions of built-up area, are supposed to influence the local LST.

Several clean images without cloud cover and noise for each year under consideration will be collected in equal numbers for the study area, taken nearly at similar dates and times. Average of these images will be computed which will provide the temperature difference between these two years.

Following this sequence, it is proposed to forecast the future urban pattern of the three study areas without supervision to reach the final inferences. (Ref. A2.4, p.28)

[11] Transition potential maps are used to model the LU changes by representing the pressures on each land use. The transition potential is an index that ranges from 0 to 1, with higher numbers indicating pixels that are more similar to places where a transition occurred during a calibration interval.
[12] Projected Year is year of assessment for which accuracy of the model is calculated.
[13] Transition matrix is a square matrix where the elements in a particular row (say, the third row) expresses the probability of transition from the said (i.e., the third) land cover category to every other land cover category.
[14] Horizon Year is the year for prediction, which is used for future planning.

Step 12: Land Value

Base unit area value (BUAV) map prepared by the Municipal Valuation Committee of Kolkata Municipal Corporation (KMC) will be studied along with change in the valuations of apartments over time to trace out any pattern visible.

Table 2.1: Growth prediction modelling steps

#	Steps	Input	Output
1	Conversion	Image of two base years	Convert image to ASCII Convert ASCII to map (.rst)
2	Land Change Model	Maps of two base years (.rst)	Maps generated with same parameter (.rst) such as background value, same land category
3	Change analysis	.rst of two base years	Change map in between land use categories (.rgf and .rst)
4	Transition potential		
4.1	Transition sub-model	Change maps	Sub-models generated by grouping the change maps
4.2	Variable transformation utility	Possible Input Variables (selected based on review papers and similar study)	Evidence likelihood transformation of the variables (input variable) done on the basis of change maps (transition map)
4.3	Test and Selection of driver variables	Input variables	Test of the potential explanatory power of a variable using Cramer's V test.
4.4	Transition sub-model structure	Model (MLPNN), driver variables, change map of base years	Generate model structure
4.5	Run transition sub-model	Run MLPNN	Transition potential maps generated (.rst/.rgf) and html file(explains run statistics)
5	Looking at the accuracy of the model for every sub-model steps 4.2 to 4.4 are rigorously changed and tested.		
6	Change prediction		
6.1	Change demand modelling	Transition potential maps, sub-models for projected year	Markov chain matrix generated for the projected year
6.2	Change allocation	Model run	Change allocation maps/predicted map generated for the horizon year
7	Validation	Predicted map and Google Earth actual Image	Overall accuracy, user's accuracy, producer's accuracy and Kappa Index used for accuracy assessment.

Step 13: Analysis

In this step an attempt will be made to assess and reason out the change dynamics.

Step 14: Recommendations

Recommendations will be proposed to address the infrastructural deficits and lack of social well-being for the horizon year. GIS tools can be used to forecast alternative scenarios with different control measures and compare the outcomes and select the right control measures.

Appendix for Chapter 2

FORMULAE FOR READY REFERENCE

A.2.1 Accuracy assessment (Liu and Mason 2016, p.100; Jensen 2015 Ch. 13)

Different measures of accuracy are listed below:

$$\text{Overall Accuracy} = \frac{\text{Sum of the correctly classified cells}}{\text{total number of cells}} \quad (A2.1)$$

$$\text{Producer's Accuracy} = \frac{\text{Total number of correct pixels in a category}}{\text{Total number of pixels of that category derived from referenced data}} * 100\% \quad (A2.2)$$

$$\text{User's Accuracy} = \frac{\text{Total number of correct pixels in a category}}{\text{Total number of pixels of that category derived fromclassified data}} * 100\% \quad (A2.3)$$

$$\text{Kappa Index,} \quad \kappa\hat{} = \frac{M\sum_{i=j=1}^{r} n_{ij} - \sum_{i=j=1}^{r} n_i n_j}{M^2 - \sum_{i=j=1}^{r} n_i n_j} \quad (A2.4)$$

Here r = number of rows in the error matrix, n_{ij}= Number of observations in (row i, column j) position, n_i = total number of observations in row i, n_j = total number of observations in column j, M = total number of observations in the matrix.

Generally, a minimum number of 50 samples for each land class category should be taken. But if the area is large or has a large number of land category (more than 12 categories) number of samples should be increased to 75 to 100 per category. Sometimes, according to the importance of any particular category, the number of samples might be increased.

A.2.2 Shannon's entropy (Bhatta 2012, p. 53)

Shannon's entropy is computed by the following formula

$$H_n = -\sum_i^n P_i * ln(P_i) \quad (A2.5)$$

Where P_i is the proportion of the variable or built-up area in the ith zone (i= individual zone) and n is the total number of zones.

To scale the entropy value from 0 to 1 a Relative or Normalized Shannon's entropy value is used

$$H_n = -\sum_i^n P_i * ln(P_i)/ln(n) \quad (A2.6)$$

Value closer to 0 measures compact distribution and closer to 1 reveals the distribution is much disperse. Higher values indicate the occurrence of sprawl.

The value of entropy ranges between 0 to ln(n). The entropy value is close to zero when the distribution is concentrated in one part while a value near ln(n) reveals evenly dispersed-distribution. The larger values of entropy indicate that the built-up area is sprawling (Sudhira, et al, 2004). Relative entropy values range between 0 and 1. A value of 0 indicates that the distribution is very compact, whereas values closer to 1 reveal that the distribution is much dispersed and urban expansion is going on.

A.2.3 Population projection (Garg 1977)

Arithmetic increase method follows the formula, $P_n = P_0 + nc$ (A2.7)

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

In Geometrical increase method, the formula is, $P_n = P_0 \left(1 + \frac{r}{100}\right)^n$ (A2.8)

Where, population P_n after n decades, P_0 is the latest known population, r is the geometric mean.
In Incremental increase method, population after nth decade

$$P_n = P_0 + nc + \frac{n(n+1)}{2}x \quad \text{(A2.9)}$$

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 Declining growth method, the formula is, $P_n = P_0 + \frac{r-r_1}{100} * P_0$ (A2.10)

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

To avoid the biasness of the result of one method, the average of Arithmetical increase, Geometrical increase, Incremental increase and Declining growth method has been taken as the projected population of the year 2021.

A.2.4 Land Surface Temperature, LST (Das and Angadi 2020; Biswas and Ghosh 2022)

Solar radiation is responsible for radiative skin temperature of the land which results in LST. To measure the radiance at the earth's surface, the atmospheric interference must be removed from the data. LST has been calculated by the following formula:

$$L\lambda = \frac{(LMAX\lambda - LMIN\lambda)}{(QCALMAX - QCALMIN)} * (DN - QCALMIN) + LMIN\lambda \quad \text{(A2.11)}$$

Here, $L\lambda$ =Spectral radiance at the sensor

$LMAX\lambda$ = Spectral radiance scaled to $QCALMAX$ in (Watts/(m^2 * sr* µm))

$LMIN\lambda$ = Spectral radiance scaled to $QCALMIN$ in (Watts/(m^2 * sr* µm))

$QCALMAX$ = Maximum quantized calibrated pixel value in DN (digital number)

$QCALMIN$ = Minimum quantized calibrated pixel valueK

The radiance is expressed as the Top of Atmosphere Brightness temperature (in Kelvin) using the thermal constants provided in metadata file

$$TB = \frac{K_2}{Ln(\frac{K_1}{L\lambda}+1)} \qquad \text{(A2.12)}$$

Where, TB = At-satellite brightness temperature (K)

$L\lambda$ = Spectral radiance in $W.m^{-2}.sr^{-1}.\mu m^{-1}$

K_1 and K_2 = Band specific thermal conversion constant from the metadata

Conversion of temperature from Kelvin to degree Celsius, $TC = TB - 273.15$ (A2.13)

In ArcToolbox, all calculations are done by Map Algebra operation. Images are carefully selected. They are either pre-monsoon or post-monsoon, cloud free images. Four images of every year are again averaged. Individual image of any season does not satisfy the explanation of temperature change. Hence, average images are proposed.

Chapter 3

THE BASE YEAR STUDY AREAS

3.1 Introduction

Kolkata Metropolitan Development Authority, KMDA, established in 1979, is responsible for the planning and development of the Kolkata Metropolitan Area, KMA located in West Bengal, India (Fig. 3.1). KMA covers 1886.67 km^2 with 4 Municipal Corporations (Kolkata, Howrah, Bidhannagar, and Chandannagore) (Fig. 1.1b), 37 Municipalities and 23 Panchayat Samitis[1]. Recently 35.26 km^2 have been added to KMA of which Baruipur contributes 4.92 km^2. Kolkata Municipal Corporation, KMC (Fig. 3.1), the biggest and the oldest municipal corporation, has experienced a rapid expansion without stringent planning, and is governed now by the provisions of the West Bengal Town and Country (Planning and Development) Act, 1979.

It may be recalled that it has been found in Chapter 1 that in the last census report published in 2011, KMC has faced an 1.67% net drop in the decadal growth rate, which, if further analysed, shows that population in the inner wards (1~100) has really dropped by 6.326% between 2001 and 2011, whereas in KMC wards 101 through 141, there has been a rise of 10.174%. Wards 142 to 144 have been added only in 2012 and not yet reflected in Census of India reports. Shrinking supply of land and associated rise in land value in the inner core and the reverse at the outer fringes might have actuated this trend.

The works by Rahaman et al. (2018), reproduced in Fig. 3.2, corroborates to these facts, where the urban expanse, shown in red patches, are found to drift towards the lower priced urban fringes being complemented by the services of arterial roads, suburban railways and metro railway services. The bar charts in Fig. 3.2, compiled from the Census of India reports, shows the decline and rise in population in the core and fringes, respectively, of KMC. KMC Wards 1 to 100 have been in existence since 1965, and regarded here as the inner wards, while Wards beyond 101 may be regarded as the outer city. The outer wards and their neighbourhoods within KMA have accommodated the spilled population from the inner wards along with in-migrated population. People from the inner wards have started migrating to the fringes which presently have improved connectivity to the employment hubs, lower cost of living, low land price or

[1] https://kmda.wb.gov.in/page/cms/introducing_kmda_011393

rent, and health and education facilities. It has resulted in increased population density in the peripheral areas.

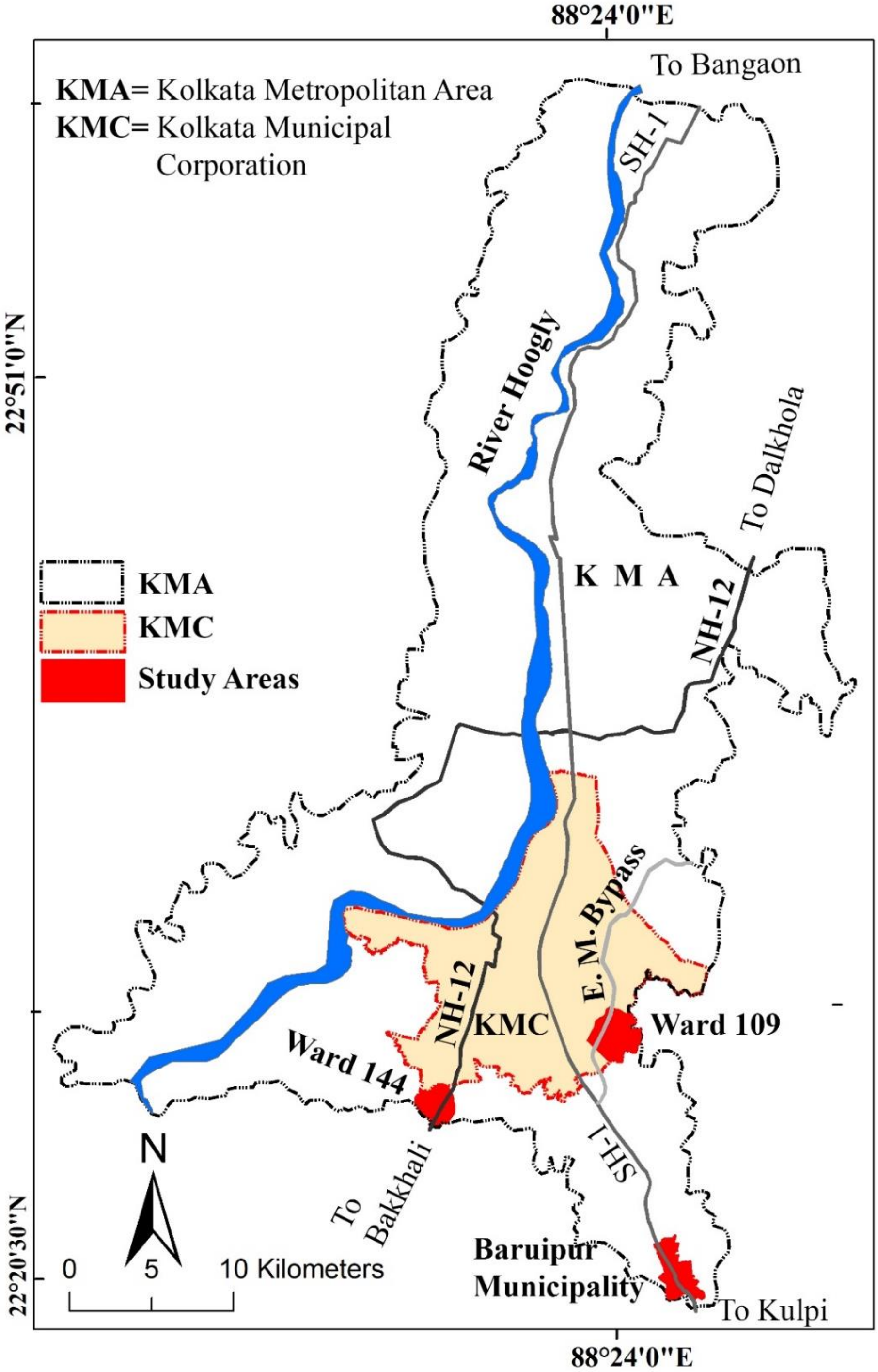


Fig. 3.1 The three study areas, marked in red, under KMA

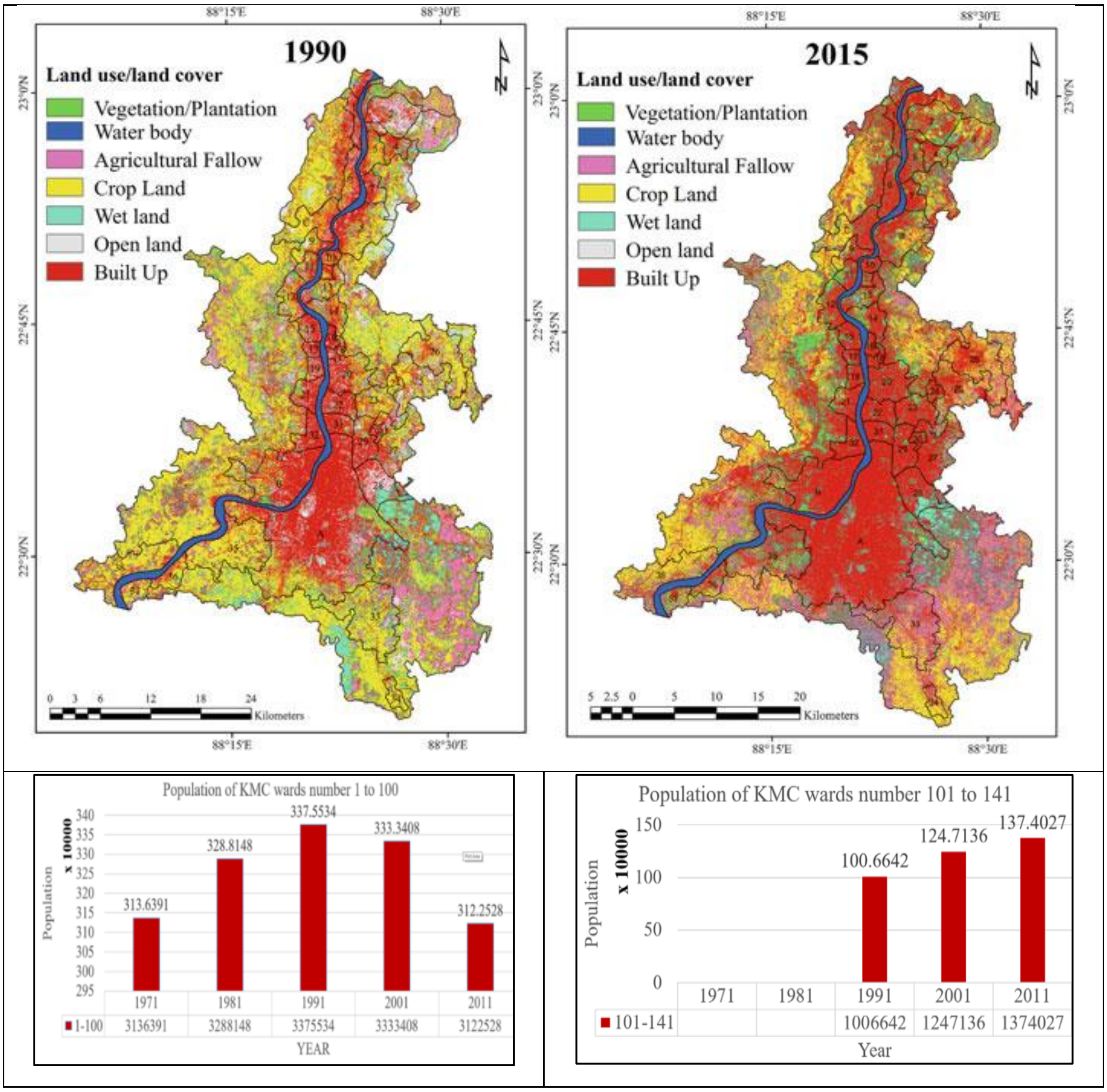
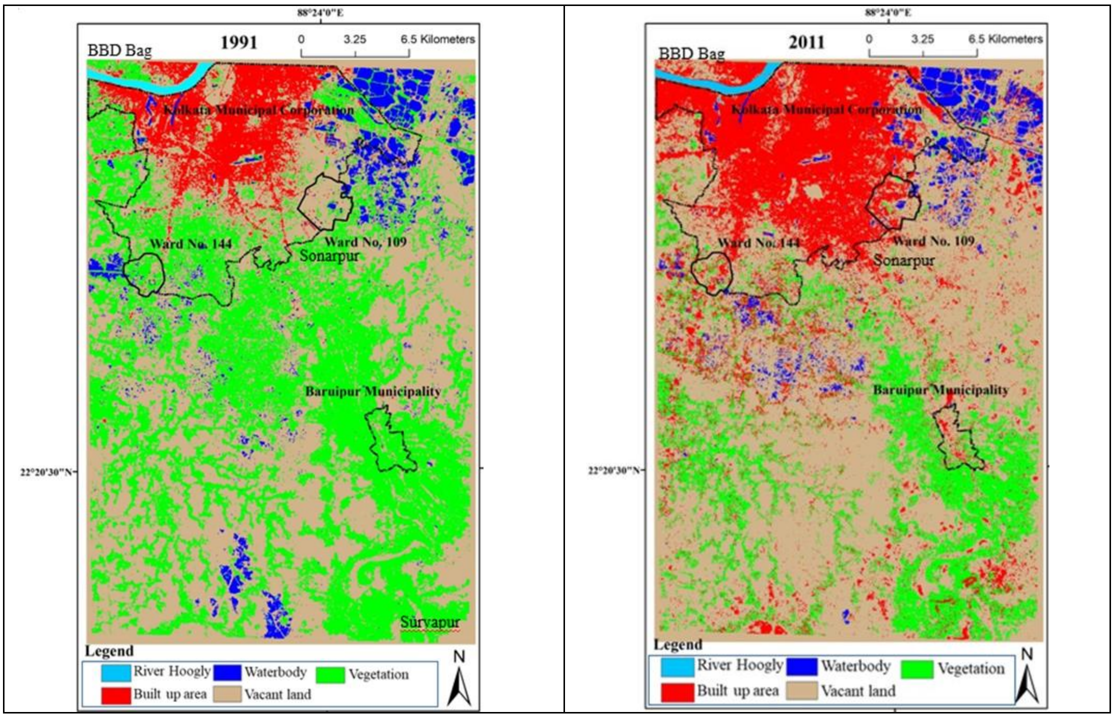


Fig. 3.2: Expansion of Kolkata (Red patch is the built up area) Ward No. 1-141 (**Source**: Rahaman, et al., 2018, Census of India – 2001, 2011)

3.2 Choice of the Study Area

Expansion of KMA towards the south-east direction is shown in Fig. 3.3, where rectangular 'Area of Interest', AOI, has been taken from BBD Bag at the north-west corner of central Kolkata to Suryapur (south-east corner), crossing of SH-1 and Alipore Road, of South 24-Parganas, studied from the images.

KMC has grown linearly along the east bank of River Hooghly flowing in the north to south-south west direction. The northern parts of KMC is nearly saturated with unplanned organic growth. Westward expansion of KMC is negated by the presence of River Hooghly and the Ramsar site of East Kolkata Wetland stops legal eastward growth. Northbound expansion is delimited by the presence of settlements along the railway corridors. But the population density along the railway corridor to the southeast had been low and presently showing tremendous growth potential. Improved connectivity and expansion of the Metro Railway have paced up this growth rate. Images in Fig. 3.2 show a south-east ward expansion of built-up area (marked in red) of KMC along the State Highway 1 (SH-1), West Bengal. Stretched blotting of red patch has extended up to Baruipur and even more southward up to Suryapur (Fig. 3.3).



Figs. 3.3: South-east expansion of Kolkata

Figs. 3.3 show that at the vicinity of KMC the built-up area is gradually expanding between 1991and 2011. Four kind of land uses has been considered, namely, ‘Hoogly river’, ‘Built-up area’, ‘Vegetation’ and ‘Waterbody’. Beyond the boundary of KMC, the next apex of red patch is at Baruipur. KMC Ward 109 juxtaposed with the city is already covered by red patch which is extending to Baruipur gradually covering southern area. KMC Ward 144 is on the south-western part, juxtaposed with the city and is gradually getting populated with red patches.

Connectivity with the city by SH-1 is one of the main reason of the southern expansion of the KMC. Similar kind of expansion can also be seen along NH-12 (Fig 3.1). Development of connectivity attract people to stay in the periphery On the other hand availability of large land holdings attract realtors to buy lands for housing and residential complexes. This causes increment of population resulting increase of built up area by conversion of agricultural lands, low land and wetlands to built-up area, encroachment of roads, traffic congestion, disproportional sewerage system etc.

In the meantime, of expansion gradually road and other infrastructural facilities become disproportional to the population and aggravate the muddled situation. As the improvement of infrastructural facilities does not contribute any monetary return to the system, they remain neglected until unless bottleneck situations come. Private developers also do not bother about the society and environment and do their own profit.

Here in this paper three areas have been selected who are in the journey of rural to peri-urbanisation to urbanisation. These three areas are all located in the surroundings of KMC. Connected with KMC by roads. But they are at their three stages of progress toward the urbanisation trajectory.

3.2.1 Case I – KMC Ward 109

Ward No. 109 (Fig. 3.4 is an administrative division of KMC. It came under the KMC jurisdiction in 1984 after the Calcutta Municipal Corporation act 1980 was enacted (January 1984) to extend its boundary by bringing adjacent areas under its jurisdiction.

Fig. 3.4: Ward 109, Kolkata Municipal Corporation

This ward is located in the south-eastern part of KMC and positioned approximately in between 22°30’N to 22°28’N and 88°23’E to 88° 25’E covering an area of 7.05 sq. km. East Kolkata Wetland (EKW), on eastern part of Kolkata - a Ramsar site, absorbs contaminants drained from Kolkata, situated in eastern and north-eastern part of the ward. Dhapa, a waste dumping ground of KMC provide livelihood to a significant number of local families by garbage farming and aquaculture, is nearly 11 km away by road from the said ward.

Eastern Metropolitan Bypass (EM Bypass) connecting north Kolkata and south Kolkata, divided the Ward 109 in east and west, passed through north and south of the ward. Both sides of this road was the focus areas of development. Vicinity of EM Bypass, connection to City of

Kolkata, suburban railway connectivity attracted people to ward number 109- as situation pushed them to move outward from the city core. Hence real estate boom and later on hospital-centric developments caused unplanned urban growth in the ward number 109. Rapid urbanisation at ward level created first level development along both sides of the EM Bypass but choked growth at interior level resulting in congested traffic movement, road-side parking, no footpath, and disproportional multi-storied houses to the road width, effluent sewerage, scarce of potable water supply, waterlogging etc.

So the area once unattractive and covered by agricultural land and vacant land in the eighties became liveable and unplanned construction and amenities in the ward after inclusion cause significant stresses in the delivery of transportation infrastructure, social and environmental services.

This individual ward level study showing development in one part and deterioration on the other will help other adjacent areas to keep provisions of providing facilities in their boundary areas before problems started to rise.

3.2.2 Case II - Baruipur Municipality, KMA

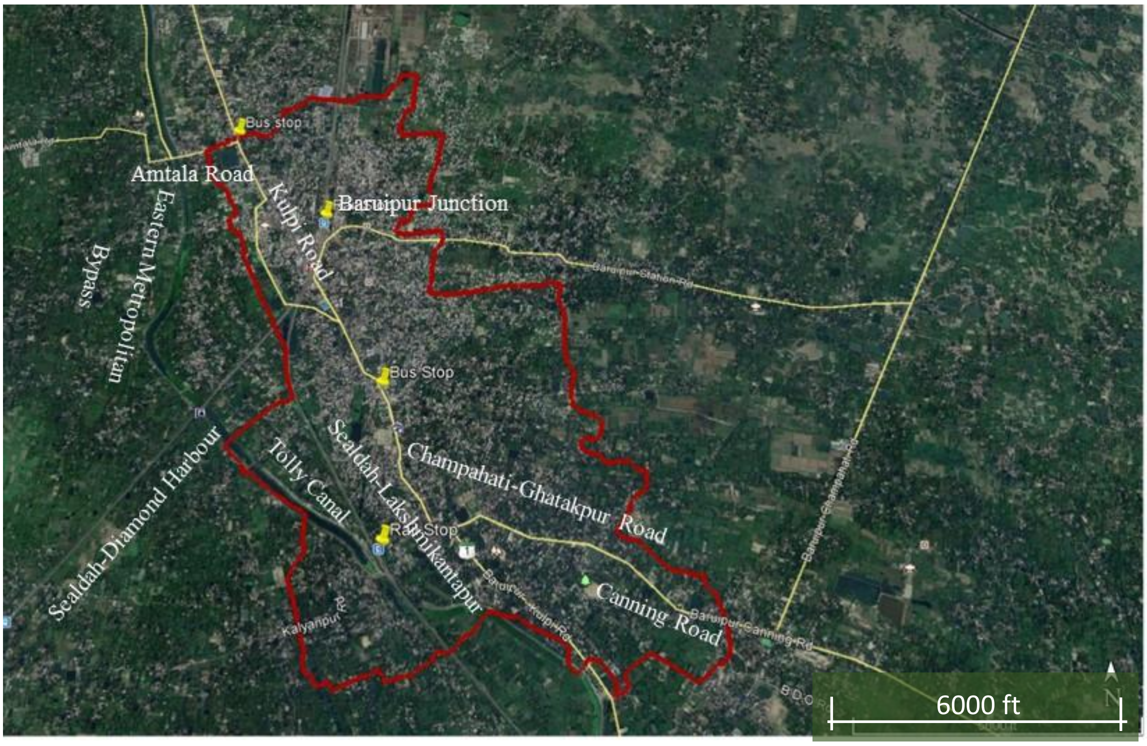


Fig. 3.5: Baruipur Municipality, Kolkata Metropolitan Area and rail and road connectivity

The Baruipur Municipality, situated in the south-eastern fringe of Kolkata Metropolitan Area (KMA) and 27 km away from the heart of Kolkata has still some potential for urban expansion, and has been chosen as one of the study areas to study the immediate impact of urban expansion.

The locational uniqueness of Baruipur Municipality is the proximity of urbanised Kolkata to its north side with the existence of the biodiversity hotspot at Sundarbans, due south (68 km by road) making the area especially important. Spatial pattern of urbanisation shows relatively more urbanisation towards its northern part while the eastern and southern boundaries of the study area remain less urbanised.

Baruipur Municipality is divided into 17 wards, between 22°39’N to 22°33’N latitude and 88°42’ E to 88°46’ E longitude, approximately and positioned at the extreme southern side of KMA on the banks of Tolly’s canal. It is connected to Kolkata by Kulpi Road via EM Bypass. Other significant roads include Canning Road radiating from the south-eastern extremity and Amtala Road radiating from the north-western extremity (Fig 3.5). Baruipur Junction railway station is connected to Sealdah railway station, located 25 km away, Sealdah being one of the three major railway stations in KMA. The railway station, situated at the intersection of Sealdah-Diamond Harbour and Sealdah-Lakshmikantapur sections of suburban railway lines, serves Baruipur and its neighbourhood. Further, the accessibility provided by the Metro rail service, located within 7 km, is also a node of attraction for the development of this area. Thus, connectivity of this area has attracted common people and the real estate builders alike. It is believed that an extension of metro rail will further escalate the attraction potential and growth of Baruipur. An attempt by the Government of West Bengal to develop Baruipur Municipality as an administrative hub has added to this attraction, though the proposal has been presently being stalled.

Fig. 3.6: KMC Ward 144, Kolkata Municipal Corporation

3.2.3 Case III – KMC Ward 144

Surrounded area of south-eastern part of KMC experienced rapid population increase because of the land saturation of KMC. Ward 144, located at the south-eastern boundary of KMC previously under gram panchayat, added to KMC in 2012 and became a part of the city. Ward 144 is located in between 22°27'9.18"N, 88°16'58.81"E- 22°26'44.87"N, 88°18'26.52"E and 22°27'39.51"N, 88°18'0.19"E - 22°26'16.17"N, 88°17'34.42"E.

Though population growth in this ward has already began with conversion of agricultural land to urban area, the ward might be in the third level of development where transition from rural to urban state has just begun a few years back and continuing.

National highway, NH-12, running through this ward along north- south provides road connectivity and helps people to commute easily to the city core. Land value was cheap. Initiation of metro railways has further attracted people. However, connectivity provided by NH-12 and Thakurpukur-Bibirhat-Bakhrihat Road, land availability in larger holdings at a cheaper rate, is attracting the realtors to acquire vacant land, agricultural land, waterbody and vegetation of this ward like other two study areas, pushing local people further away into other informal sectors.

3.3 Conclusions

Being congested at the city core with little opportunity of intervention, outskirt of the city mainly southward, is growing horizontally and vertically, revealing gradual declination of water bodies, vegetation, vacant land and agricultural land. Thus bordering areas are on a verge of becoming a single urban patch that would affect their socio-economic structure. Temporal analysis show change in land character, population increase along with household, abandonment of agricultural activity in the face of land purchase for speculative purposes, change in gender based occupation structure step-by-step. This tendency of changes necessitate early policy interventions to provide basic amenities in the bordering areas of KMA for sustainable planning.

So the land dynamics of these three areas – around urban areas merging into rural landscape surrounding the greater Kolkata region - will recognize the upcoming problems of other surrounded areas of Kolkata region and the result of this research work can be applied to those areas for sustainable management.

A thorough analysis is essential to recognise the trend of urbanisation and stages of changes. To direct this trend to a sustainable future it requires planning intervention at the earliest.

Chapter 4

PROJECTED LULC FOR THE STUDY AREAS IN 2040

4.1 Introduction

This chapter explores the land use land cover (LULC) changes of the three study areas (KMC Ward 109, Baruipur Municipality and KMC Ward 144 all within KMA) and model the spatial and temporal land dynamics with different socio-economic, physical and environmental variables so that the learning can be applied for predicting the state of future year.

This process follows four steps, namely,

1. Collection of Google Earth and satellite images with the study area being subseted from the original images (Jensen 2015),
2. Spatio-temporal change analysis (Eastman, 2012; Jensen 2015), and
3. Growth prediction by transition potential and change allocation (Eastman, 2012).
4. Validation for a projected year and prediction for the horizon year.

The process begins with collection of images from Google Earth and raw Landsat satellite images from the United States Geological Survey data portal, USGS EarthExplorer[1], for a set of previous years for the three study areas. Universal Transverse Mercator (UTM) coordinate system map projection with World Geodatic System, 1984 (WGS 84) Datum and UTM Zone 45N[2] has been used for all the works. The raw images collected from USGS EarthExplorer are subseted (Bhatta, 2012 p. 41) using the ward or municipal maps. Also, the Google Earth images have been digitised and various features like points (viz., schools, hospitals and workplaces), polyline (e.g., road, railway line) and polygon (namely, built-up area, vacant lands, water body, and vegetation) (Liu and Mason, 2016, p.166) are combined and stored in the geodatabase.

The spatio-temporal change analysis is conducted by,

1) ArcGIS 10.2[3] and
2) IDRISI Selva (ver. 17.0) (Eastman, 2012), while,
3) Statistical analyses are conducted by open-source FRAGSTATS (McGarigal et al., 2012)[4]

ArcGIS and IDRISI ingest digitised images of a study area for two different years from the Google Earth application and identify the areas with different land use (LU) classes (viz., 'built-

[1] https://earthexplorer.usgs.gov/
[2] Liu and Mason, 2016, Chapter 14.2
[3] https://www.esri.com/about/newsroom/arcwatch/the-best-of-arcgis-10-2/#:~:text=ArcGIS%2010.2%20streamlines%20complex%2C%20multistep,generate%20statistically%20valid%20hot%20spots.
[4] https://www.fragstats.org/index.php/documentation

up area', 'vacant land', 'water body', 'vegetation' and 'stadium and open space') and compute percent changes between these two time stations. Simultaneously, ERDAS Imagine 2014 takes LANDSAT images and GPS data collected by a handheld Garmin GPS machine to produce a supervised classification image. In supervised image classification (Liu and Mason 2016, p.96) the image pixels will be categorized to certain LU classes following the Gaussian maximum likelihood classification (MLC) algorithm (Lillesand et al., 2015). Accuracy assessment has been conducted for this image and further processed using FRAGSTATS for patch level, class level and landscape level statistical analyses (Mcgarigal 2015, Bhatta 2012) to quantity LU fragmentations (Hardin et al., 2007). The Shannon entropy (Shannon 1948, Thomas 1981, Yeh and Li 2001, Bhatta 2010 p. 104) of classified image is computed to measure urban sprawl (Sudhira et al., 2004).

The growth prediction starts with preparation of transition map, that shows changes in land cover between two time-separated images of a study area, generated by the change analysis process in IRDISI Selva and the sub-models (Eastman 2012, p. 77) are extracted. The driver variables (Eastman 2012, p. 277) need to be chosen based on prior experience, availability of data, transformed and tested repeatedly before finally importing them to the sub-model structure. Euclidian distance of each variable has been computed and extracted from the point or polyline features of the digitised images. For the selected variables, transformation using evidence likelihood method (Eastman 2009 p. 238,254; Eastman 2020a, p. 203; Eastman 2020b, p. 281) has yielded acceptable accuracy. The variables are evaluated with the Cramer's V test (Eastman 2009, p. 254) to eliminate the insignificant variables and incorporate the rest in the transition sub-model evaluation structure. Once the transition sub-model structure is formed, the model is executed using multi-layer perceptron (Eastman 2009, p.239, 255) procedures. The model is tuned, built, and run to generate transition potential maps. Transition potential maps (Eastman 2012, p.268) are used by 'change demand model' (Eastman 2009, p.240) for the prediction year. Markov Chain Model (MCM) (Eastman 2009, p.231, 240) is used for 'change demand model' to produce the probability of transition from one category of LU to another category, known as transition probability matrix (Eastman 2009, p. 183, 231, 240). Transition potential maps and transition probability matrix are used by the change allocation module (Eastman 2012, p.271) to generate the prediction maps (Eastman 2009, p.240) for the prediction year. The predicted results are compared with the actual image and accuracy assessment has been done and 'overall accuracy' and kappa index (Liu and Mason 2016, p. 100) are computed. Once accuracy reaches the expected value, the growth prediction process is used to predict the LULC for the horizon year.

4.2 KMC Ward 109

KMC Ward 109, shown in Fig. 4.1, belongs to KMC Borough 12 and encompasses parts of Haltu (Kalikapur), Santoshpur (Barokhola, Nandan Kanan, Purba Diganta and Survey Park), Ajoy Nagar, Hiland Park, Chak Garia, New Garia, Srinagar, Hatibari, Nayabad, Bikash Guha Colony, Panchasayar (Shahid Smrity Colony and Baghajatin Park), Budher Hat and Mukundapur (Singh Bari, Nitai Nagar, Purbalok, Stadium Nagar, Jamuna Nagar, Ahalaya Nagar, Green Park, Chit Kalikapur, Satyajit Kanan, and Vivekananda Park) in the South-Eastern fringe of Kolkata within 88°24'2.68"E and 88°23'56.71"E longitudes and 22°29'2.83"N and 22°29'24.92"N latitudes measuring 705.27 ha.

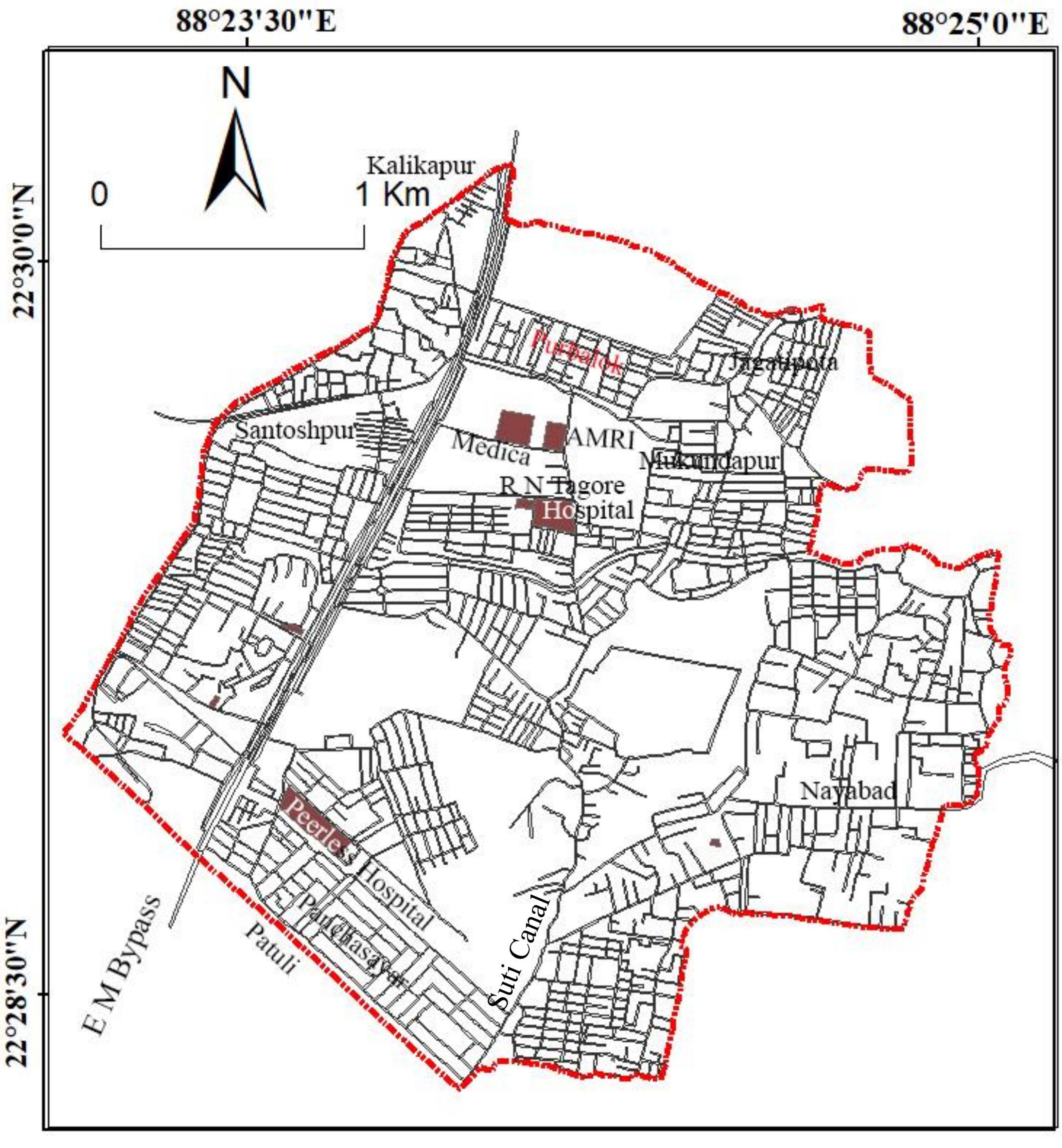


Fig. 4.1: Roads and hospitals in KMC Ward 109

Proximity to the CBD of Kolkata by road, suburban and metro rail services, access to airport via the Eastern Metropolitan (EM) Bypass, upcoming metro facilities connecting Salt Lake, New Town and airport, and close access to the health facilities in the hospitals in East Kolkata have attracted people to congregate in the KMC Ward 109 whereby the open spaces are facing horizontal and vertical urban transformation in absence of timely intervention from the local planning authorities, cutting down the spaces left for providing the basic amenities to people, in the form of roads, water, sanitation and recreation, etc., for future extensions.

4.2.1 Spatio-Temporal Change Analysis of KMC Ward 109

The LULC of KMC Ward 109 has been classified into five LU classes, namely, 'built-up area', 'vacant land', 'water body', 'vegetation' and 'stadium and open space'. The spatio-temporal change analysis has been performed using ArcGIS 10.2 and IRDISI Selva 17.0, while statistical analysis has been done using FRAGSTATS, all showing reasonable degree of convergence.

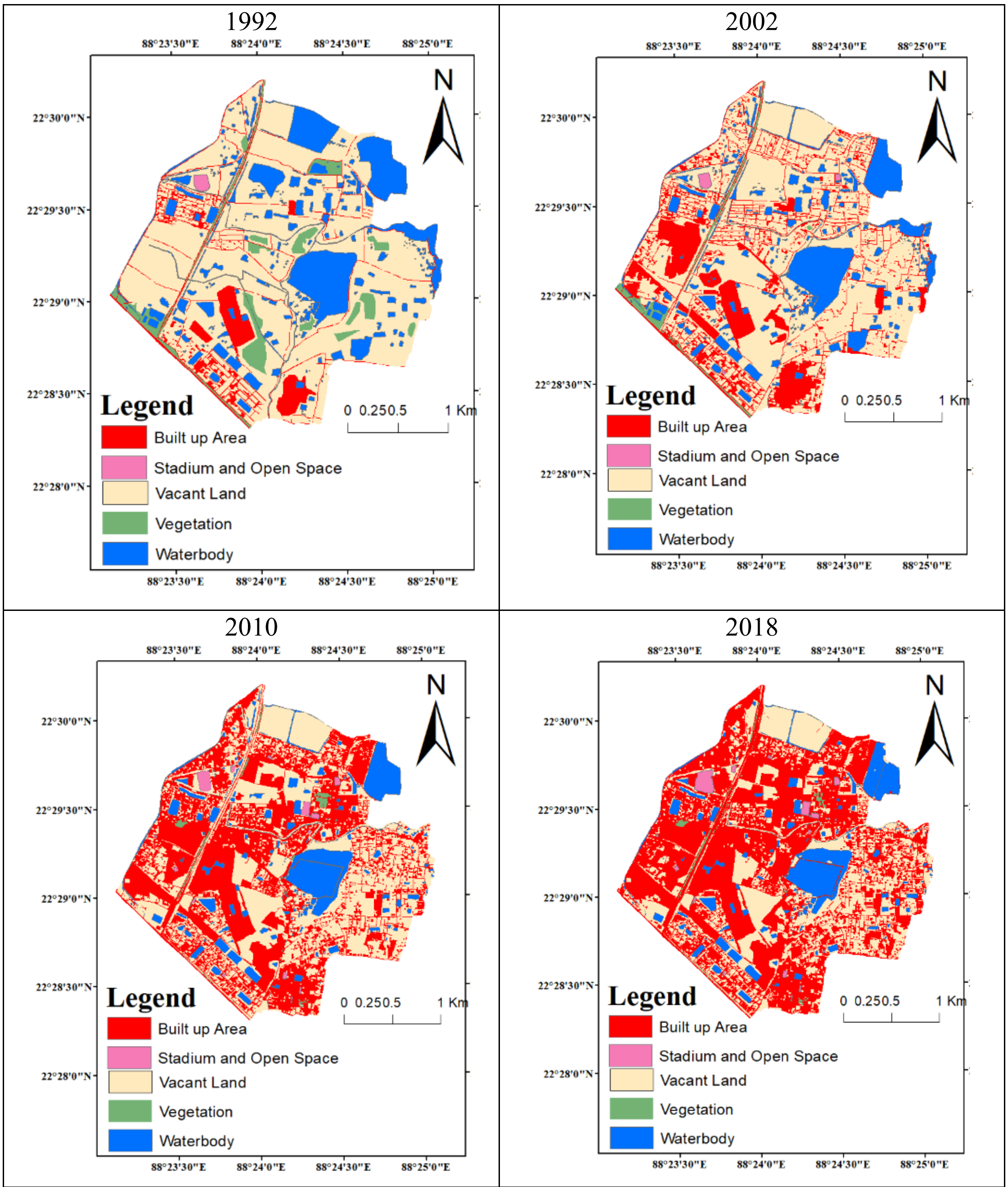
4.2.1.1 Change Analysis using ArcGIS for KMC Ward 109

As mentioned in the methodology discussed in Chapter 2, four thematic maps (Liu and Mason 2016, p.152) for KMC Ward 109 has been developed from the Google Earth application for the years 1992, 2002, 2010 and 2018. Digitised layers of thematic maps, with schools, hospitals and workplaces as point features, road and railway line, etc. as polyline features, while built-up area, vacant lands, water body, and vegetation etc., as polygon features, are stored in the geodatabase (Liu and Mason 2016, p.166). The topology operation has been run next to compute areas of each class in ArcGIS and shown in Figs. 4.2 for those four years.

The maps show gradual sprawl of built-up area and simultaneous shrinking of vacant lands, vegetation and water bodies in the ward. Between 1992 and 2018, overall share of built-up area has increased nearly seven fold, while vegetation has become one-tenth that of earlier and water bodies have been halved. As mentioned earlier, since 1982, the accessibility provided by the E. M. Bypass, the more recent New Garia Suburban Railway Station and Kavi Subhash and Shahid Khudiram Metro Railway Stations and the upcoming Metro service along the EM Bypass are the root causes in converting Ward 109 as an attraction hotspot that triggering unprecedented construction works ignoring other beneficial land uses, especially the very important Ramsar site in the form of East Kolkata Wetland (EKW).

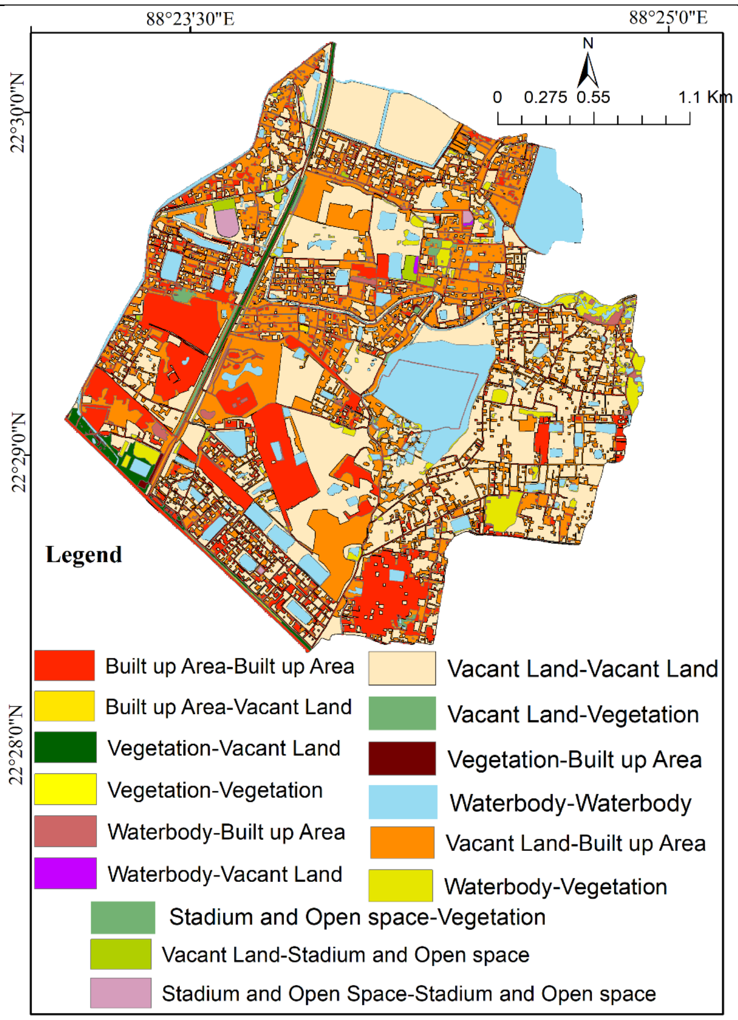
4.2.1.2 Change Analysis using IDRISI Selva for KMC Ward 109

The thematic digitised maps of 2002 and 2010 for KMC Ward 109 are considered as the two base years. The maps are converted to raster/ASCII and inserted as input to the Land Change Modeler (LCM) module in IDRISI Selva for change analysis. It computes the land cover (LC) changes between 2002 and 2010 and the changes in hectares (ha) by LC classes are listed in Fig. 4.3.



Classes	**1992**	**2002**	**2010**	**2018**
Built-up Area	8.60	21.13	45.17	54.88
Vacant Land	64.37	61.02	41.37	32.33
Waterbody	21.11	16.00	11.87	11.08
Vegetation	5.60	1.50	0.68	0.63
Stadium and Open Space	0.32	0.35	0.90	1.09

Figs. 4.2: Land use distribution in KMC Ward 109 (in percent)



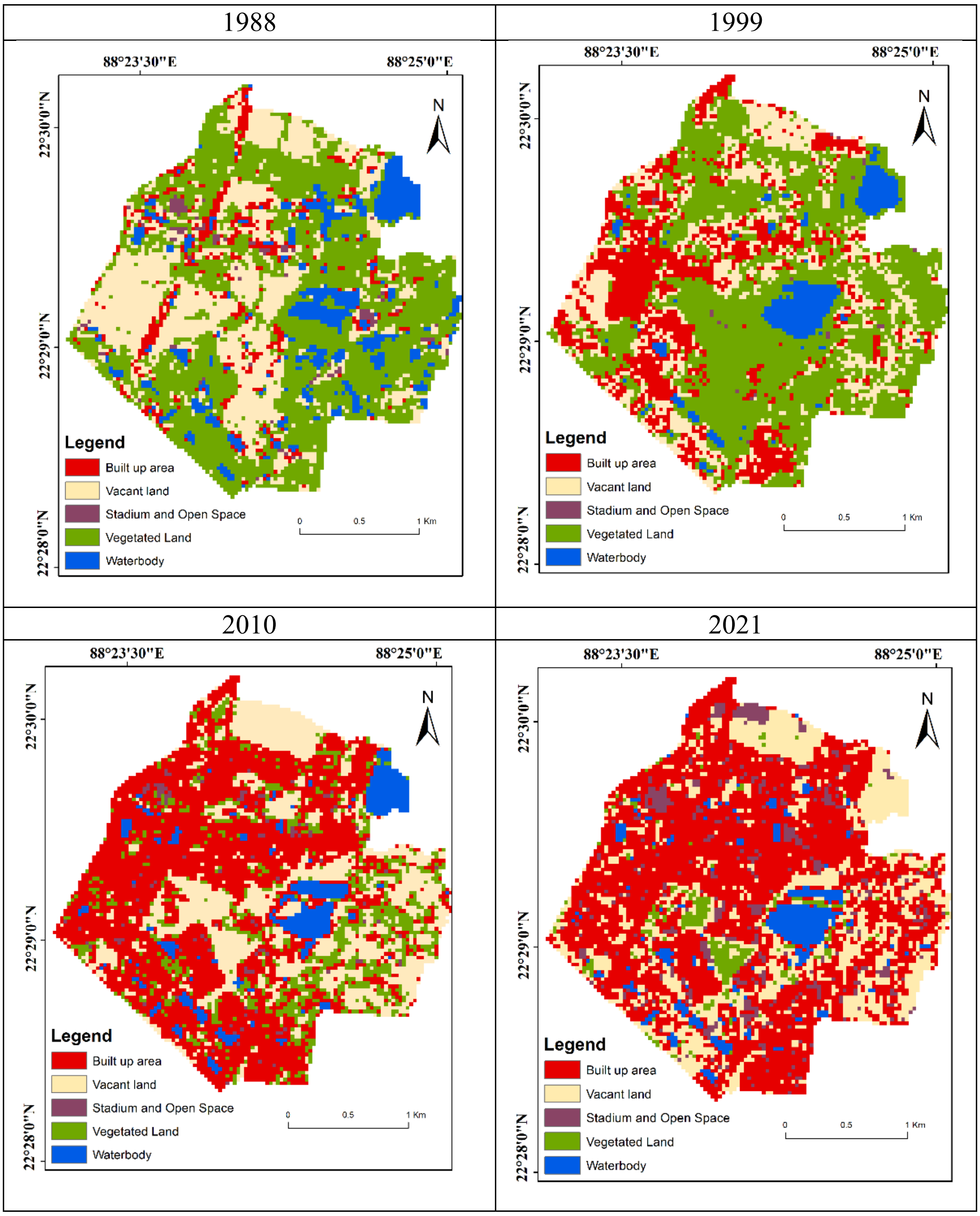
		Land cover (LC) in 2010 (ha)				
	Classes	Built-up area	Stadium and open space	Vacant land	Vegetation	Water-body
LC in 2002 (ha)	Built-up area	136.82	00.68	11.39	0	0
	Stadium and open space	0	2.30	0	2.3	0
	Vacant land	173.32	2.93	250.48	3.3	0.43
	Vegetation	1.2	0	8.80	0.48	0
	Waterbody	7.28	0.37	21.01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

Fig. 4.3: LU change map and transition matrix for KMC Ward 109 between 2002 and 2010

The transition matrix in Fig. 4.3 shows the land use (LU) transition between 2002 and 2010 in hectares (ha). 173.32 ha of vacant land has been transformed to built-up area, which is the highest among all the transformations. Vacant lands are those lands which are not yet developed and constructed (Xiaoqing, et al., 2020) and should be used in a planned way. 7.28 ha of waterbody has been transformed to built-up area, and more alarmingly, another 21.01 ha waterbody has been converted to vacant land highlighting need for governance. In this context it may be noted that intrusion of new urban areas and introduction of high rises often require demolition of older constructions. Hence, it is quite insignificant if built-up areas assume vacant land attire (11.39 ha in the transition matrix).

4.2.1.3 Change Analysis for Ward 109 by Statistical Method using FRAGSTATS

Four Satellite images of 1992, 2002, 2010 and 2021 (Table 4.1) have been downloaded from the USGS EarthExplorer, pre-processed to extract the map of Ward 109 and Gaussian Maximum Likelihood Classification algorithm (Lillesand et al. 2015) is employed for their supervised classification using the GPS data from a handheld Garmin GPS for identifying the training areas. The GPS data has further been employed once again to conduct post-classification ground truth verification. However, for the older images the validations have been conducted using Google Earth images of contemporary periods.



Figs. 4.4: LU maps of KMC Ward 109 for the years 1988, 1999, 2010 and 2021.

The accuracy of the classification model is assessed by evaluating the producer's, user's and overall accuracy and kappa coefficient (Eqs. A2.1~4 in the appendix to Chapter 2) along with the transition error matrix or, simply error matrix (Jensen 2015, Ch. 13).

Table 4.1: Detail of satellite images used in FRAGSTATS

Year	Description	Path and Row	Projection	Spatial resolution
1988	Landsat-5	138 and 44	World Geological Survey 84/UTM, Zone 45	30m
1999	Landsat-5	138 and 44		30m
2010	Landsat-TM	138 and 44		30m
2021	Landsat 8	138 and 44		30m

Figs. 4.4 shows the LU maps of 1988, 1999, 2010 and 2021 generated by supervised classification using Gaussian maximum likelihood algorithm. They show steady increments in the red patches indicating merger and sprawl of built-up areas. Large number of trees have been felled to provide concrete pavements by the roads. Receding share of water bodies in Figs. 4.2 and 4.4 can be corroborated with the experience of the senior residents. Vacant land is also transforming to built-up area and by 2021 the ward is nearly packed with built-up patches, marked in red, that has gradually consumed whatever small patches of other LU classes existed.

Table 4.2: Accuracy assessment for KMC Ward 109 for the years 2010 and 2021

Error matrix, 2010

Classes	Water Bodies	Vacant Land	Stadium & Open Space	Built-up Area	Vegetated Land	Total	Producer's accuracy	User's accuracy
WB	**29**	0	0	0	0	**29**	93.5	100
VL	0	**39**	0	0	0	**39**	88.64	100
SOS	0	0	**23**	0	0	**23**	100	100
BUA	2	3	0	**83**	1	**89**	98.81	93.26
Veg	0	2	0	1	**16**	**19**	94.12	84.21
Total	**31**	**44**	**24**	**84**	**17**	**`199**		

WB = Waterbody, VL= Vacant Land, SOS = Stadium and Open Space, BUA= Built-up Area, Veg = Vegetated Land

$$Overall\ accuracy\ = 190/199\ = 95.47\%$$

$$Kappa\ Index = \frac{199*(29+39+23+83+16)-\{(29*31)+(39*44)+(23*24)+(89*84)+(9*17)\}}{199^2-\{(29*31)+(39*44)+(23*24)+(89*84)+(9*17)\}} = 0.937$$

Error matrix, 2021

Classes	Water Bodies	Vacant Land	Stadium & Open Space	Built-up Area	Vegetated Land	Total	Producer's accuracy	User's accuracy
WB	**51**	0	1	0	3	**55**	100	92.3
VL	0	**53**	0	0	2	**55**	96	96
SOS	0	2	**53**	0	0	**55**	98	96
BUA	0	0	0	**67**	0	**67**	100	100
Veg	0	0	0	0	**53**	**53**	91	100
Total	**51**	**55**	**54**	**67**	**58**	**285**		

WB = Waterbody, VL= Vacant Land, SOS = Stadium and Open Space, BUA= Built-up Area, Veg = Vegetated Land

$$Overall\ accuracy\ = 277/285\ = 97.20\%$$

$$Kappa\ Index = \frac{285*(51+53+53+67+53)-\{(55*51)+(55*55)+(54*55)+(67*67)+(53*58)\}}{285^2-\{(55*51)+(55*55)+(54*55)+(67*67)+(53*58)\}} = 0.965$$

Accuracy assessment for the images in 1988 and 1999 are not possible since high-resolution Google Earth images during 1988 and 1999 were absent, thus negating any scope of accuracy assessment. Referring to Table 4.2, for the years 2010 and 2021, overall accuracies are 95.47% and 97.20% and Kappa statistics (Liu and Mason, 2016) are 0.937 and 0.965, respectively, which are pleasingly satisfactory.

Once the classification model is established and LU maps of 1988, 1999, 2010 and 2021 are created, LULC changes in urban sprawl are quantified using two methods, namely,

- Shannon's entropy (using ArcGIS and Excel)
- Class and landscape level metrics (using FRAGSTATS).

4.2.1.3.1 Shannon's Entropy at KMC Ward 109

KMC Ward 109 has been divided into four zones (north-east, north-west, south-east and south-west). Shannon's entropy, an indicator of the urban sprawl for four zones over four years is provided in Table 4.3.

Table 4.3: Entropy (**E**) and Relative Entropy (**RE**) in Ward 109 (Bhatta 2012, p. 53-54)

Years	ZONES									
	North East		North West		South East		South West		TOTAL	
	E	RE	E	RE	E	RE	E	RE	E	RE
1988	0.16	0.06	0.27	0.10	0.12	0.04	0.20	0.07	0.76	0.28
1999	0.27	0.10	0.37	0.14	0.25	0.09	0.36	0.13	1.25	0.46
2010	0.36	0.13	0.37	0.14	0.36	0.13	0.31	0.11	1.40	0.52
2021	0.54	0.20	0.26	0.10	0.61	0.22	0.55	0.20	**1.96**	0.72

Temporal entropy values in Table 4.3 show that the built-up area is gradually sprawling since the values are approaching $\ln 4$ (= 1.3862943611191). From 1988 to 2010, the relative or normalized entropy value increased which shows distribution is dispersed. Since higher entropy values imply sprawling (Sudhira, H. S., et. al., 2003), a total entropy value of 1.96 in Ward 109 proves that urban sprawl is in full swing.

4.2.1.3.2 Class and Landscape Level Metrics at KMC Ward 109

The class level and landscape level metrics in Table 4.4 obtained from FRAGSTATS show spatial characteristics of LULC classes over time. The 'Class Area' (CA)[5], and 'Percentage of Land' (PLAND)[6] data show that the built-up area has been absolutely dominant with percentage of area increasing from 53.64 ha (7.6%) in 1988 to 433.89 ha (61.46%) in 2021. On the contrary, CA and PLAND of the vegetation have gradually lost their dominance, 349.92 ha (49.57%) in

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[5] CA ≡ Class area is the sum of the areas of all urban patches, that is, total urban area in the landscape, expressed in has, and the results are$\geq$ 0. (McGarigal 2015, p. 90)

[6] PLAND ≡ Sum of all patch areas divided by total landscape area times 100, (percentage, no units, with a range 0 to 100). (McGarigal 2015, p. 90)

1988 to a meagre 24.84 ha (3.52%) in 2021. Likewise, CA (PLAND) of vacant land has dropped from 215.82 ha (30.57%) to 168.57 ha (5.85%). CA and PLAND of waterbodies have been halved almost, and that is alarming since the East Kolkata Wetland (EKW) contributed to waste water reclamation and control of LST. High 'Total Edge' (TE)[7] (McGarigal 2015, p. 71) compared to low 'Largest Patch Index' (LPI)[8] (84180m and 16.96%, respectively, in 1988 to 90570 and 2.91%, respectively in 2021) for vacant land indicates fragmentation of vacant lands.

Table 4.4: Class level and landscape level metrics from FRAGSTATS for KMC Ward 109

Year	Class Level Metrics for 1988 to 2021					Landscape Level Metrics	
	LU types	CA(Ha)	PLAND (%)	LPI (%)	TE(m)	NP	SPLIT
1988	Built-up Area	53.64	7.60	0.74	45810	536	6.4065
	Vegetation	349.92	49.57	34.04	99090		
	Vacant land	215.82	30.57	16.96	84180		
	Stadium and Open Space	10.26	1.45	0.26	8700		
	Water body	76.32	10.81	2.04	35940		
1999	Built-up Area	157.32	22.28	9.69	77010	532	4.8223
	Vegetation	349.56	49.52	44.02	94290		
	Vacant land	155.88	22.08	2.21	100530		
	Stadium and Open Space	2.25	1.32	0.24	2460		
	Water body	40.95	6.80	2.05	12390		
2010	Built-up Area	366.84	51.96	47.90	111330	539	4.2163
	Vegetation	99.81	14.14	1.96	80430		
	Vacant land	181.08	25.65	4.65	74220		
	Stadium and Open Space	10.71	1.52	0.18	11760		
	Water body	47.52	6.73	1.93	17820		
2021	Built-up Area	433.89	61.46	59.78	116340	548	2.7734
	Vegetation	24.84	3.52	0.93	17430		
	Vacant land	168.57	5.85	2.91	90570		
	Stadium and Open Space	41.31	5.85	0.52	33780		
	Water body	37.35	5.29	1.19	10760		

At the landscape level, 'Number of Patches' (NP)[9], shows increasing trend between 1988 and 2021. 'SPLIT'[10] index (McGarigal 2015, p. 151) is clearly reducing from 1988 to 2021. Lowering SPLIT Index from 6.4065 to 2.7734 and Largest Patch Index (LPI) of built-up area

[7] TE ≡ Sum of lengths of all edge segments involving the corresponding patch type, meter, ≥ 1.

[8] LPI ≡ In class level, it indicates the area of the largest patch of every class, in percent, while in landscape level, it indicates percent of landscape of the largest patch. (McGarigal 2015, p. 96)

[9] NP ≡ In class level, it indicates the number of urban patches of each class, number, ≥ 1, while in landscape level, it indicates number of patches in the landscape (≥ 1). (McGarigal 2015, p. 149)

[10] SPLIT or Splitting index ≡ Total landscape area squared divided by the sum of patch area squared, all patches in landscape, no units, range being 1 ≤SPLIT≤ number of cells in the landscape squared

being 59.78 in 2021 implies the fact that urban patches are fusing and monotonous urban patch areas are emerging, indicating yet more urbanisation. Thus, KMC Ward 109 is too susceptible to urban sprawl with dominance of built-up area that is consistently replacing vegetation, water body and vacant land affecting the landscape by retarding its biodiversity and environmental balance.

4.2.1.4 Summarising Change Analysis Observations in KMC Ward 109

The results of change analysis done by different methods converge to similar observations. To summarize the key observations inferred from all the methods are

- Built-up area has become dominant with vegetation and vacant land gradually receding
- Built-up area is mainly converted from vacant land
- The south-west quarter of KMC Ward 109 had the least share of built-up area till 2010 (Table 4.3) but vide Figs. 4.4, in 2021 urban sprawl has been fast and thick
- The urban patches are fusing and swelling
- Vacant lands are getting fragmented over time
- Rapid depletion of water bodies has become alarming.

4.2.2 Growth Prediction for KMC Ward 109

Though Ward 109 is nearly super-saturated with built-up area, to assess the accuracy of the predicted future map, two digitized base year maps for the years 2002 and 2010, prepared in ArcGIS 10.2, have been processed in IDRISI Selva 17.0, which uses MLPNN-based (Jensen 2015, p.448) land change modeler (LCM) and Markov chain algorithms (Eastman 2009, p. 231). Thus transition potential maps and predict future map for the year 2018 are generated. The projected map is compared with the actual map from the Google Earth application for its accuracy by computing ‘overall accuracy’ and ‘kappa coefficient’. For comparison, there must be a one-to-one data correspondence between the base maps. The ‘overall accuracy’ and Kappa statistics being satisfactory, the process is repeated for the proposed horizon year, i.e., 2040. This study will provide a methodology to gather an ex-ante view of other peripheral fringe areas and help to plan accordingly so as to elude the adverse effects of unplanned growth in future.

4.2.2.1 The MPLNN-Markov Chain-based Growth Prediction Model

In this research work, the general prediction methodology is presented in Fig. 4.5 in a flowchart form. The growth prediction computation has five stages, namely, data collection, data pre-processing, transition potential and change demand modelling, accuracy assessment and prediction. In the data collection stage, images of two base years are selected for the study area.

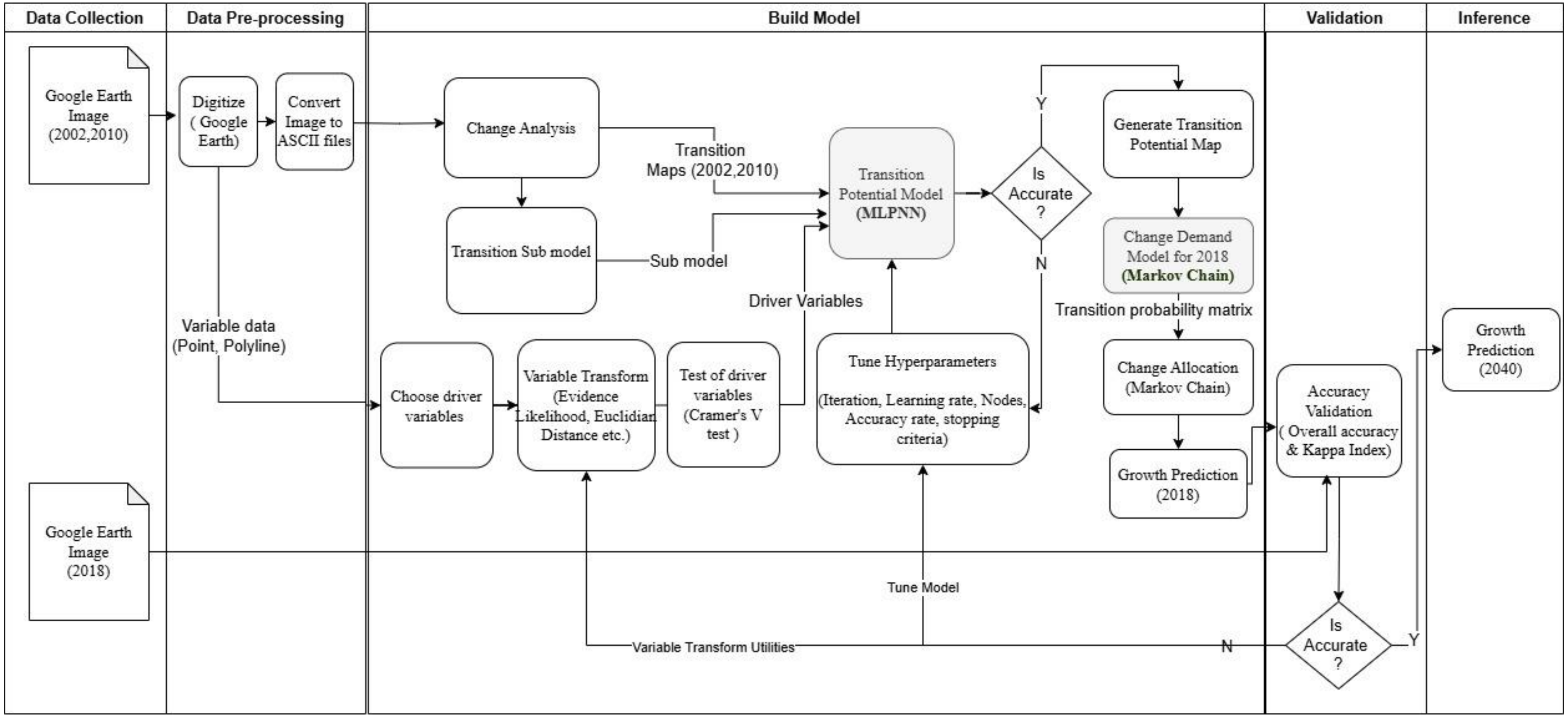

Fig. 4.5: Flowchart of MLPNN and Markov chain models

The images are digitised and necessary pre-processing is done in ArcGIS so that the images may be exported to IDRISI Selva 17.0 for change analysis. To generate the transition potential maps, a MLPNN-based classification algorithm has been adopted. The three key inputs to the transition potential modelling are the transition maps of base years, the sub-models, and the driver variables. While transition maps are generated and sub-models are selected from change analysis process, driver variables are to be chosen based on prior experience, transformed and tested before importing to model structure. Euclidian distance of each variable is calculated and extracted from point or polyline features of the digitised images. For the selected variables, evidence likelihood transformation **(**Eastman 2009, p. 254) yield acceptable outcome. The variable is tested with Cramer's V test **(**Eastman 2009, p. 254) to select driver variables.

Once the transition sub-model structure is formed, the model is executed using multi-layer perceptron procedures. The model uses half of the change pixels for training and the remaining half for validation. The model generates predicted class memberships for each of the validation pixels at each iteration and reports the aggregate accuracy as well as a skill score. The skill score represents the difference between the calculated accuracy using the validation data and expected accuracy. The model structure supports dynamic learning rate procedure (Eastman 2009, p.255) which can monitor and modify the learning rate through iterations. The model can be terminated on the basis of number of iterations, root mean square error, or, accuracy rate threshold. The model is tuned based on hyper parameters[11] such as learning rate[12], hidden layer[13] nodes[14], stopping criteria[15], accuracy rate and skill score[16]. Once the model is built, it is run to generate transition potential maps.

Transition potential maps are used by the 'change demand model' for the prediction year. The Markov Chain Model (MCM) is used for 'change demand' to produce the probability of transition from one category to another category. Markov Chain Model (MCM) generates transition probability matrix. Transition potential maps, transition probability matrix and target year are used by change allocation to generate a prediction map for the prediction year. Prediction map shows the changes in LU categories. The predicted results are compared with actual image and accuracy assessment is done based on 'overall accuracy' and 'kappa' index. The overall accuracy is acceptable if the value exceeds 85% (Congalton and Green 2009, p.56).

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[11] The process determines the optimal set of parameters for achieving best performance.
12 : Software determines progressive learning rate which automatically adjusts the speed of network's weight during training
[13] MLPNN layers consists of nodes which are interconnected and help in processing and transform data from input to output. It must have at least three layers: input, one or more hidden and output layer.
[14] Nodes are the computational unit. Each node does calculations based on inputs and their weights.
[15] The error on the validation should be less than the last time done.
[16] Difference between measured accuracy and expected accuracy according to the transition and persistence. It varies 0 to 1. Skill measure 1 indicates perfect prediction.

For kappa index, a value greater than 0.80, or 80%, indicates strong agreement, between 0.40 and 0.80 (i.e. 40–80%) would mean moderate agreement while a value below 0.40 (i.e., 40%) represents poor agreement (Landis and Koch 1977). In case accuracy is below expected values, the model is re-trained with separate sets of hyper-parameters or variables are transformed using separate transformation utilities. Once accuracies have been attained, the growth prediction process is used for prediction for the horizon year.

4.2.2.2 Transition Sub-model and Selection of Driver Variables

The transition map between the base years 2002 and 2010, shown in Fig. 4.3, is generated from the change analysis (Eastman, 2020a, Ch. 6, Eastman 2020b, exercise 3-8). On the basis of transition maps, sub-models (Eastman, 2020a, p.202-205) listed in Table 4.5 and aligned with the purpose of the study, are created. Each sub-model identifies the transition potential of five LU classes, namely, built-up areas, vacant land, vegetation, waterbodies, and stadium and open spaces. These sub-models are later grouped to drive the underlying determinants of prediction.

Table 4.5: Sub-models generated from transition maps

Sub-model	Changes from	Changes to
change_to_built	Vacant land, Vegetation, Water body	Built-up area
change_to_vacan	Built-up area, Vegetation, Water body	Vacant land
change_to_veg	Water body, Vacant land	Vegetation
change_to_stad	Water body, Vacant land, Built-up area	Stadium and open space

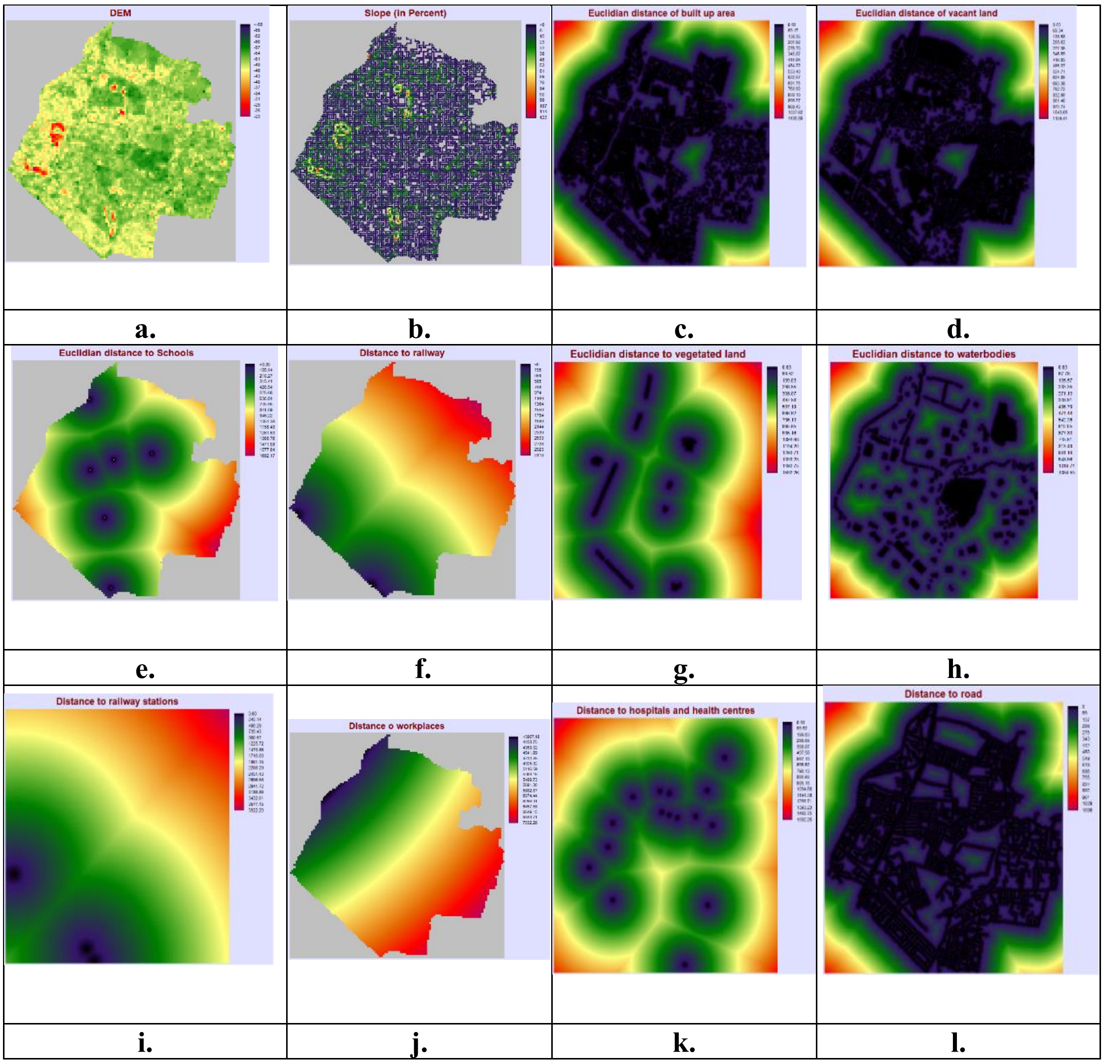
The driver variables have initially been chosen from similar other research works (Mithun et al., 2022; Vinayak et al., 2021; Shi et al., 2021; Samat et al.,2020; Shoyama et al., 2018; and Nasiri et al., 2017), by interviewing stakeholders and considering the ease of availability of data. Twelve variables are selected as listed in Table 4.6. These variables are quantified for the Euclidian distances, transformed by evidence likelihood, and tested with Cramer's V before including in the transition potential model structure.

Table 4.6: The driver variables for growth prediction for KMC Ward 109

#	Variable Category	Variable
1	Socio-economic	Distance to built-up area
2		Distance to schools
3		Distance to workplaces
4		Distance to hospitals and health services
5	Utilities	Distance to roads
6		Distance to railway
7		Distance to railway stations
8	Physical area	Digital Elevation Model (DEM)
9		Slope in percent
10	Environmental	Distance to waterbody
11		Distance to vegetation
12		Distance to vacant land

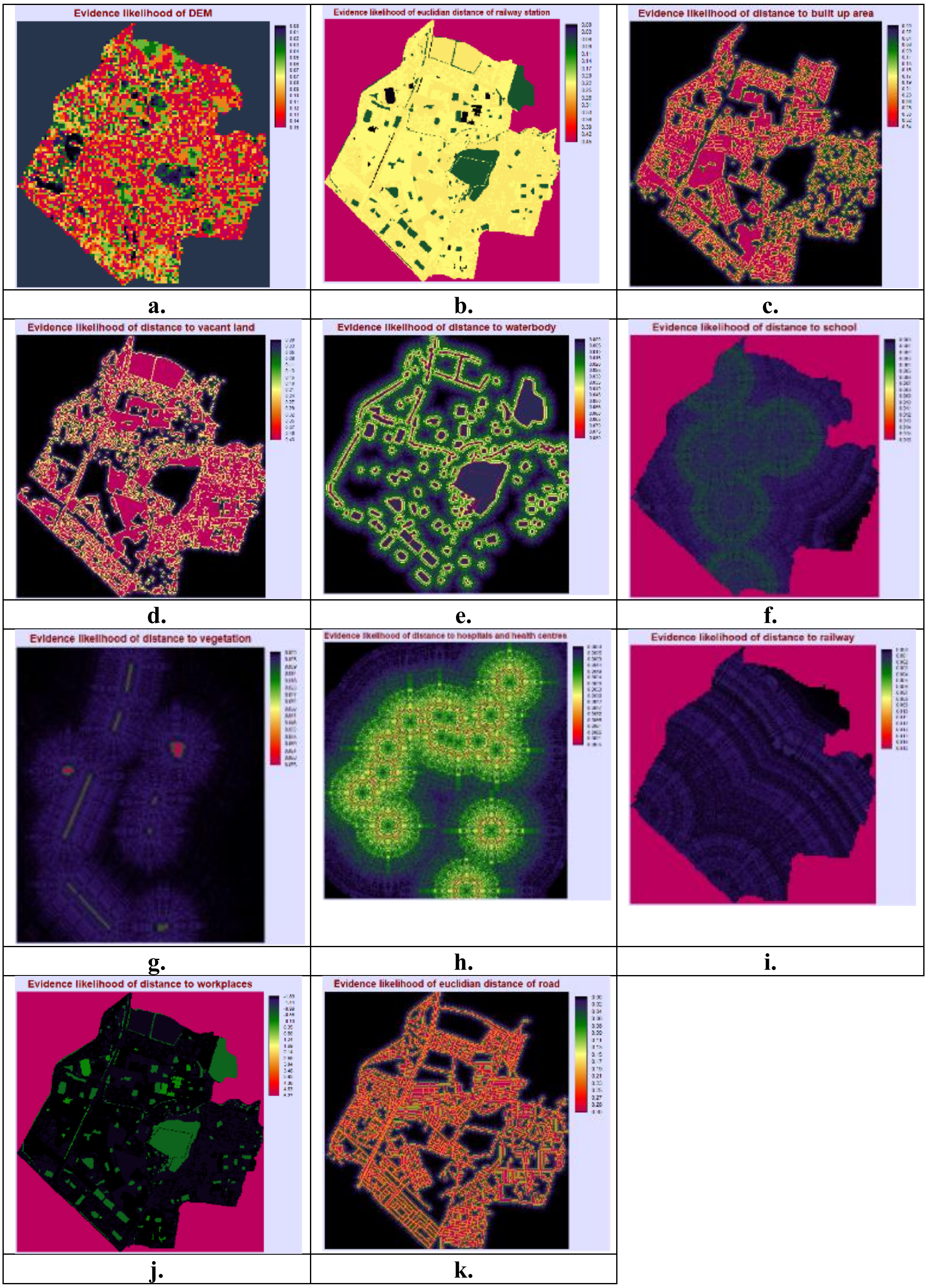
Euclidian distance of all the variables except DEM and slope have been computed in ArcGIS. Figs. 4.6 show DEM, slope and Euclidian distance maps of the remaining 10 variables. This Euclidian maps are inputs for transition potential model.

Evidence likelihood transformation is an efficient variable transformation method usually yielding higher accuracy of the model. This transformation is applicable for categorical variables or a continuous variable that has been binned into classes. This had been used for the selected variables and maps in Figs. 4.6 have been generated.

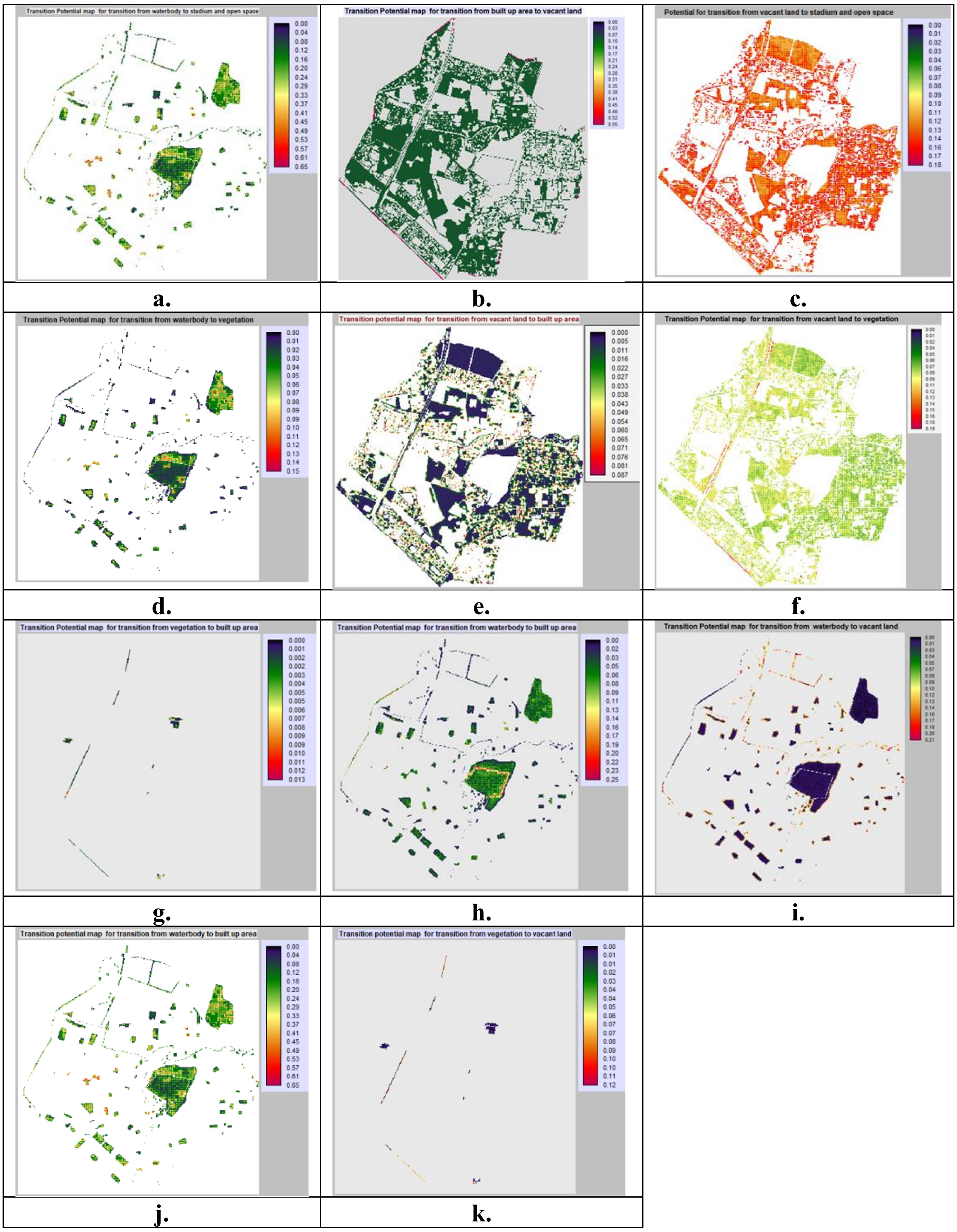


Figs. 4.6: Representations of **a.** DEM, **b**. Slope, and Euclidian distances to **c**. built-up area, **d**. vacant land, **e**. schools, **f**. railway line, **g**. vegetation, **h**. water bodies, **i**. railway station, **j**. workplace, **k**. hospitals and health centres, and **l**. road at KMC Ward 109

Before applied to the model, the Euclidian distance maps and evidence likelihood maps need to be tested in Cramer's V test (Eastman 2009; Yaghoobi et al. 2022). The Cramer's coefficient of correlation (Hasan et al., 2020) is computed between variables or driving forces of LULC change and transformed areas. It shows the relationship between the variable and LULC category and to total land features (Eastman, 2009). Cramer's V values around 0.15 or larger indicate that the potential explanatory value of the variable is acceptable and if it exceeds 0.4 it is good (Hasan et al., 2020). The results of Cramer's V Test on selected variables is given in Table 4.7. The maps generated by the evidence likelihood transformation method are shown in Figs. 4.7.



Figs. 4.7: Evidence likelihoods of **a**. DEM, and Evidence likelihood of Euclidian distances of **b**. railway station, **c**. built-up area, **d**. vacant land, **e**. water body, **f.** school, **g**. vegetation, **h**. hospitals and health centres, **i**. railway, **j**. workplaces and **k**. road at KMC Ward 109



Figs. 4.8: Transition potential maps of **a.** waterbody to stadium and open space, **b.** built-up area to vacant land, **c.** vacant land to stadium and open space, **d.** waterbody to vegetation, e. vacant land to built-up area, **f.** vacant land to vegetation, **g.** vegetation to built-up area, **h.** waterbody to built-up area, **i.** waterbody to vacant land, **j.** water body to stadium and open space and **k.** vegetation to vacant land, for KMC Ward 109.

Table 4.7: Testing of variables with Cramer's V testing method at KMC Ward 109

#	Explanatory Variables	Cramer's V
1	Slope in percent	0.0552
2	DEM (not finally included)	0.1805*
3	Evidence likelihood of Euclidian distance of built-up area	0.4001
4	Evidence likelihood of Euclidian distance of vegetation	0.4541
5	Evidence likelihood of Euclidian distance of vacant land	0.4683
6	Evidence likelihood of Euclidian distance of waterbody	0.4505
7	Evidence likelihood of Euclidian distance of roads	0.2027
8	Euclidian distance to workplace	0.1700
9	Euclidian distance to rail stations	0.1800
10	Euclidian distance to railways	0.1300
11	Euclidian distance to hospitals	0.1330
12	Euclidian distance to schools (not finally included)	0.1180*
* Variables 2 and 12 do not significantly influence the accuracy of MLPNN and excluded		

4.2.2.3 Transition Potential and Change Allocation at KMC Ward 109

The transition potential model has been used to generate transitional potential maps for each sub-model for each land transition as depicted in Figs. 4.8.

They are used by the 'change demand model' to predict for the prediction year. Markov Chain Model (MCM) is used to produce the probability of transition from one category to other. MCM generates transition probability matrix which is used by the 'Change Allocation Model' to derive changes for the prediction year and generate prediction maps.

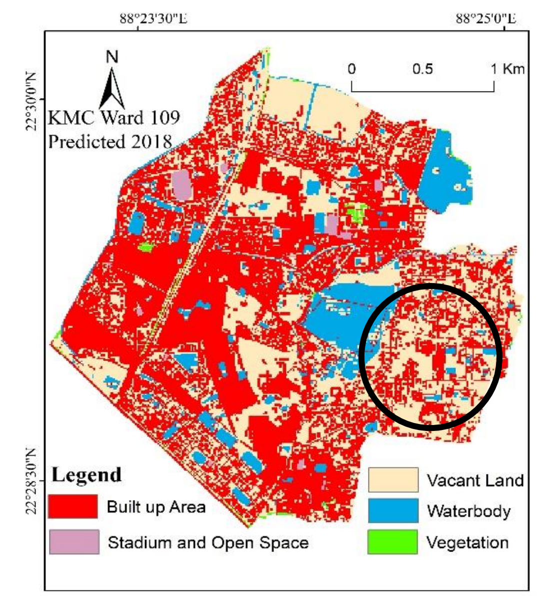
4.2.2.4 Prediction and Accuracy Assessment for KMC Ward 109

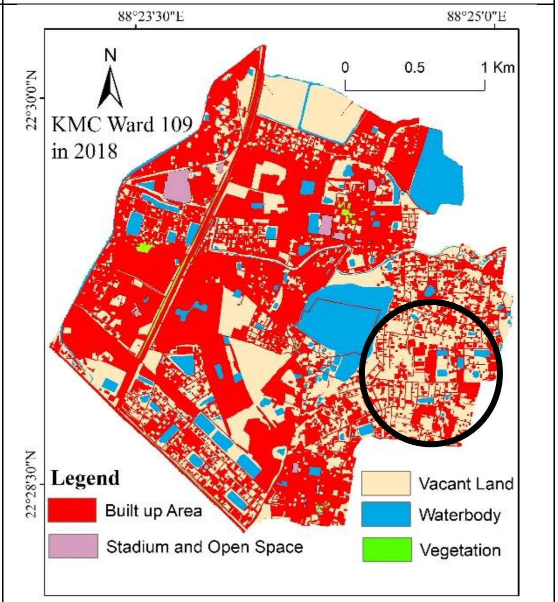
The prediction map for the year 2018 has been generated (Figs. 4.9) and validated with actual image through accuracy assessment in Table 4.8.

The maps in Figs. 4.9 show the similar pattern of urban sprawl. Actual map shows 63.4% of land use is built-up area and predicted map shows 59% and vacant land actually has 22.9% but prediction says it is 30.3%. The difference between actual and predicted is of 31.03 Ha. It means if the prediction forecast is studied well in advance this trend of conversion can be managed well. However, precariously, predicted reduction in waterbody exceeded the actual quantity.

In case of under-estimation of built-up area and waterbody indicates present situation will be worse than it is predicted. So early intervention is essential for planning the built-up area pattern. In case of over estimation of vacant land and built-up area, the situation is good and the bigger plots need to be protected in future. Regarding stadium and open space, the big chunk of open space in the north can be secured so that no encroachment is possible. Accuracy of the map (Fig. 4.10), validated with Google Earth image, is presented in Table 4.8.

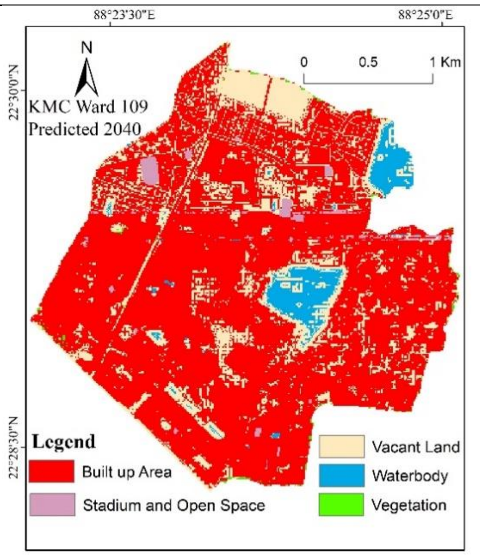
Predicted	Actual





Land uses	2018 (Actual)	2018 predicted	Difference
Vegetation	24.3 (3.4%)	3.19 (0.5%)	21.11 ha
Built-up Area	447.3 (63.4%)	416.27 (59.0%)	31.03 ha
Water body	36.2 (5.1%)	62.08 (8.8%)	25.88 ha
Stadium and other open space	36 (5.1%)	10.08 (1.4%)	25.92 ha
Vacant Land	161.6 (22.9%)	213.8 (30.3%)	52.2 ha

Figs. 4.9: Predicted LU of 2018 and actual LU for 2018 in ha and percent for KMC Ward 109



Land uses	2040
Vegetation	2.7
Built-up Area	526.73
Water body	27.9
Stadium and other open space	10.08
Vacant Land	137.93
Total	705.34

Fig. 4.10: Predicted land use of 2040 in hectare for KMC Ward 109

Accuracy assessment in Table 4.8 shows 95% overall accuracy and 0.93 kappa index which is acceptable for further simulation. Validation of the map shows that its overall accuracy is 95% which is very good for studies. Likewise, accuracy at individual categories show that referenced pixels of the built-up area are classified at 99% accurately, vacant land's reference pixels have been 87% rightly classified. Only 1 pixel of built-up area is misclassified. In case of vacant land out of 35 classified pixels 33 are rightly classified. Waterbody classification is 100% accurate. Likewise, vegetation and stadium and open space have 88% and 93% accuracy of data in classification. Kappa index shows high degree of accuracy. The predicted map of 2040 in Fig. 4.10 shows increment in of built-up area with big patches of water bodies wilting. In 2018 actual waterbody conversion has exceeded the predicted amount. Hence, in 2040 other big patches might be challenged too if not intervened now. This will heavily affect environment, necessitating immediate vigilance and planning. Conversion of vegetation and waterbody to the built-up area in urban expansion can still be stopped by proper governance.

Table 4.8: 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%		

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

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

Construction of Eastern Metropolitan Bypass disturbed the East Kolkata Wetland and encouraged urban expansion. Increased built-up area from 21.13% in 2002 to 45.17% in 2010 was already alarming. On the basis of these two years, LULC for 2018 has been predicted. Transition maps, compiled in one transition map (Fig 4.3) grouped to make sub-models to find out changes (Tab 4.5), can be used more accurately to stop encroachment of water body, vegetation and vacant land for which this research thrives.

The research indicates the variables, which are not same for each and every region, responsible for changes identified through Cramer's V test, are grouped keeping some and discarding the rest (Tab 4.7). Thus, before planning, this forecasting model can be implemented for other fringe areas of KMA by the planners to figure out the short term and long term sustainable planning demands. Fig. 4.9 and overall accuracy shows the actual and predicted map of KMC Ward 109 for the year 2018 which is 95% accurate. Accuracy at individual category (Tab 4.8) shows 99% accuracy for the built-up area. How the waterbody and vacant lands are vanishing could be taken into consideration at an early stage. Since the situation in this ward is already serious so planning is required as early as possible which are suggested in the later pages. So the fringe areas which are already saturated can follow this planning idea.

Significant transitions were detected from waterbody to vacant land and vacant land to built-up area and transitional potential images (Fig. 4.8) have been generated with high precision. Samples are extracted from the two land cover maps that has undergone the transitions being modelled as well the areas that could have changed but did not. This transitional potential map shows the vulnerable areas prone to changes.

Unconstrained land dynamics till 2040 (Fig 4.10) shows 526.73 ha or 74.68% of built up area and 25.32% non-built up area of which only 0.04% is water body. So the environmental problem as well as soico-economic and demographic problems can be studied in detail. Problems of water logging, traffic congestion, and inadequate sewerage system etc., well known problems of unplanned urbanisation, are manifested. This trend of environmental degradation can be restrained or controlled with proper planning.

4.3 Baruipur Municipality, KMA

Baruipur Municipality, established in 1869, needs to be studied in depth as an example of a non-saturated area with room for further expansion. It covers an area of 950 ha (as per the municipality record), though officially Baruipur Municipality covers 905 ha, and studies reveal that the municipality area is 608.77 ha. It (Fig. 4.11) is located within 88°26'11.61"E in the north, 88°27'6.87"E in the south, 22°21'42.56"N, in the east and 22°21'10.49"N, in the west.

4.3.1 Spatio-Temporal Change Analysis of Baruipur Municipality, KMA

The Spatio-temporal change analysis over a period of ten years between 2010 and 2020 have been carried out using three different tools and convergence of observations has been achieved. The tools involved are ArcGIS 10.2 and IRDISI Selva 17.0 while the statistical analysis has been conducted with FRAGSTATS.

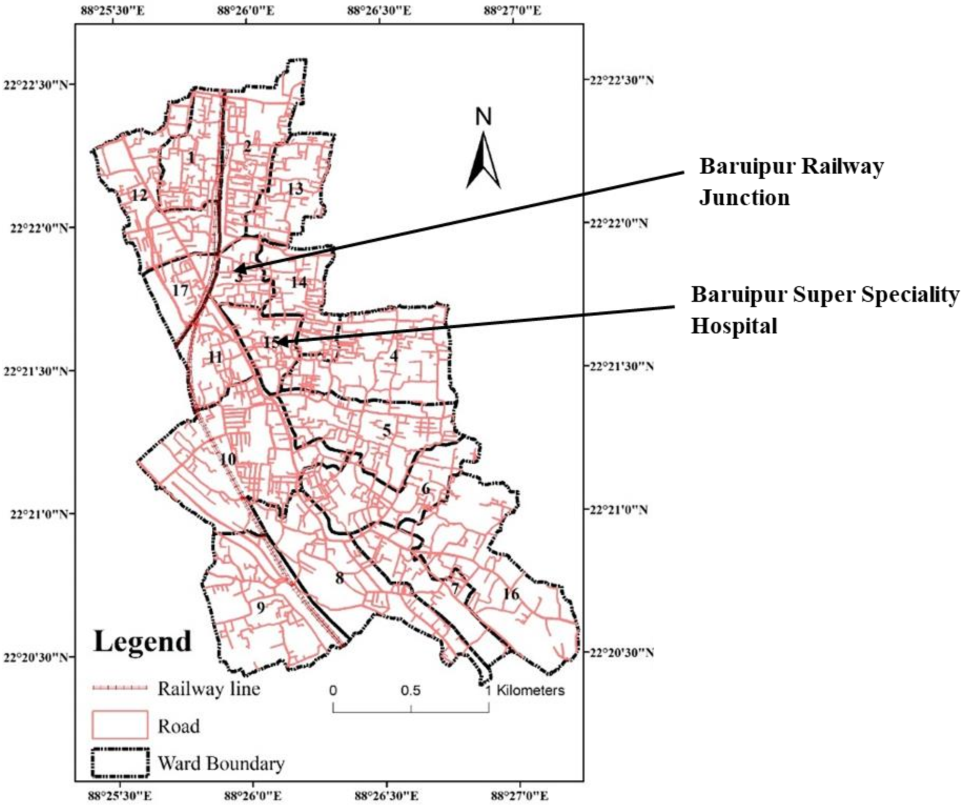


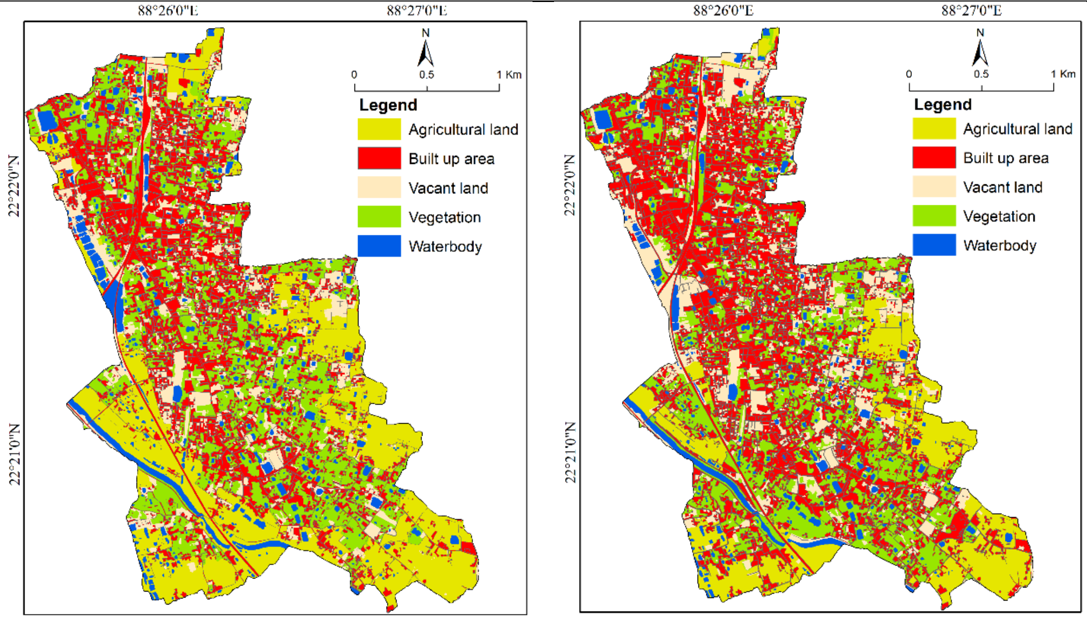
Fig. 4.11: Baruipur Municipality with ward boundaries

4.3.1.1 Change Analysis using ArcGIS for Baruipur Municipality, KMA

Two thematic maps for Baruipur Municipality has been developed from the Google Earth application for the years 2010 and 2020. The land use land cover (LULC) has been classified again into five LU classes, namely, 'agriculture land', 'built-up area', 'vacant land', 'vegetation' and 'water body'. Digitised layers of thematic maps such as schools, hospitals and workplaces as point feature, roads and railway lines, etc., as polyline feature, and built-up area, vacant lands, water body and vegetation, etc., as polygon feature are combined and stored in geodatabase as before and the topology operation has been run to compute areas of the classes in ArcGIS as in Figs. 4.12. Fig. 4.12 shows that between 2010 and 2020 the built-up areas have gained the most, from 33.59% to 42.73%. Agricultural land and vegetation have decreased, from 25.29% to 22.34%, and 23.32% to 19.14%, respectively. Vacant land and waterbody too have reduced from 11.68% to 10.80% and 6.13% to 4.99%, respectively.

4.3.1.2 Change Analysis using IDRISI Selva for Baruipur Municipality, KMA

Fig. 4.13 shows that between 2010 and 2020, vacant land, agricultural land, vegetation and waterbodies have predominantly been converted to built-up area and to vacant land to a lesser degree. 5.4 ha of built-up area has also been converted to vacant land. 4.79 ha of water bodies transformed to vacant land. Though vegetation has gained area from built-up area, vacant land, vegetation and agricultural land (0.96+6.8+36.29+1.43 = 45.48 ha) but the conversion of vegetation (30.93+21.88+0.8+0.21 = 53.82 ha) to other categories has negated the overall benefit.



Land use	2010	2020
Built-up area	33.59%	42.73%
Vegetation	23.32%	19.14%
Vacant land	11.68%	10.80%
Waterbody	6.13%	4.99%
Agricultural land	25.29%	22.34%

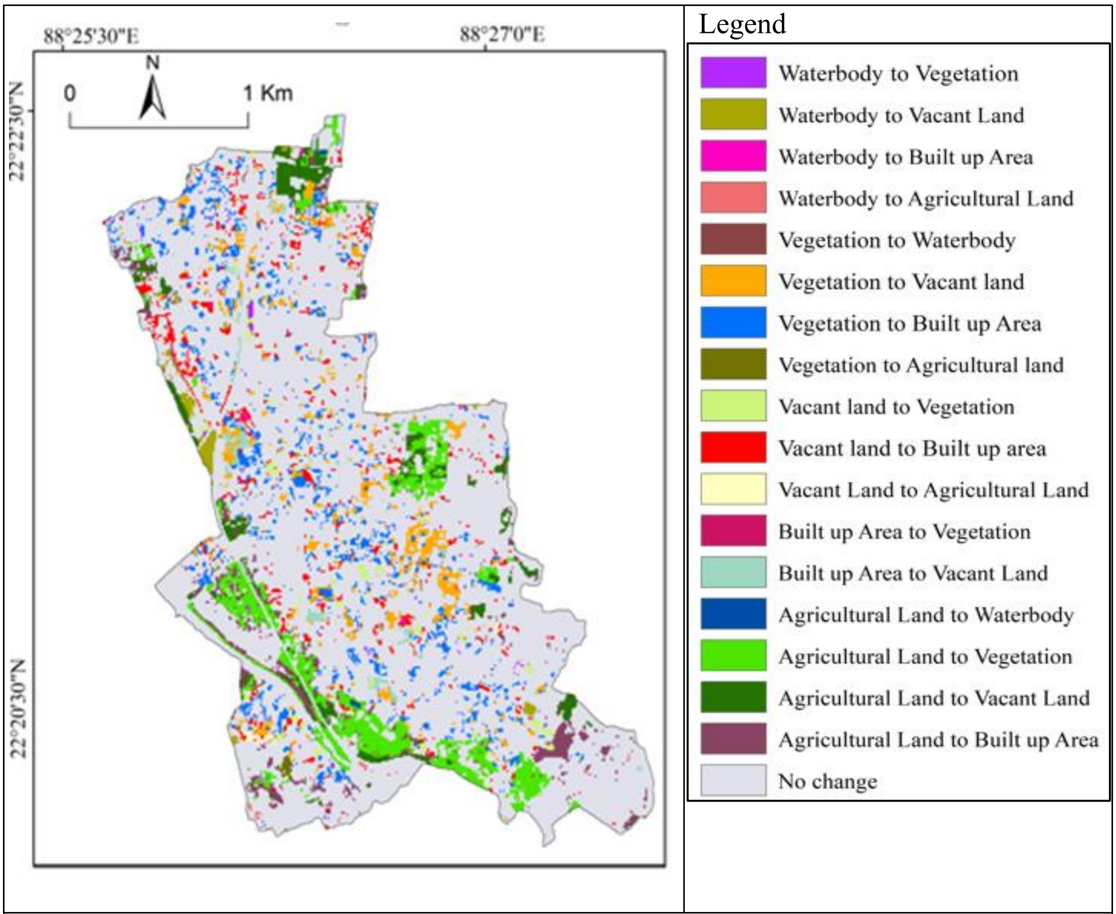
Figs. 4.12: LU maps and LU distribution of Baruipur Municipality, KMA, 2010 and 2020

4.3.1.3 Change Analysis by Statistical Method using FRAGSTATS for Baruipur Municipality, KMA

Four satellite images of 1991, 2001, 2011 and 2021 (Table 4.9) are downloaded from the USGS Earth Explorer, pre-processed to extract Baruipur Municipality and Gaussian MLC algorithm is used again for supervised classification. GPS data is used for identifying training areas from subseted images and post classification ground truth verification is done.

Table 4.9: Detail of satellite images used in FRAGSTATS

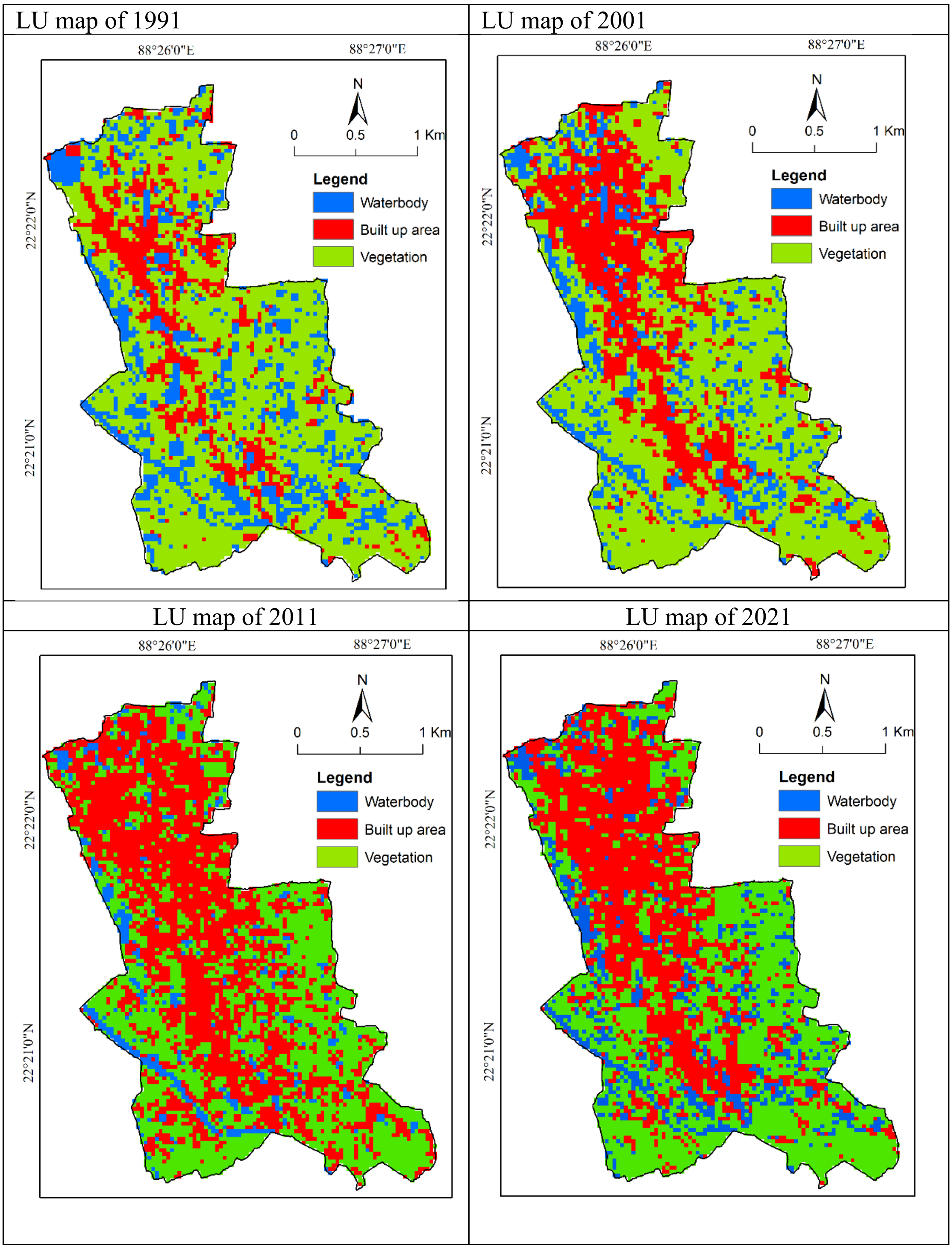
Image	Date of acquisition	Cell Size and Projection
Landsat 5 TM	02.02.1991	30m and Universal transverse Mercator Projection
Landsat 5 TM	12.01.2001	
Landsat 5 TM	24.01.2011	
Landsat 8	03.01.2021	



		Land cover during 2020				
		Built-up area	**Vacant land**	**Agricultural land**	**Vegetation**	**Water body**
Land cover during 2010	**Built-up area**	**188.64**	5.40	0.04	0.96	0
	Vacant land	16.82	**48.81**	0.70	6.8	0.03
	Agricultural land	16.31	17.26	**86.82**	36.29	0.43
	Vegetation	30.93	21.88	0.8	**92.7**	0.21
	Waterbody	0.59	4.79	0.49	1.43	**28.95**

Fig. 4.13: Change map of Baruipur Municipality from 2010 to 2020 in ha

Figs. 4.14 show the land use (LU) maps of 1991, 2001, 2011 and 2021 generated by supervised classification. It shows the gradual proliferation of red patches indicating built-up area. He northern part is transforming faster than the southern part along the State Highway SH-1 (Fig. 3.1). Tables 4.10 lists the results of accuracy assessments of the supervised classification model through kappa index and error matrix.



Figs. 4.14: LU maps of Baruipur Municipality, KMA for years 1991, 2001, 2011 and 2021

Referring to Table 4.10 for the years 2011 and 2021, overall accuracies are 94 %% and 93.89% and Kappa statistics are 0.898 and 0.904, respectively, which are pleasingly satisfactory.

Once the classification model is established and LU map of 1991, 2001, 2011 and 2021 is created, LULC change in urban sprawl is quantified using the following two methods.

I. Shannon Entropy using ArcGIS and Excel
II. Class and landscape level metrics using FRAGSTATS.

Table 4.10: Accuracy Assessment of the years 2011 and 2021 for Baruipur Municipality

Error matrix, 2011

	Reference Data				
	Classes	**Built-up Area**	**Vegetation**	**Waterbody**	**Totals**
Classified Data	Built-up Area	**22**	0	4	26
	Vegetation	0	**41**	3	44
	Waterbody	0	1	**53**	54
	Totals	22	42	60	124

$$Overall\ accuracy\ = 116/124\ = 94\%$$

$$Kappa\ Index = \frac{124*(22+41+53)-\{(26*22)+(44*42)+(54*60)\}}{124^2-\{(26*22)+(44*42)+(54*60)\}} = 0.898$$

Error matrix, 2021

	Reference Data				
	Classes	**Built-up Area**	**Vegetation**	**Waterbody**	**Totals**
Classified Data	Built-up Area	**33**	0	1	34
	Vegetation	1	**66**	5	73
	Waterbody	0	3	**70**	73
	Totals	34	69	76	180

$$Overall\ accuracy\ = 169/180\ = 93.89\%$$

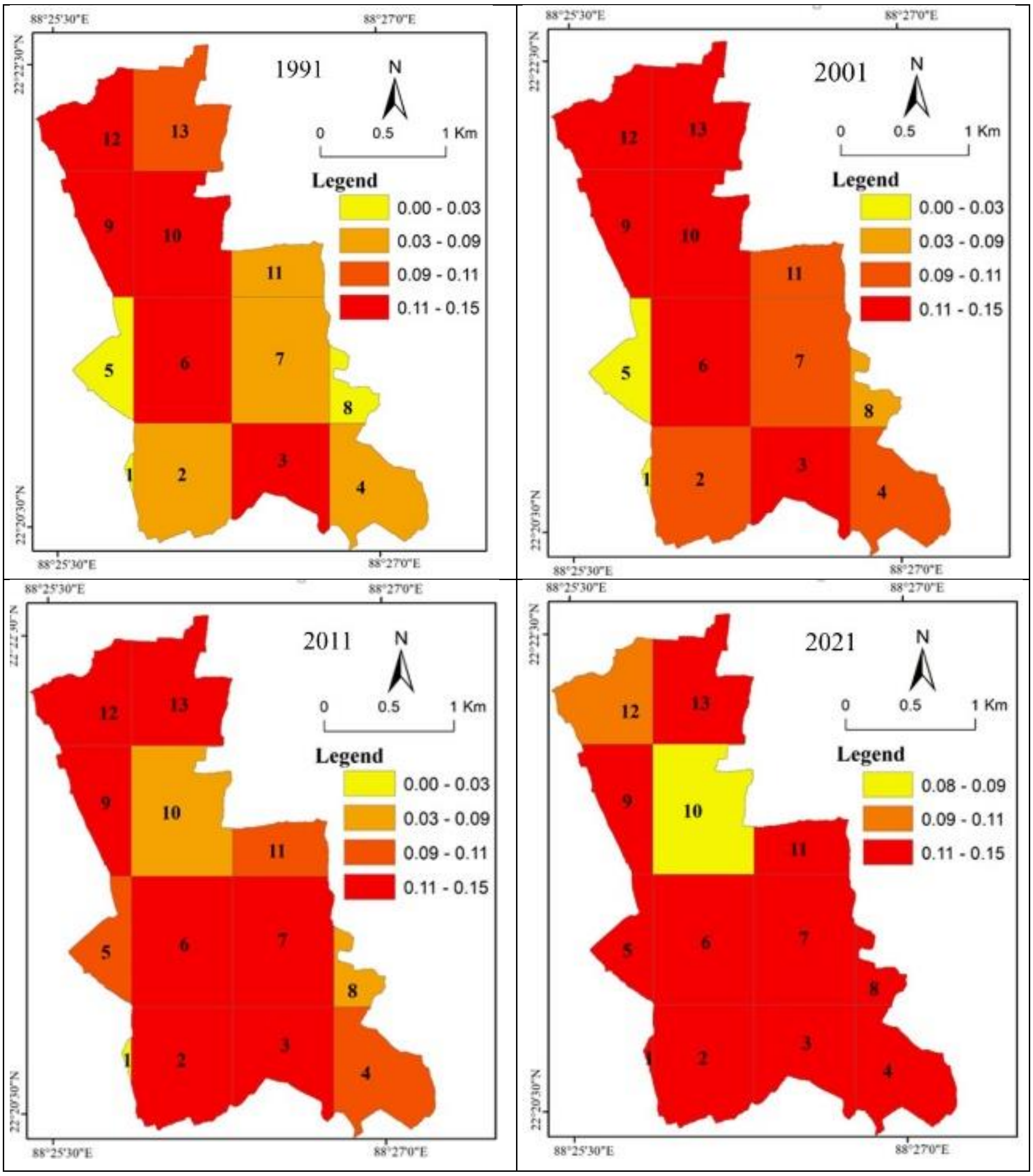
$$Kappa\ Index\ = \frac{180*(33+66+70)-\{(34*34)+(73*69)+(73*76)\}}{180^2-\{(55*51)+(55*55)+(54*55)+(67*67)+(53*58)\}}\ = 0.904$$

4.3.1.3.1 Shannon's Entropy for Baruipur Municipality, KMA

The study area has been divided into 13 panels with grid IDs 1 to 13 by Fishnet operation in ArcGIS, over which Shannon's entropies have been calculated for the years 1991, 2001, 2011 and 2021 (Figs. 4.15) and in MS Excel using Eqs. A2.5 and A2.6 from Chapter 2.

Table 4.11: Built-up area (BUA in ha), Shannon entropy (E) level and Relative entropy (RE) showing distribution of built-up area in Baruipur Municipality, KMA for the years 1991 to 2021

IDs	**1991**			**2001**			**2011**			**2021**		
	BUA	**E**	**RE**	**BUA**	**E**	**RE**	**BUA**	**E**	**RE**	**BUA**	**E**	**RE**
1	0.00	0.00	0.00	0	0	0.00	0	0	0.00	0.31	0.14	0.05
2	3.19	0.06	0.02	6.87	0.10	0.04	13.89	0.13	0.05	22.25	0.15	0.06
3	9.11	0.13	0.05	9.81	0.13	0.05	14.21	0.15	0.06	23.48	0.15	0.06
4	4.77	0.09	0.04	6.37	0.11	0.04	6.46	0.11	0.04	13.23	0.15	0.06
5	0.09	0.01	0.00	0.18	0.01	0.01	3.45	0.11	0.04	4.99	0.13	0.05
6	17.56	0.14	0.05	30.23	0.15	0.06	40.89	0.14	0.06	45.4	0.13	0.05
7	6.72	0.09	0.03	10.8	0.11	0.04	17.64	0.14	0.05	27.43	0.15	0.06
8	0.26	0.03	0.01	1.08	0.08	0.03	0.82	0.07	0.03	2.09	0.12	0.05
9	13.91	0.15	0.06	17.96	0.15	0.06	22.22	0.13	0.05	22.63	0.13	0.05
10	25.60	0.15	0.06	41.4	0.13	0.05	54.64	0.09	0.03	55.12	0.08	0.03
11	2.20	0.08	0.03	3.13	0.10	0.04	3.21	0.10	0.04	10.23	0.15	0.06
12	8.60	0.13	0.05	18.36	0.15	0.06	25.92	0.13	0.05	29.99	0.11	0.04
13	7.90	0.11	0.04	20.93	0.15	0.06	32.07	0.13	0.05	31.9	0.13	0.05
Total	99.91	1.17	0.46	167.12	1.38	0.54	235.42	1.44	0.56	289.05	1.73	0.68



Figs. 4.15: Shannon entropy level of Baruipur Municipality, KMA for 1991 to 2021

Table 4.11 shows that that from 1991 to 2021 the distribution of built-up area is getting dispersed as the total entropy value has increased from 1.17 in 1991, 1.38 in 2001, 1.44 in 2011 and 1.73 in 2021 and has exceeded $\frac{1}{2}\ln n = 0.5 \cdot \ln 13 = 1.2824745$.

Figs. 4.15 show from 1991 to 2021 central and northern parts of the study area are gradually experiencing compact distribution since their built-up area is almost covering the net. At IDs 9, 10, 12 and 13, the relative entropies are approaching zero in 2021 since they have compact distribution of built-up area. In case of the southern part, the increasing relative entropy value indicates sprawling. Hence, the distribution of relative entropy suggests compact central part with urban sprawl in the outer panels of Baruipur Municipality, KMA.

4.3.1.3.2 Class and Landscape Level Metrics for Baruipur Municipality, KMA

FRAGSTATS has been employed to generate class level and landscape level metrics in Table 4.12 showing spatial characteristics of LULC classes over time.

Table 4.12: Class and landscape level metrics of Baruipur Municipality for 1991 to 2021

Year	Class Level Metrics					Landscape Level Metrics	
	Types	**CA(ha)**	**PLAND (%)**	**LPI (%)**	**NP**	**NP**	**SPLIT**
1991	Water body	133.11	21.85	2.23	234	383	2.76
	Vegetation	375.03	61.57	60.36	26		
	Built-up Area	**100.98**	**16.57**	**5.69**	**123**		
2001	Water body	97.92	16.08	1.55	232	389	3.85
	Vegetation	311.12	53.60	21.53	101		
	Built-up Area	**200.08**	**30.32**	**30.83**	**120**		
2011	Water body	88.11	14.47	1.51	221	458	5.45
	Vegetation	270.72	50.44	21.91	111		
	Built-up Area	**250.29**	**41.09**	**33.81**	**126**		
2021	Water body	44.19	7.26	1.33	153	477	7.0
	Vegetation	200.26	47.49	21.72	123		
	Built-up Area	**325.67**	**45.26**	**38.08**	**101**		

Legend:
CA ≡ 'Class area' is the sum of the areas of all urban patches
PLAND ≡ Sum of all patch areas divided by total landscape area times 100
TE ≡ Sum of lengths of all edge segments involving the corresponding patch type, measured in meter
LPI ≡ In class level, it indicates the area of the largest patch of every class, in percent, while in landscape level, it indicates percent of landscape of the largest patch.
NP ≡ In class level, it indicates the number of urban patches of each class, number, ≥1, while in landscape level, it indicates number of patches in the landscape (≥1).
SPLIT or Splitting index ≡ Total landscape area squared divided by the sum of patch area squared, all patches in landscape, no units, range being 1 ≤SPLIT≤ number of cells in the landscape squared

Table 4.12 shows receding trend for waterbody and vegetation in CA, PLAND and LPI at class level with increasing trend of CA, PLAND and LPI for built-up area. But for NP, other than vegetation, all LU show downward trend indicating fragmentation of vegetation. In supervised classification it is difficult to separate vegetation, agricultural land and vacant land accurately. Hence fragmentation of vegetation indicates fragmentation of vacant land and agricultural land as well. At landscape level, NP and SPLIT Index are increasing which indicate heterogeneity and fragmented urban sprawl over time (Pal et al., 2024).

4.3.1.4 Summarising Change Analysis Observations at Baruipur Municipality

The results of change analysis, done by different methods, converge to similar observations. To summarize, the key observations are:

- Built-up areas have gradually become the foremost LU while vegetation and vacant land have gradually lost their dominance.
- Added built-up area is derived from vacant land, vegetation and water body.
- Urban expansion has created fragmentation of water body and vegetation land.
- Urban sprawl is predominant in central to northern parts of Baruipur Municipality

4.3.2 Growth Prediction for Baruipur Municipality, KMA

Two digitized base year maps for the years 2010 and 2020, prepared in ArcGIS 10.2, have been processed in IDRISI Selva 17.0, which uses MLPNN based land change modeler (LCM) and Markov Chain algorithms to generate transitional potential maps and predict future map for the year 2023 respectively and compared with the actual map taken from the Google Earth. The 'overall accuracy' and Kappa statistics being satisfactory, the process is repeated for the proposed horizon year, i.e., 2040.

4.3.2.1 Transition Sub-model and Selection of Driver Variables

The transition maps for 2002 and 2010 is used to identify the transition sub-models (Table 4.13). Driver variables have been pre-selected from similar research works. 13 variables are selected, quantified (Euclidian distance), transformed (evidence likelihood), tested (Cramer's V) and listed in Table 4.14 before inclusion to the transition potential model structure. Two variables, distance to school, and distance to workplaces, have been finally discarded.

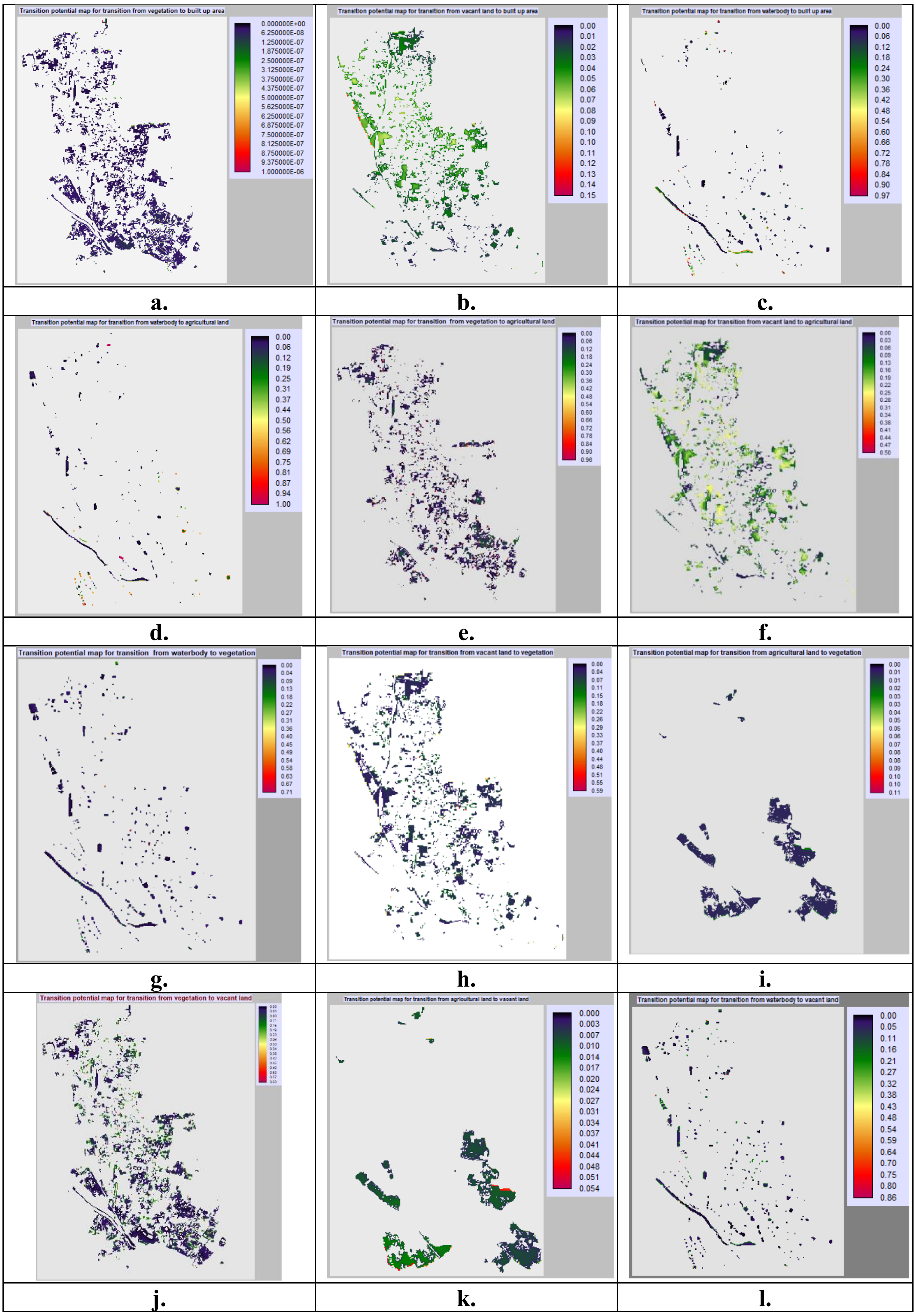
Table 4.13: Sub-models formed from the transition maps of Baruipur Municipality, KMA

Sub-model	Changes from	Changes to
Change_to_built-up area	Vacant land, Agricultural land, Vegetation, Water body	Built-up area
Change_to_vegetation	Vacant land, Agricultural land, Water body	Vegetation
Change_to_vacant_land	Agricultural land, Vegetation, Water body	Vacant land
Change_to_agricultural_land	Vacant land, Vegetation, Water body	Agricultural land

4.3.2.2 Transition Potential and Change Allocation at Baruipur Municipality

The transition potential model is used to generate transitional potential maps for each sub-model for each land transition.

Transition potential maps in Fig. 4.16 are used by 'Change Demand Model' along with prediction year. Markov Chain Model (MCM) is used to produce the probability of transition from one category to other categories. Markov Chain Model (MCM) generates transition probability matrix which is used by the 'Change Allocation Model' to derive changes for the prediction year and generate prediction maps.



Figs. 4.16: Transition potential maps of **a**. vegetation to built-up area, **b**. vacant land to built-up area **c**. waterbody to built-up area, **d**. waterbody to agricultural land, **e**. vegetation to agricultural land, **f**. vacant land to agricultural land **g**. waterbody to vegetation, **h**. vacant land to vegetation, **i**. agricultural land to vegetation **j**. vegetation to vacant land **k**. agricultural land to vacant land **l.** waterbody to vacant land

Table 4.14: Variables for growth prediction for Baruipur Municipality with Cramer's V test

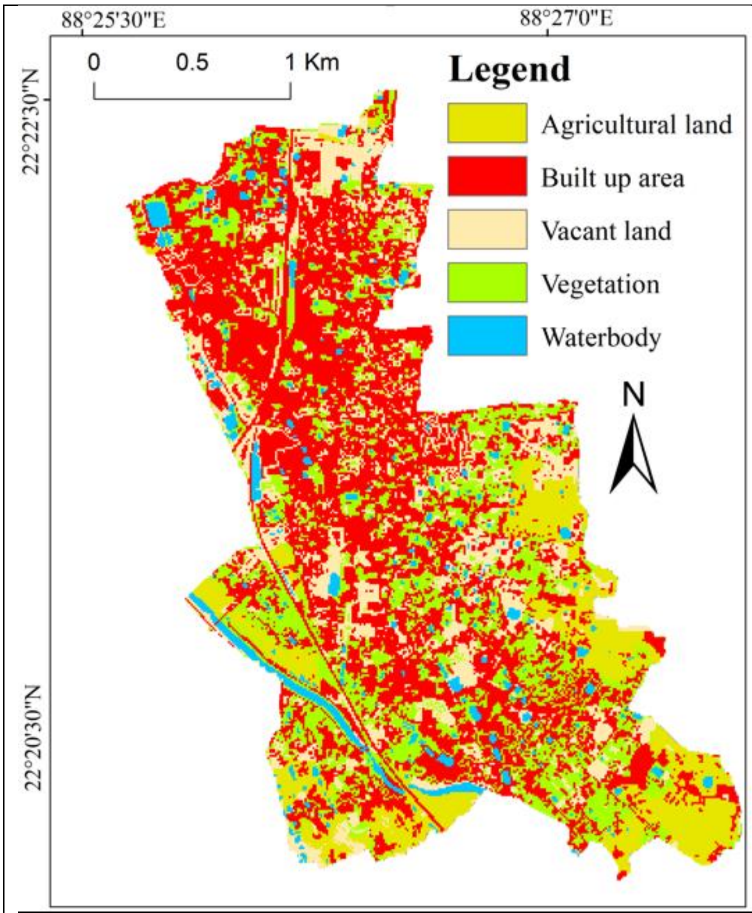
No.	Variable Category	Variable	Distance method	Evidence Likelihood	Cramer's V test
1	Socio-economic	Distance to built-up area	Euclidian distance	Yes	0.7021
2		Distance to schools	--do--	Yes	0.08 *
3		Distance to workplaces	--do--	Yes	0.1381 *
4		Distance to agricultural land	--do--		0.1844
5		Distance to hospitals and health services	--do--		0.1949
6	Utilities	Distance to roads	--do--		0.1844
7		Distance to railway	--do--	Yes	0.1129
8		Distance to railway stations	--do--		0.2419
9	Physical area	Digital Elevation Model (DEM)	--do--	Yes	0.1747
10		Slope in percent	--do--		0.0270
11	Environmental	Distance to waterbody	--do--	Yes	0.4570
12		Distance to vegetation	--do--	Yes	0.4946
13		Distance to vacant land	--do--	Yes	0.4748
* These variables are not included in the Transition Sub-model structure.					

4.3.2.3 Prediction and Accuracy Assessment for Baruipur Municipality

The prediction map for the year 2023 has been generated (Figs. 4.17) and validated with actual image through accuracy assessment.

Accuracy assessment (Fig. 4.17) shows 97.50% overall accuracy and 0.97 kappa index which is acceptable for further simulation. This classification will be helpful for further use since there are no significant confusion between the classes, signified by the user's accuracy and producer's accuracy attaining nearly 100% values. Specifically, for built-up area the user's accuracy is 95% while the producer's accuracy is 100%. Reference pixels have been 97.57% rightly classified for vacant land. In case of vacant land all pixels have been rightly classified. Kappa index (0.97) too endorses high accuracy of the map.

Predicted map for 2040 shows nearly doubling of built-up area from 33.59% in 2010 (Fig. 4.12) to 60% in 2024 (Fig. 4.18), and halved waterbody, 6.13% in 2010 to 3.5% in 2024. Thus, in 2040 other big patches might vanish as well, which will have a telling effect on the environment. Gradual decrease of vegetation from 2010 (Fig. 4.12) to 2040 will affect the food security to KMA since historically Baruipur had a predominantly agrarian land use.



Class	Area (ha)
Built-up Area	273.25
Vacant land	101.46
Agricultural land	71.43
Vegetation	134.63
Waterbody	28.00
Total	608.77

		Reference Data						
		Built-up Area	Vacant Land	Agricultural Land	Vegetation	Waterbody	Total	User's accuracy
Classification data	Built-up Area	38	1	0	1	0	40	95%
	Vacant Land	0	40	0	0	0	40	100%
	Agricultural	0	0	39	1	0	40	97.50%
	Vegetation	0	0	0	40	0	40	100%
	Waterbody	0	0	0	2	38	40	95%
	Total	38	41	39	44	38	200	
	Producer's accuracy	100%	97.57%	100%	90.90%	100%		

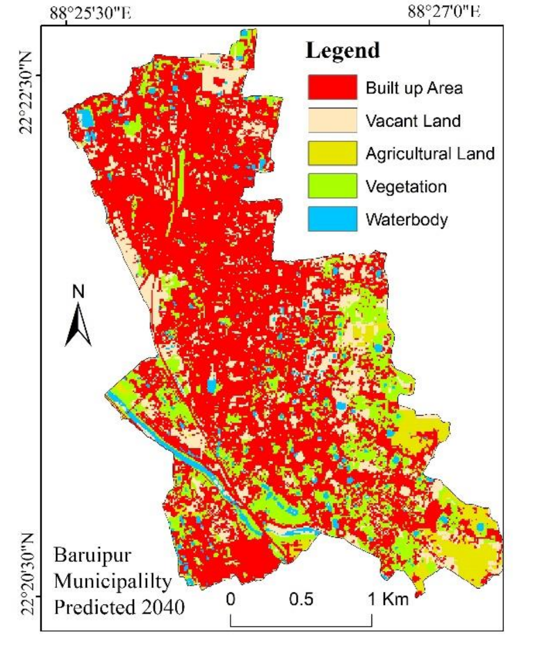
$$Overall\ accuracy\ = 195/200\ = 97.50\%$$

$$Kappa\ Index = \frac{195*200-\{(40*38)+(40*40)+(39*40)+(40*40)+(40*38)\}}{180^2-\{(40*38)+(40*40)+(39*40)+(40*40)+(40*38)\}} = 0.97$$

Fig. 4.17: Predicted map of 2023 and accuracy assessment for Baruipur Municipality, KMA

In the predicted change map of Baruipur Municipality between 2020 to 2040 shown in Fig. 4.19, one can easily notice the expansion of physical urban built-up area at the expense of agricultural land, vegetation, vacant land and waterbodies. Southward extension of E.M. Bypass, northward extension Metro Railway along the E.M. Bypass and rail connectivity of the area with the city core of Kolkata, and saturation of Rajpur-Sonarpur Municipal area, would result in rapid development of the area and influx of population from nearby Kolkata Metropolitan Area (KMA).

Projected land cover for 2040	Projected potential for transition for 2040



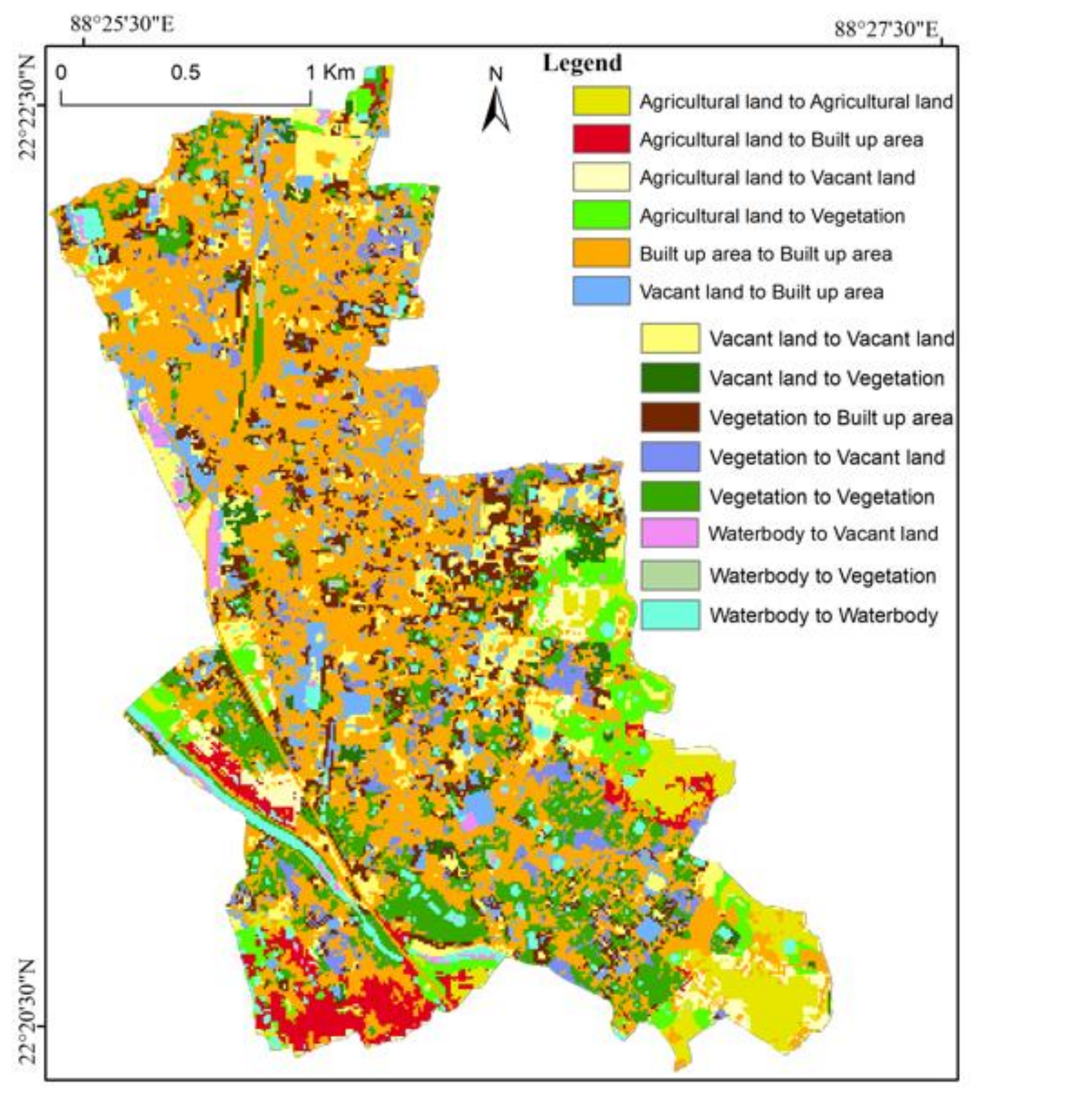
Class	Area (ha)
Built-up Area	364.69 (60%)
Vacant land	96.02 (16%)
Agricultural land	27.92 (4.5%)
Vegetation	98.60 (16%)
Waterbody	21.54 (3.5%)
Total	608.77

Fig. 4.18: Projected land cover for 2040 for Baruipur Municipality, KMA

Visual representation of prediction map (Fig 4.18) shows the saturated situation in the central part of Baruipur and gradually engulfing the outer area covered by vegetation and agriculture. Vegetation and agricultural lands are transformed into vacant land and slowly converted into built up area.

Easy availability of large chunk of vacant lands is attracting realtors' investments in large proportion and new built-up areas are appearing putting the crop, vegetable and fruit delivery chain in jeopardy. The complex nature of land use in the central region that accommodates Baruipur Railway Station, markets and the Super-speciality Hospital, is forcing people to move to the outer Wards of Baruipur Municipality putting pressure on the agrarian LU. Hence immediate planning interception is essential.

This visual representation of changes will help the planners put constrains in Baruipur and using the variables predict other fringe areas and do accordingly so that the sustainable development will be possible.



		Land cover at 2040				
		Built-up	Agricultural	Vegetation	Vacant	Water body
Land cover at 2020	Built-up	**253.69**	0	0	0	0
	Agricultural	20.6	**27.71**	25.28	15.26	0
	Vegetation	51.5	0	**59.02**	27.74	0
	Vacant	38.9	0	12.18	**47.06**	0
	Water body	0	0	2.12	5.96	**21.54**

Fig. 4.19: Predicted change map of Baruipur Municipality between 2020 and 2040 in ha

4.4. KMC Ward 144

KMC Ward 144 in Fig. 4.20, the last of the study areas have been included in KMC in 2012, is located inside 88°18'1.82"E in the north, 88°17'48.67"E in the south, 22°26'45.50"N, in the east and 22°27'13.77"N in the west covering 446.91 ha. It is in an early stage of urbanization. Indian Institute Management, Calcutta (IIM-C) or IIM Joka and Employee's State Insurance Corporation (ESIC) Hospital are the important landmarks in this ward, while Diamond Harbour

Road, a portion of National Highway 12, NH-12, and Thakurpukur-Bibirhat Road are two key roads serving this ward.

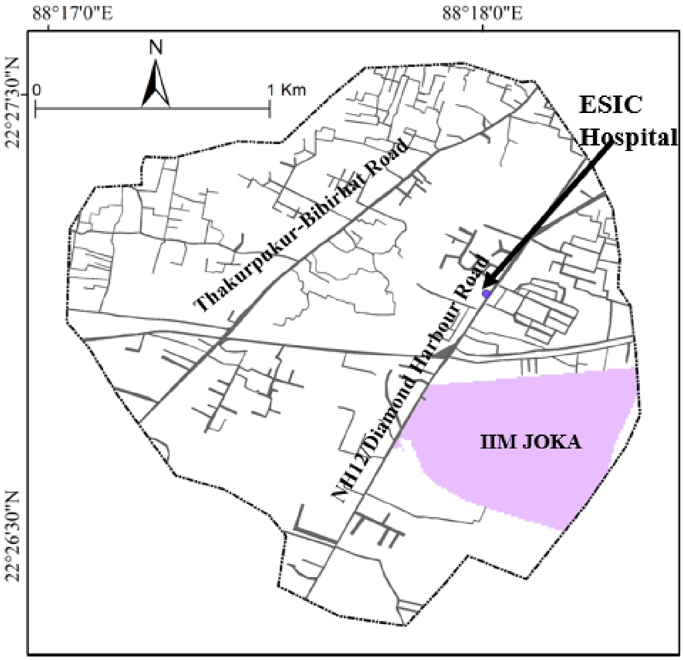


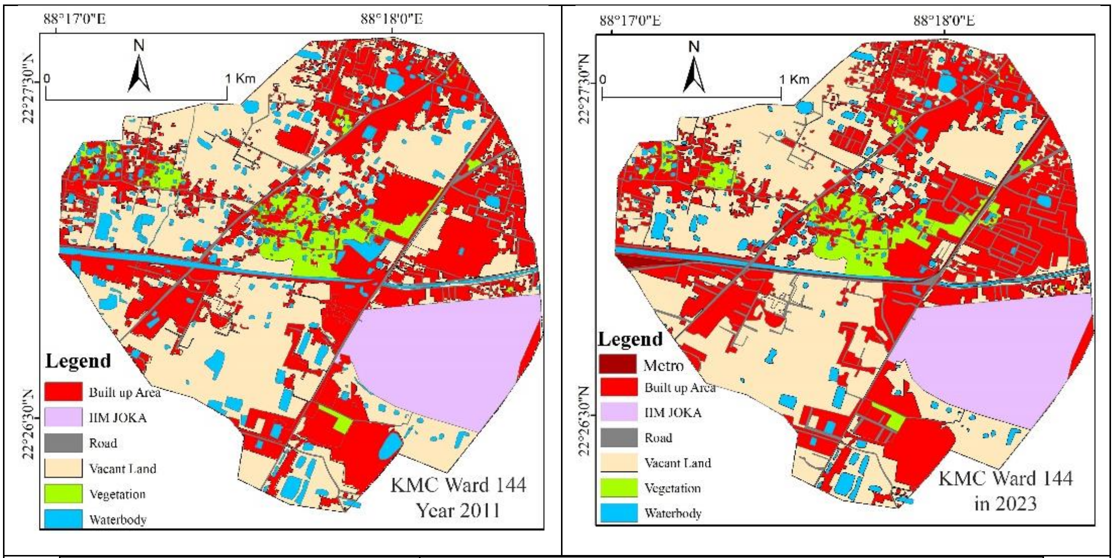
Fig. 4.20: Roads in KMC Ward 144

4.4.1 Spatio-Temporal Change Analysis of KMC Ward 144

The LULC of KMC Ward 144 are classified into once again five LU classes, namely, 'built-up area', 'vegetation', 'water body', 'vacant land' and 'IIM Joka'. The spatio-temporal change analysis over a period of 12 years (2011 to 2023) have been done using three tools to inspect their convergence. Change analysis using ArcGIS 10.2, IRDISI Selva 17.0 and statistical analysis using FRAGSTATS have been attempted.

4.4.1.1 Change Analysis using ArcGIS for KMC Ward 144

Two thematic maps for KMC Ward 144 has been developed from the Google Earth application for the years 2011 and 2023.The digitised layers of thematic maps such as schools, hospitals and workplaces as point feature, road, railway line etc. as polyline feature, built-up area, vacant lands, water body, vegetation etc. as polygon feature are combined and stored in geodatabase and topology operation has been run to calculate areas of the classes in ArcGIS, which are shown in Figs. 4.21.



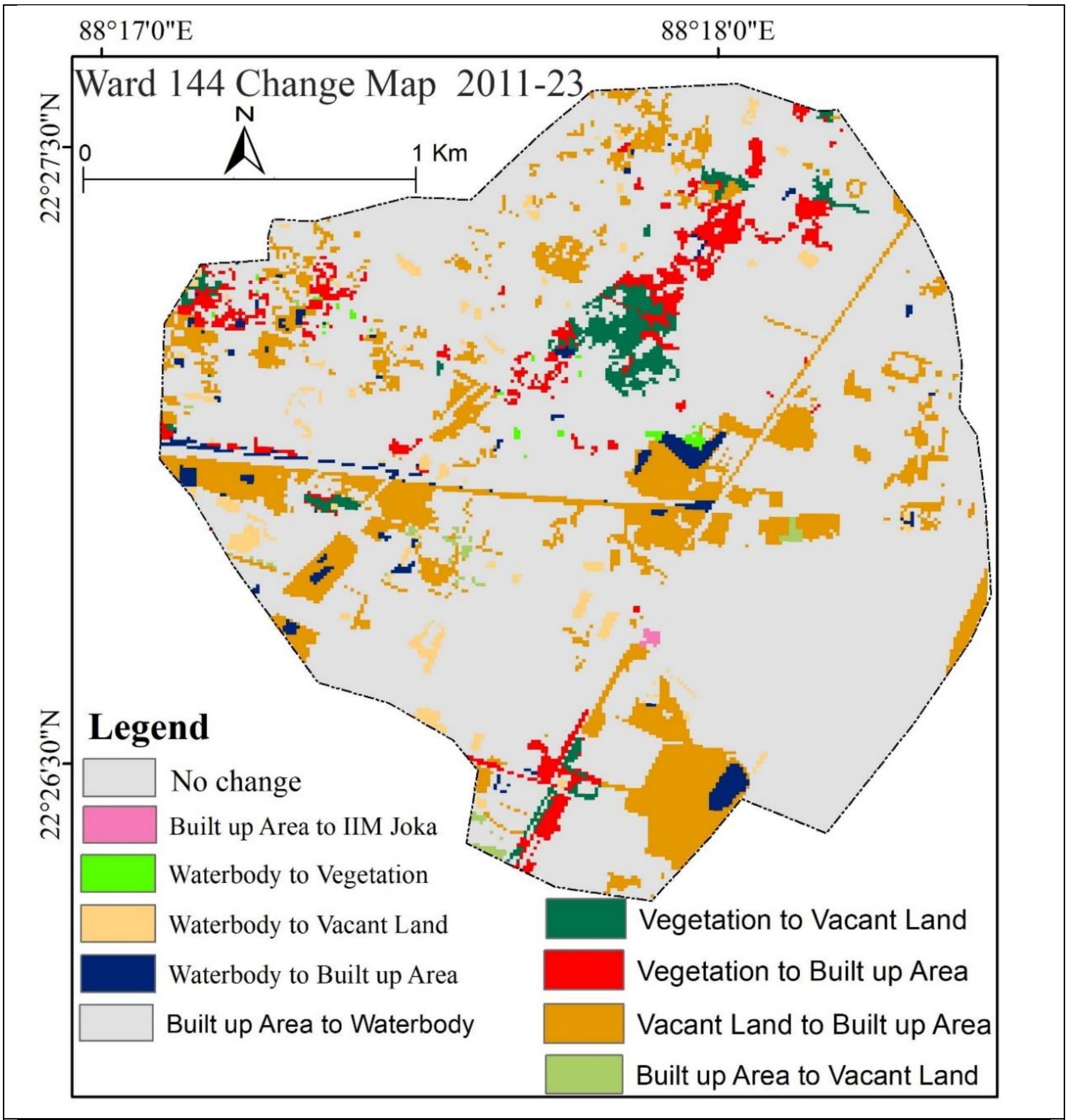
	Areas of KMC Ward 144 in Percent	
Classes	2011	2023
Built-up area	21.96	39.14
Vacant land	48.71	39.37
Vegetation	9.32	4.40
Waterbody	8.13	5.10
IIM Joka	11.87	11.87

Figs. 4.21: Land use distribution of KMC Ward 144 (in percent) for the years 2011 and 2023

The digitised map of Ward 144, show that the red patch is gradually expanding along the roads indicating urbanisation is mainly happening along the main roads. Within 12 years the built-up area increased from 21.96% (2011) to 39.14% (2023) and vacant land, vegetation and waterbody reduced. Vacant lands are mainly agricultural in nature. Decrease in agricultural land has already been seen in KMC ward 109 and Baruipur Municipality areas.

4.4.1.2 Change Analysis using IDRSI Selva for KMC Ward 144

These two thematic digitised maps of 2011 and 2023, as mentioned in Section 4.4.1.1 are considered as the base years and converted to raster/ASCII to be inserted as input for the LCM module of IDRISI Selva to conduct change analysis. It calculates LC changes between base years 2011 and 2023. LC change map and quantitative changes (in ha) in land cover classes are shown in Fig. 4.22.



Land-cover in 2011		Land cover at time 2023 (ha)				
	Land cover (ha)	Built-up Area	Vegetation	Waterbody	Vacant Land	IIM-C
	Built-up Area	96.45	0	0	1.27	0.25
	Vegetation	14.26	18.80	0	8.27	0
	Waterbody	6.14	0.77	22.60	6.81	0
	Vacant Land	58.03	0	0	159.59	0
	IIM-C	0	0	0	0	0

Fig. 4.22: Change map and transition matrix of LU for Ward 144 between 2011 and 2023

Fig. 4.22 shows the changes of land uses from 2011 to 2023 which shows built-up area has gained land and other categories are gradually losing their dominance. Waterbody has contributed 0.77 ha land to vegetation. Though built-up area has changed to vacant land (1.27 ha), but gaining from vacant land (58.03 ha) has been more than its contribution. Vacant land has contributed to built-up area but gained land from waterbody (6.81 hectare) and vegetation (8.27). Thus, the gain in vacant land has been surpassed by the incurred loss. Waterbody has mostly changed to vacant land and built-up area.

Most importantly, LU change map is showing conversion of waterbody along canals, i.e., encroachment of the waterbody is continuing and it is an ominous sign for urbanisation. Canal is very much required for sewerage system and encroachment of it creates problems of waterlogging, pollution in the area. So in the long run this should be taken care of by the government authority.

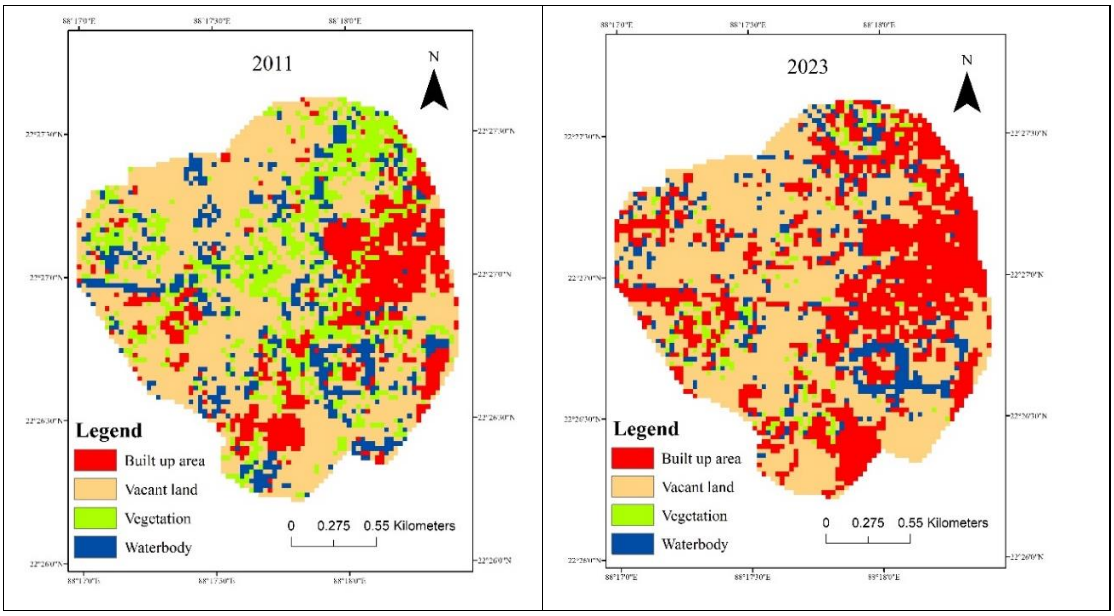
4.4.1.3 Change Analysis Statistics by FRAGSTATS for KMC Ward 144

Two satellite images of 2011 and 2023 (Table 4.15) has been collected from the USGS Earth Explorer, pre-processed to extract Ward 144 and Gaussian Maximum Likelihood Classification algorithm is used for supervised classification. The GPS data (using Garmin GPS) is used for identifying training areas from subseted image and post classification ground truth verification.

Table 4.15: Detail of satellite images used in FRAGSTATS for KMC Ward 144

Image	Date of acquisition	Spectral Band	Cell Size
Landsat 5 TM	24.02.2011	1,2,3,4,5,7	30m
Landsat_9	01.11.2023	1,2,3,4,5,7, 8, 9, 10, 11	30m

Figs. 4.23 shows the LU maps for the years 2011 and 2023 thus formed. Built-up area (red patch) are mainly concentrated in the north-eastern quarter. Gradually the patch cover increased. In 2011, land use distribution shows the supremacy of vacant land in the KMC Ward 144. But within 12 years there is a steep fall of vegetation and increase of built-up area.



Figs. 4.23: The LU map of KMC Ward 144 in 2011 and 2023 after supervised classification

Table 4.16 lists the results of accuracy assessments of the supervised classification model through kappa index and error matrix, which has proved satisfactory.

Table 4.16: Error matrix of 2011 and 2023 for KMC Ward 144

Error matrix of 2011

	Reference data					
	Class	Waterbody	Vegetation	Vacant Land	Built-up Area	Total (User)
Classification data	Waterbody	45	0	0	2	47
	Vegetation	0	60	1	0	61
	Vacant land	1	1	49	0	51
	Built-up area	2	0	0	41	43
	Total (Producer)	48	61	50	43	202

Overall accuracy = $\frac{195}{202}$ x 100= 96.53%

$$Kappa\ Index = \frac{202*(45+60+49+41)-\{(47*48)+(61*61)+(51*50)+(43*43)\}}{202^2-\{(47*48)+(61*61)+(51*50)+(43*43)\}} = 0.9530$$

Error matrix of 2023

	Class	Waterbody	Vegetation	Vacant Land	Built-up Area	Total (User)
Classification data	Waterbody	38	0	2	0	40
	Vegetation	0	19	0	0	19
	Vacant land	3	0	77	0	80
	Built-up area	2	0	3	56	61
	Total (Producer)	43	19	82	56	200

Overall accuracy = $\frac{195}{200}$ x 100= 95%

$$Kappa\ Index = \frac{200*(38+19+77+56)-\{(40*43)+(19*19)+(80*82)+(61*56)\}}{200^2-\{(47*48)+(61*61)+(51*50)+(43*43)\}} = 0.9283$$

Referring to Table 4.16 for the years 2011 and 2023, overall accuracies are 96.53%% and 95% and Kappa statistics are 0.9530 and 0.9283, respectively, which are pleasingly satisfactory.

Once the classification model is established and LU maps of 2011 and 2023 have been created, LULC change in urban sprawl is quantified using the following two methods:

I. Class and landscape level metrics using FRAGSTATS
II. Shannon Entropy using ArcGIS and Excel

4.4.1.3.1 Class and Landscape Level Metrics for KMC Ward 144

FRAGSTATS generate class level and landscape level metrics shown in Table 4.17, which shows spatial characteristics of LULC classes over time.

FRAGSTATS results (Table 4.17) show that CA (85.41 to 16.29), LPI (85.41 to 16.29) and TE (61980 to 17190) have been reduced remarkably for vegetation but for built-up area CA (76.32 to 153.36), LPI (8.12 to 18.20) and TE (35190 to 58740) have increased. These three parameters indicate less fragmentation, complexity and enlargement in structural pattern of built-up area. For vacant land, CA and TE have decreased but LPI shows nearly no change which indicates less fragmentation and less complexity in structural pattern. It means homogeneity of vacant land is present, however, vegetation is losing its dominance (CA, LPI) and going through fragmentation (TE). For water body, CA, NP and TE have decreased showing the fragmentation and losing prominence gradually.

Table 4.17: Class level metrics of KMC Ward 144 for the years 2011 and 2023

Year	Class level metrics				Landscape level metrics	
	Types	CA	LPI	TE	NP	SPLIT
2011	Built-up Area	76.32	8.12	35190	424	4.56
	Vacant Land	227.16	45.55	84270		
	Vegetation	85.41	5.13	61980		
	Waterbody	58.05	2.17	44760		
2023	Built-up Area	153.36	18.20	58740	397	4.15
	Vacant Land	237.33	45.25	75930		
	Vegetation	16.29	0.26	17190		
	Waterbody	39.96	1.03	36000		

Legend:
CA ≡ 'Class area' is the sum of the areas of all urban patches
PLAND ≡ Sum of all patch areas divided by total landscape area times 100
TE ≡ Sum of lengths of all edge segments involving the corresponding patch type, in meter
LPI ≡ In class level, it indicates the area of the largest patch of every class, in percent, while in landscape level, it indicates percent of landscape of the largest patch.
NP ≡ In class level, it indicates the number of urban patches of each class, number, ≥1, while in landscape level, it indicates number of patches in the landscape (≥1).
SPLIT or Splitting index ≡ Total landscape area squared divided by the sum of patch area squared, all patches in landscape, no units, range being 1 ≤SPLIT≤ number of cells in the landscape squared

At the landscape level analyses NP and SPLIT have reduced between 2011 and 2023 (424 in 2011 and 307 in 2023 and 4.56 in 2011 to 4.15 in 2023). Nearly constant SPLIT Index from 4.5639 to 4.1534 and Largest Patch Index (LPI) of built-up area (8.12 in 2011 to 18.2038 in 2023) implies the fact that built-up patches are fusing and monotonous urban patch areas are showing up at the expense of vegetation, water body and vacant land compromising its landscape diversity and environmental balance. This analysis reveals changing landscape characteristics at all levels of classification.

4.4.1.3.2 Shannon's Entropy for KMC Ward 144

The study area has been divided into four zones (north-east, north-west, south-east and south-west) while computing Shannon's entropy to judge urban sprawl for these four zones over four years (Table 4.18)

Table 4.18 shows that KMC Ward 144 is experiencing urban sprawl since its relative entropy is gradually approaching unity in 2023. The Ward is said to facing dispersed distribution of built-up area since its Shannon's entropy value has already crossed the halfway mark of ln 4 = 1.3862943611199, i.e., 0.693.

Table 4.18: Distribution of Shannon's entropy and Relative entropy of KMC Ward 144

	2011			2023		
Zones	**Built up area (ha)**	**Shannon's Entropy**	**Relative entropy**	**Built up area (ha)**	**Shannon's Entropy**	**Relative entropy**
SW	15.80	0.29	0.11	24.11	0.34	0.13
SE	23.74	0.32	0.12	49.23	0.36	0.13
NW	2.89	0.09	0.03	20.02	0.31	0.11
NE	33.89	0.36	0.13	60.00	0.34	0.13
Total	**76.32**	**1.07**	**0.39**	**153.36**	**1.35**	**0.50**

The built-up areas are maximum in the north-east and the south-east segments, thus the western part can be planned without major constraints.

4.4.1.4 Summarising Observations for Change Analysis for KMC Ward 144

The results of change analysis done by different methods converge to similar observations. To summarize the key observations inferred from all the methods are

- Built-up areas have become the foremost land use. Vegetation and vacant land have gradually lost their dominance.
- Water bodies are being transformed to built-up area and vacant land.
- Urban patches are fusing, vegetation and vacant land fragmentising and landscape level number of patches decreasing indicating urbanisation
- Upward trend of urban sprawl indicates added built-up areas seeking immediate planning intervention

4.4.2 Growth Prediction in KMC Ward 144

Two digitized base year maps for the years 2011 and 2023, prepared in ArcGIS 10.2, have been processed in IDRISI Selva 17.0, which invokes MLPNN based land change modeler (LCM) and Markov Chain algorithms to generate transitional potential maps.

4.4.2.1 Transition Sub-model and Selection of Driver Variables

The transition maps for 2011 and 2023 are used to identify the transition sub-models and listed in Table 4.19.

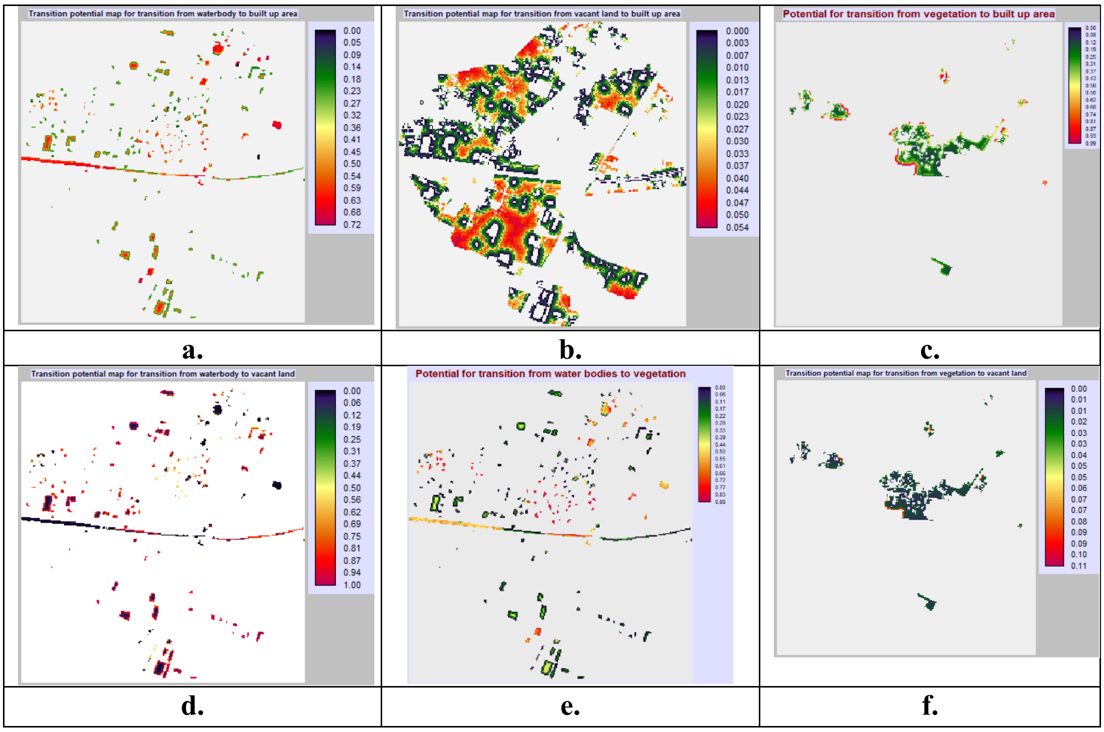
Table 4.19: Sub-models formed from the transition maps of KMC Ward 144

Sub-model	Changes from	Changes to
Change_to_built-up area	Vacant land, Vegetation, Water body, IIM Joka	Built-up area
Change_to_vacant_land	Vegetation, Water body	Vacant land

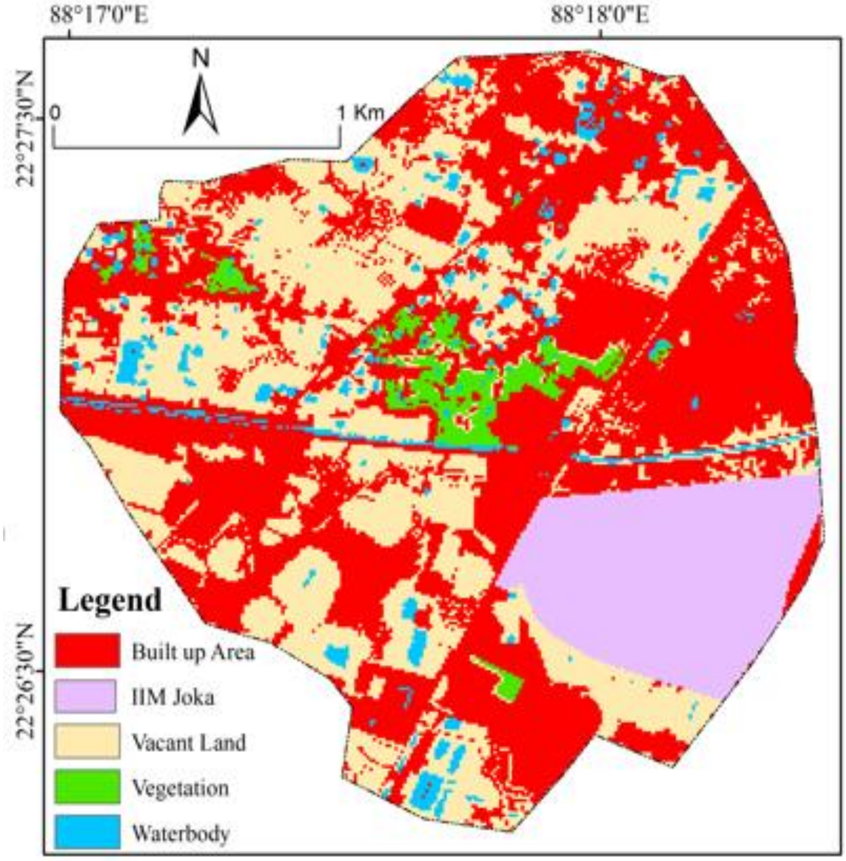
As before, eleven driver variables have been pre-selected from the similar research works. They have been analysed for their relevance and listed in Table 4.20. These variables are quantified (Euclidian distance), transformed (evidence likelihood), tested (Cramer's V) and two variables are rejected before including the remaining nine in the transition potential model structure.

Table 4.20: Variables for growth prediction for KMC Ward 144 along with Cramer's V test

#	Variable Category	Variable	Distance method	Evidence Likelihood	Cramer's V test
1	Socio-economic	Distance to built-up area	Euclidian distance	Yes	0.3447
2		Distance to schools	--do--	Yes	0.08*
3		Distance to workplaces	--do--	Yes	0.0760
4		Distance to hospitals and health services	--do--		0.2403
5	Utilities	Distance to roads	--do--		0.1298
6		Distance to metro railway	--do--		0.1225
7	Physical area	Digital Elevation Model(DEM)	--do--	Yes	0.012*
8		Slope in percent	--do--		0.012*
9	Environmental	Distance to waterbody	--do--	Yes	0.4433
10		Distance to vegetation	--do--	Yes	0.3508
11		Distance to vacant land	--do--	Yes	0.5122
* These variables are not included in the Transition Sub-model structure.					



Figs. 4.24: Transitional potential maps **a**. water body to built-up area **b**. vacant land to built-up area **c**. vegetation to built-up area **d**. water bodies to vacant land **e**. Water bodies to vegetation **f**. vegetation to vacant land for KMC Ward 144



Class	Area (ha)	Area (%)
Built-up Area	212.22	47.54
Vacant Land	150.97	33.82
Waterbody	13.07	2.93
Vegetation	17.09	3.83
IIM-C	53.07	11.88
Total	446.91	100.00

Fig. 4.25: Projected land cover for 2040 for KMC Ward 144

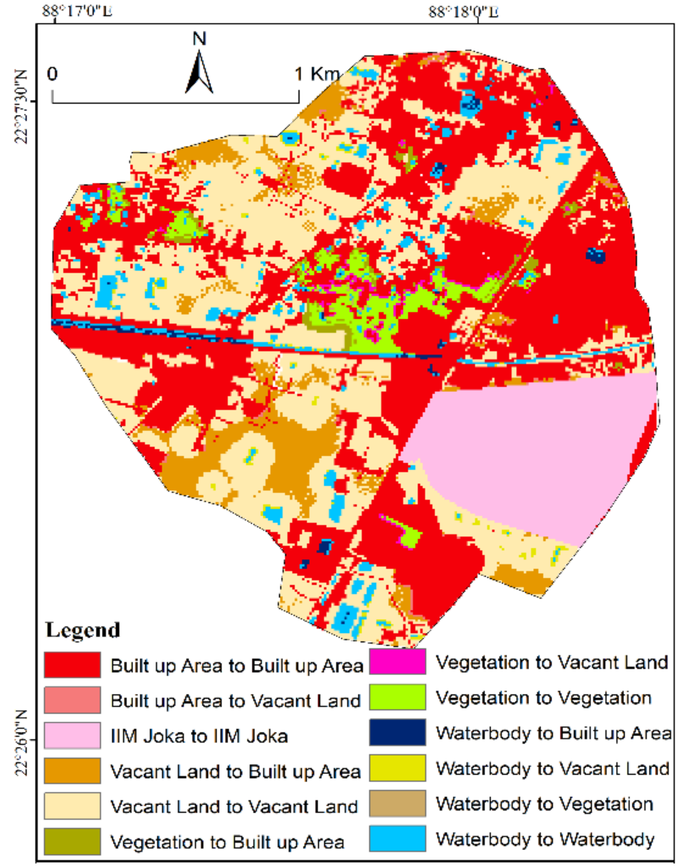
4.4.2.2 Transition Potential and Change Allocation for KMC Ward 144

The transition potential model is used to generate transitional potential maps for each sub-model for each land transition.

4.4.2.3 Prediction and Accuracy Assessment for KMC Ward 144

The prediction map for year 2040 has been generated (Fig. 4.25). Since current year (2023) have been taken as base year, there are no possibility to conduct a validation with actual image through accuracy assessment.

Fig. 4.25 show that in 2040, the built-up area will cover 47.54% of the ward area which is now 39.14% (Fig. 4.21). Vacant land will be still around 33.82%. Reduction of water bodies and vegetation from 2011 are really alarming. Expansion of metro railways might bring in the changes faster than predicted. Like other two study areas this ward might also lose its rural character, develop haphazardly and ultimately be in a chaotic condition.



	Land cover at 2040					
Land cover at 2023	Sl	1	2	3	4	5
	1	173.41	0	0	1.54	0
	2	**4.47**	12.79		2.4	0
	3	2.7	0.28	17.09	2.73	0
	4	**31.64**	0	0	144.30	0
	5	0	0	0	0	53.07

1. Built-up Area 2. Vegetation 3. Waterbody 4. Vacant Land 5. IIM Joka
2. All measurements are in ha

Fig. 4.26: Land use change map and transition matrix of the KMC Ward 144 in between 2023 and 2040 (predicted)

The change map in Fig. 4.26 shows that vacant land has the highest probability of transforming to built-up are by 2040. Like other study areas, vegetation and water bodies have also high probability of changing to built-up area. By 2040, 2.4ha of vegetation and 2.73ha of water bodies might change to vacant land. Compared to 2023, year 2040 shows high rate of changes for every class which indicates more construction works to follow. These alterations in future LULC must be complemented with adequate planned infrastructural supports.

This prediction of LULC alterations should integrate the results from transitional potential maps (Fig. 4.24) where vulnerability of changes of waterbody to built-up area is evident. Very obvious, vacant land will be changed to built-up area but proper planning is required earliest to manage the situation fast so that the horizon year might have better situation. Table 4.12 shows decline in number of patches (NP) of waterbody and increase in fragmentation or splitting of land (SPLIT). This trend in Fig 4.24d is showing changes from water bodies to vacant land. Canals should not be blocked like KMC Ward 109. Fig 4.24f, shows vegetation will also be vanished by 2040 without proper vigilance. Gradual increase of entropy value also indicates the tendency of dispersal of built-up area. This quantitative measurement directs towards sprawling. Short term and long term planning would help in stopping irregular and unsustainable development.

This research findings can give urban planners and policymakers valuable insights into the shifting patterns of LULC, enabling them to make informed and productive decisions about sustainable development. The current investigation has further corroborated the efficacy of integrating GIS and remote-sensing data in facilitating LULC change analysis and forecasting future LULC scenarios. However, it should be noted that the classification accuracy of LULC and predictive outcomes are subject to the resolution of satellite images.

4.5 Concluding Remarks

The alteration of LULC in the year of 2040 shows infilling[17] of land areas in the fringe areas of KMA, namely, KMC Ward 109, KMC Ward 144 and Baruipur Municipality. The study of land dynamics in these fringe areas are need to be studied in light of population changes and environmental effects. Holistic study along with highly accurate prediction map will help to understand the future LULC outcome without constraints that will help in planning for a sustainable management of the study area.

The LU map of 2040 shows the changes and also map location of spatial changes which shows a gradual increment of built-up area and remarkable reduction in water body and vegetation. These probable changes are correlated with management of road network, proximity of vegetation, vacant land, water body and built-up area. For KMC Ward 109 proximity of vacant land, for Baruipur Municipality proximity to built-up area and for KMC Ward 144 proximity to vegetation play most influential role, and discussed in Chapter 5. Heterogeneous land uses

[17] the practice of building on unused or underutilized land in an established urban area, thereby enhancing population density of the locality

cause fragmented land dynamics that make the area vulnerable to changes, forbids linear supply lines of water, sewer, sewerage and roads.

This LULC prediction with socioeconomic and environmental study could assist in creating more effective planning for sustainable development and from that standpoint, socioeconomic and environmental factors, namely, population growth, land value and LST have been studied in the next chapter.

Chapter 5

DISCUSSIONS

5.1 Introduction

Rapid unplanned urban growth in the fringes around the core of Kolkata has overrode whatever meagre regulations exist[1], thereby adversely affecting the changing society, land value and its environment. Keeping pace with the growth of the city, decentralisation, peripheral growth and residential growth primarily took place along transportation corridors NH-12 and SH-1 (Fig. 3.1) causing drastic LU change from rural to urban that further questions local food security, bio diversity and environmental issues.

Discussions in Chapter 4 reveal that, the three study areas, namely, KMC Ward 109, largely served by EM Bypass the suburban railways and the metro railway service, the Baruipur Municipality, served by SH-1, the suburban railways and the metro railway service and the KMC Ward 144, served by NH-12 and the upcoming metro railways, are at three different stages of urban transformation. KMC Ward 109 possess an alarming share of built-up area, followed by Baruipur, while Ward 144 is only a new addition to this list, after been included into KMC in 2012. Comparative study of the land use dynamics of these three areas is likely to assist the planners to intercept unplanned urbanisation at any other prospective peripheral KMC ward or other fringes of KMA while they get the urban make over in a planned manner, depending on whether they are in ripe, intermediate or nascent stages.

To collect property taxes, KMC has formed a Municipal Valuation Committee (MVC, under KMC rule 1980). Vide their recommendation, KMC has been divided into seven Base Unit Area Value (BUAV) zones[2], marked A through G, as shown in Fig. 5.1 based on land value, service availability and infrastructure on offer, etc. This property tax system, however, exempts the poor from their property tax bracket whereby all R.R. colonies/EWS/BSUP (Refugee Relief and Rehabilitation Colony/ Economically Weaker Section/ Basic Services to the Urban Poor) settlement come under category E and all bustee/thika/slum settlements come under category

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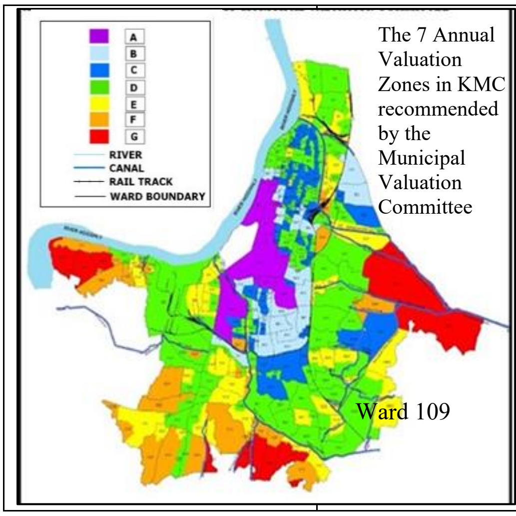
[1] KMC Land Use Development and Control Plan (LUDCP) excluding Wards 45 and 63 (amended in 1996), KMC LUDCP for Ward 45 (amended in 1997), KMC LUDCP for Ward 63 (amended in 1997), Vision 2025: Perspective Plan of CMA: 2025, Draft Final Report (December 2000), LUDCP for Calcutta Metropolitan Area excluding CMC, BMC, Kalyani (amended in 1998), The East Kolkata Wetlands (Conservation and Management) Act, 2006, EKW (C&M) (Amendment) Act, 2011, to name a few, which are quite old, and needs to be reassessed, updated and amended regularly for rightful implementation. (**Source:** https://kmda.wb.gov.in/ludcp/home/ludcp_search_new)

[2] Unit Area Assessment System, KMC, https://www.kmcgov.in/KMCPortal/jsp/UAASystemHome.jsp

G, irrespective of their location. From central Kolkata to outskirt of KMC area, the Base Unit Area Value in rupees /square feet /annum, ₹/sq.ft/p.a. decreases. Purple represents category 'A' with BUAV of ₹85/sq.ft/p.a. and yellow indicates category 'E' with BUAV of ₹30/sq.ft/p.a.



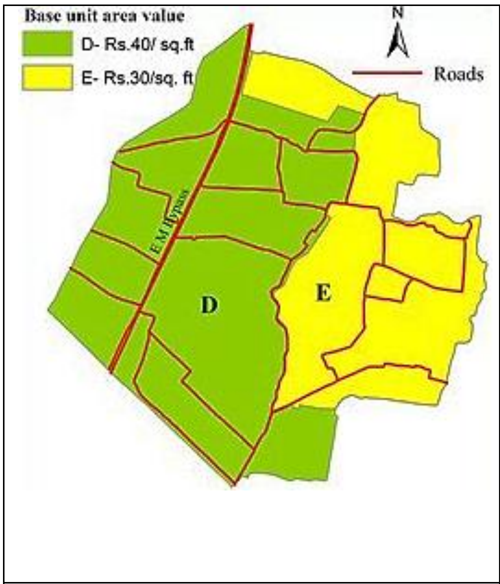
Land Categories and BUAVs	
Block category	Base Unit Area Value ($₹/ft^2\ p.a$)
A	85
B	65
C	50
D	40
E	30
F	20
G	15

Fig. 5.1: Categories of land as per final recommendation of Municipal Valuation Committee (**Source**: https://www.kmcgov.in/KMCPortal/jsp/kolkata_City_Map.html)

5.2 KMC Ward 109

People living in Kolkata invested in apartments here for proximity to Kolkata and its facilities. The lands on the western part of KMC Ward 109 falls under Category D, while the eastern part of ward 109 belong to category E, originally earmarked for the urban poor. Here built-up areas have initiated along the areas adjoining E M Bypass, and later propagated further east towards the East Kolkata Wetland (EKW) with population upsurge and rural to urban immigration. Part of KMC Ward 109 in the vicinity of EM Bypass (Fig. 5.2A) belong to category 'D' having BUAV of ₹$40/ft^2 p.a.$ which has already flourished with high rises and hospitals. Though the eastern part of Ward 109 (Fig. 5.2A and 5.2B) is under category 'E' with ₹$30/ft^2 p.a.$ BUAV, and earmarked for the urban poor yet as indicated in Figs. 5.3A and 5.3B and field surveys, unplanned growth have pervaded this area too. Not only the built-up areas have increased, simultaneously, small holding units and small plots have been merged and transformed to high-rises and residential complexes. Numerous four- and five-storeyed premises have been built without adequate means of access (The Kolkata Gazette, 2009) and inadequate turning radius for larger vehicles at the intersection. Consequently, in case of any calamity, like a fire outbreak or an earthquake, evacuation and providing emergency relief is grossly compromised and life is at stake.

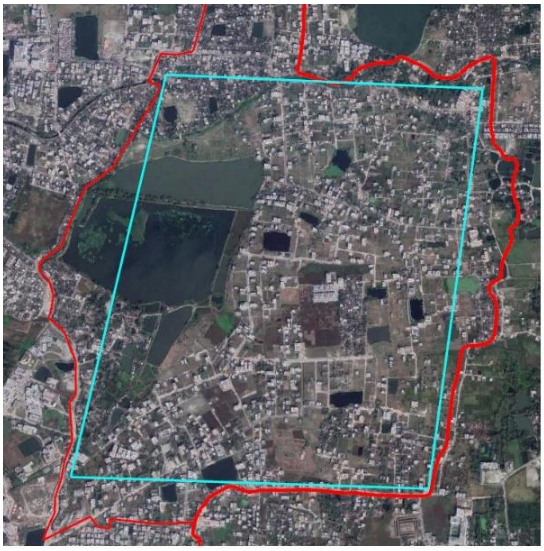
Areas near the EM Bypass have witnessed the transformation of arable lands to residential and other land usage. Spreading built-up area is encroaching non-built spaces filling them in with horizontal and vertical urban expansion. This expansion and burgeoning population has forced construction of bore wells for ground water and enhancing ground water depletion. Further, development in KMC Ward 109 has impaired the natural east-bound drainage.



a.	b.
Settlements in Ward 109 under Government Notified EWS (Economically Weaker Section) and BSUP (Basic Services to Urban Poor) schemes fall under category 'E'	

Figs. 5.2: **a.** Categorisation of land as per the recommendation of Municipal Valuation Committee in KMC Ward 109, **b.** Ward 109 on Google Earth

The mouzas like Mukundapur and Nayabad in Ward 109, once filled with water bodies and marshy land, has seen a massive construction spree and presently hardly recognisable as wetland. Intermittent culverts have been provided for the approach roads through the waterbodies disturbing the natural slopes for drainage. Sporadic filling in of waterbodies for human use has disturbed the natural gradient with associated post-shower waterlogging.



a.

b.

Figs. 5.3: Part of Ward 109 showing the state of land category E during **a**. 2011 and **b**. 2021

However, continuing without a detail master plan would challenge providing straight reaches of roads, drains, water supply and sewage disposal pipelines for future. This apart, encroachments on the Suti canal banks (Fig. 4.1) and inadequate desilting has curbed its carrying capacity. This too has disturbed the drainage with waterlogging and vector breeding in stagnant water. To manage the problem drainage pipe lines and pumping station have been laid across a large part of Ward 109 which is time- and cost intensive.

However, till date people prefer a stay in KMC Ward 109 due to its high accessibility. Big residential complexes having apartments worth ₹12170 to ₹16160 per sq. ft.[3] are purchased by people from high income group (HIG). Again, around Nayabad, a few km off EM Bypass, this price is around ₹4500 per sq. ft. and targeted by people from middle income group (MIG).

Housing complexes, retail shops, educational institutes, medical establishments, messes and so on are creating newer occupational opportunities and attracting more people. Locals as well people from neighbouring countries come here for medical aids. Pan-India nursing staffs flock too. At Mukundapur, open space has been converted to hospitals and commercial areas (viz., Metro Cash and Carry), while in Nayabad and Mukundapur limits of small water bodies and agricultural lands are gradually been encroached for to widen built-up area.

As the ward gradually flourished as a cluster of trip attraction points, number of sub-arterial roads came up to support the population. Bus routes and auto rickshaw facilities have followed. However, the road intersections thus formed are usually inadequate with impaired visibility and insufficient turning radius. Gradually land infilling began, letting population intensify. E. M. Bypass has been widened from four lanes to eight lanes to serve more population and vehicles. Since added facilities means added attraction, EKW has now become increasingly susceptible to conversion and encroachment.

Expansion of built-up area is associated with rise in population and corresponding reduction in arable lands and water bodies, which challenges the food security. Insufficient road width, congested transportation, conflict between paratransit and transit travel modes, inadequate parking space, inadequate potable water sanitation, sewerage system and waste disposal too are problems associated with rapid and unsupervised urbanisation. Over-extraction of groundwater has created land subsidence in many places in Nayabad (Suganth and Elango, 2020).

Kolkata Municipal Corporation (KMC) had been considering to convert all sali land (farmland) to bastu (homestead) land on the city's south eastern fringe[4], which has been challenged by the environment activists for reasons too obvious. This promotion could set land transfer a lucrative

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[3] https://housing.com/in/buy/searches/AGye8AH0S1Y1, 2024 (accessed on10.01.2025 at 02:30)
[4] https://www.telegraphindia.com/states/west-bengal/corporation-proposes-to-turn-agriculture-land-in-calcutta-pockets-into-homestead/cid/1731120,copied on 09/06/2020..at 4:25 pm

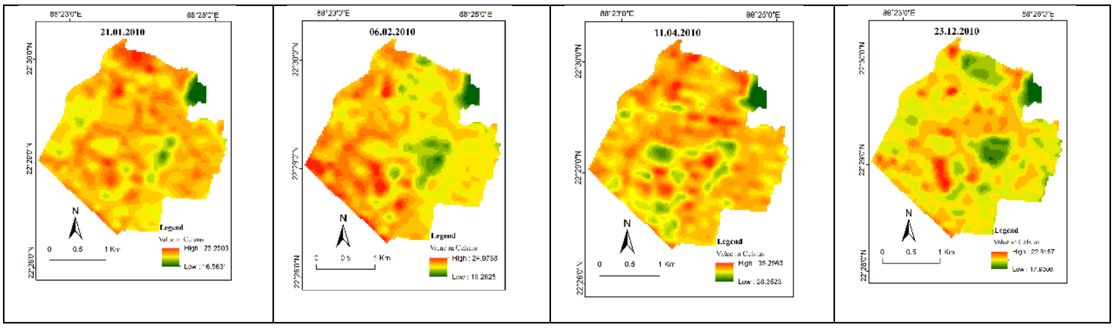
means of money making and threatening the existence of EKW. One could easily find that land brokerage and small-time construction business have become an alternate livelihood in the shrinking job market alongside the bigger realtors, while the uncertainty of wetland-based earnings has pushed people to shift into such occupations.

Table 5.1: Economic Structure, KMC Ward 109 (Data in %)

		Work Participation rate to total population	Marginal worker w.r.t total worker	Main worker w.r.t total worker	Non-worker
1991	Total	27.59	0.03	99.97	72.41
	Male	23.98	0.02	99.98	
	Female	3.60	0.12	99.88	
2001	Total	36.57	5.43	94.57	63.43
	Male	27.49	4.29	95.71	
	Female	9.08	8.87	91.13	
2011	Total	41.64	13.44	86.56	58.36
	Male	29.23	8.48	91.52	
	Female	12.40	25.13	74.87	

Source: Census of India (1991, 2001, 2011)

Table 5.1, compiled from the Census of India shows that the numbers of marginal workers in Ward 109 increased from 0.03% of the total workers in 1991 to 13.44% in 2011. A larger mass of people is opting for livelihoods like street vendors, agricultural labourers, constructing building-labourer, and fourth-class staff in the hospitals, etc. Again, Table 5.1 shows decrease in main worker from 99.97% in 1991 to 86.56% in 2011. The trend of involving casual labourers has reduced the share of main workers. Increased employment in informal sectors could be one more reason.



Figs. 5.4: Sample LST images in KMC Ward 109 to compute average LST for the year 2010

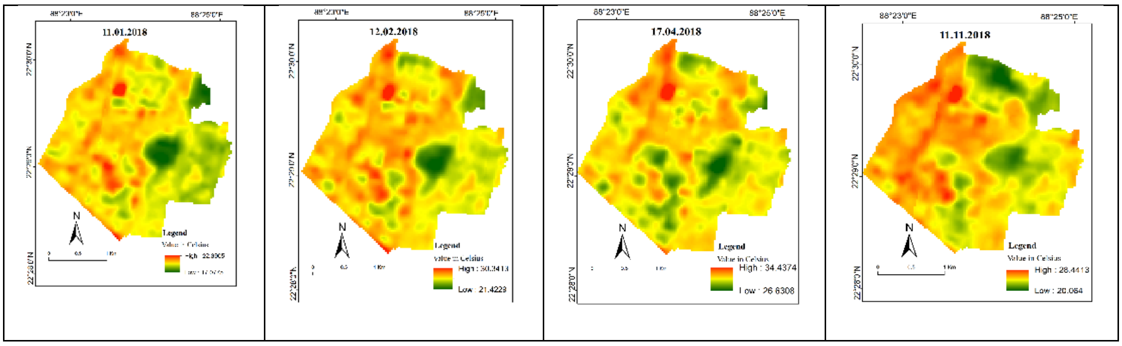
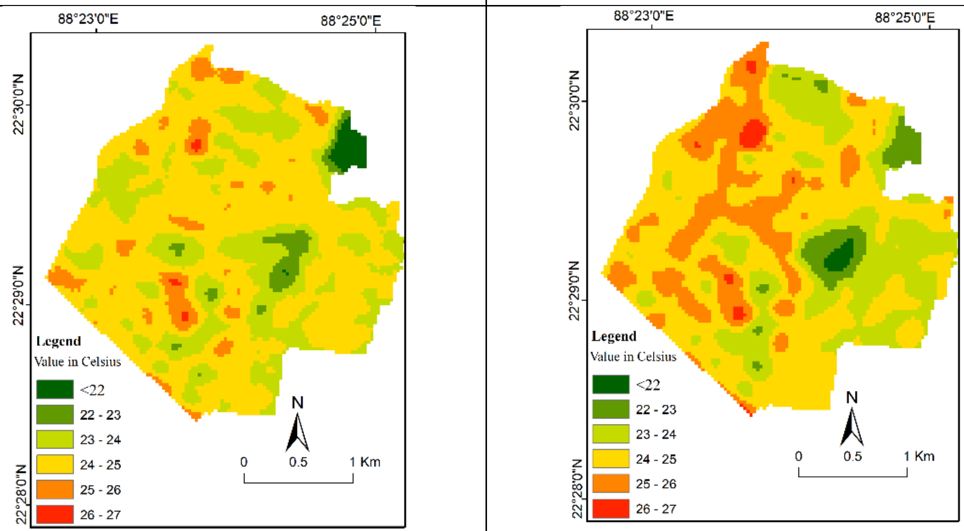


Fig. 5.5: Sample LST images in KMC Ward 109 to compute average LST for the year 2018

Though the share of non-worker is decreasing, yet its share has exceeded 50% in 2011. Female work participation in 1991 was only 3.60% which has increased to 12.40% in 2011 but increasing number of female marginal workers (0.12% in 1991 and 25.13% in 2011) is not too promising. Share of females in main worker is decreasing, and the socioeconomic divide has widened.

On the other hand, uncontrolled construction and denudation have been heating up the city environment. Figs. 5.4 and 5.5 show four representative cloud-free thermal states collected in similar times during 2010 and 2018 for Ward 109 through thermal bands of Landsat 5 TM (band 6) and Landsat 8 (band 10) to compute the average land surface temperature (LST) being shown in Fig. 5.6. The samples are collected between January to April and again in November and December, the colder months, to have clear images. Thus, the averages in Figs. 5.6 are not the average of temperatures round the year.

2010	2018



2010				2018			
Image	Date of acquisition	Spectral Band	Thermal Band	Image	Date of acquisition	Spectral Band	Thermal Band
Landsat 5 TM	21.01.2010	2,3,4,5	Band 6	Landsat 8	11.01.2018	4,5,3,6	Band 10
Landsat 5 TM	06.02.2010	2,3,4,5	-Do-	Landsat 8	12.02.2018	4,5,3,6	-Do-
Landsat 5 TM	11.04.2010	2,3,4,5	-Do-	Landsat 8	17.04.2018	4,5,3,6	-Do-
Landsat 5 TM	23.12.2010	2,3,4,5	-Do-	Landsat 8	11.11.2018	4,5,3,6	-Do-

Figs. 5.6: Average LST for years 2010 and 2018 in KMC Ward 109 with information of satellite images used in LST calculation

Proliferation of the red patches (26-27°C) in 2018 in Fig. 5.6 proves that the area is manifesting higher land surface temperature with passage of time. The high temperature zones are noticed near E. M. bypass, the large commercial areas, the slums and the bare grounds. Zones below

22°C is not accounted since they mostly involve waterbodies. Table 5.2 shows a break-up of LST distribution by area.

Compared to 2010, areas with LST under 22-23°C, 25-26°C and exceeding 26 °C have increased in 2018 while areas with LST under 23-24°C and 24-25°C have reduced. Areas within 24 to 25°C have receded since a large portion of land in the Nayabad area in the north-east of Ward 109, where mainly bare grounds used to exist, have presently become built-up area.

Table 5.2: LST distribution during 2010 and 2018 in KMC Ward 109

		Area (ha)				
		22-23°C	**23 -24°C**	**24-25°C**	**25-26°C**	**>26°C**
Year	**2010**	25.11	202.77	409.7	47.34	0.63
	2018	38.07	168.12	349.38	134.91	8.2

Gradually small dwelling units have begun nurturing little greeneries, urban gardens or urban farms that has rendered some areas cooler and, pleasingly, pushed to within 23-24°C in 2018. However, in some other places of the ward, where an average of 23-24°C existed in 2010, has increased to 24-25°C by 2018. Around the E. M. Bypass in the central part of KMC Ward 109, the areas under 23-24°C and 24-25°C in 2010, have been shifted to 25-26°C band in 2018 since huge constructions have replaced the marshy lands. Further, Fig. 5.6 reveals that compared to 2010, areas with average LST in excess of 26°C (0.63ha) in 2010 has increased manifold in 2018 to 8.2ha. The areas with average LST more than 26°C mainly correspond to large commercial areas. The stadium, railway stations and factories too fall in the highest temperature bracket, since bare ground and aluminium shaded roofs exposed to sun get heated, heating up the local niche. The local slums and colonies are also in 25-26°C and more than 26°C brackets, where field surveys reveal that roofs of the small dwelling units are predominantly comprised of corrugated sheets. Housing material, medium of cooking and cooking inside tin-shaded room cause high surface and air temperature, however, their smaller overall dimensions makes it difficult to quantify at the micro level.

The graph in Fig. 5.7 shows the departures in LST between 2010 and 2018 for each LU class, where, in the built-up and vacant areas the LST has gone up by 0.22°C and 0.4°C. There are no perceptible changes in LST over waterbodies, vegetation and stadium and open space. Adding greeneries in the built-up area and vacant lands and putting shackle on construction can only restrict the upward trend in LST and prevent formation of urban heat island.

Since 1991 the population has increased 1.616 fold by 2001, which grew another 1.716 times in the next ten years. However, number of households grew 1.865 fold in between 1991 and 2001, while in next ten years the growth in household is 1.854 times (Table 5.3). Thus, the population growth rate rose while growth rate of the households declined a bit. It could be due to space crunch or advent of work fleets who shared their stays, for example, the nursing staffs in the many hospitals and construction workers, who stay together for a cheaper accommodation. Further, many apartments have been procured by the non-resident Indians, who do not stay in those apartments or rent them.

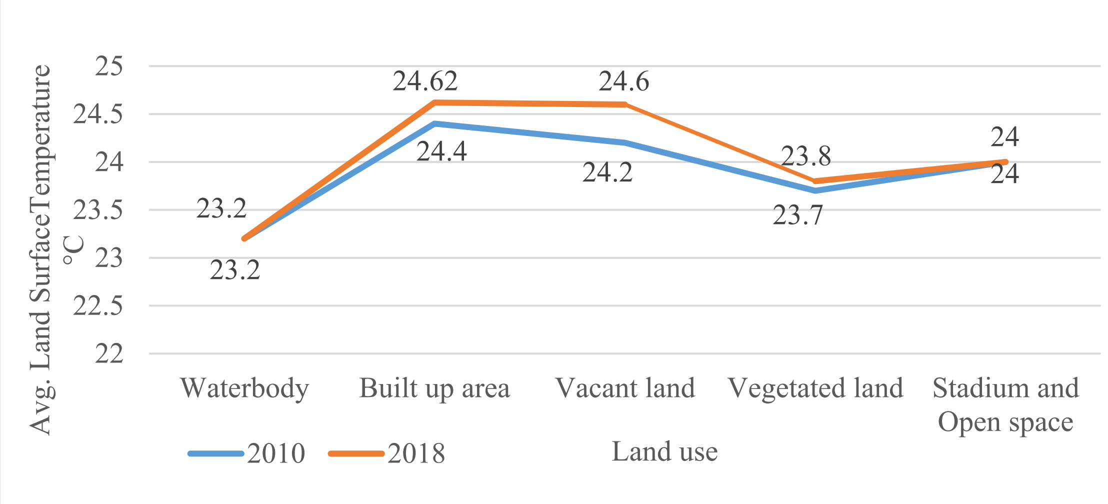


Fig. 5.7: Variation of LST versus LU class between 2010 and 2018 in KMC Ward 109

Table 5.3: Decadal growth rate of population and number of household in KMC Ward 109

Year	Population		Number of Households		Decadal Growth rate (Population)	Decadal Growth rate (Household)
1991	23271		4693		-	-
2001	37610	1.616 fold rise	8756	1.865 fold rise	61.57%	86.58%
2011	64567	1.716 fold rise	16238	1.854 fold rise	71.72%	85.45%

By the arithmetical increase method, geometrical increase method, incremental increase method and decreasing rate of growth method[5], the projected population of 2021 for the KMC Ward 109 are found out to be 85215, 107476, 97857, and 117512, respectively. Thus, the projected population for 2021 may been taken as 102015, an average of all the numbers above.

Table 5.4: Projected land cover for KMC Ward 109 in percent

Classes	2002	2018	2040 (Projected)
Built-up area	21.1	63.5	74.7
Vacant land	61	22.9	19.6
Vegetation	1.6	3.40	0.34
Water body	16	5.10	3.96
Stadium and Open Space	0.3	5.10	1.40

Information from the HTML file generated by the growth prediction model obtained from Idrisi Selva, are shown in Tables A5.1 and A5.2 in Appendix A.5 p.104 shows the driving variables

[5] Water Supply Engineering, S. K. Garg, 37th ed., Khanna Publishers, 1977

responsible for these changes. They are distance to vacant land (most influential), distance to waterbody, distance to railway stations, distance to railway lines, distance to built-up area, slope, distance to hospitals, distance to workplaces, distances to road and vegetation (least influential).

Considering the growth prediction results in Table 5.4, by the horizon year 2040, the built-up area would pervade more than 70% of KMC Ward 109. If it happens and goes unaddressed, infrastructural demand would lag far behind people's needs, and then people might encroach EKW or seek refuge to some other fringes, where lies need for some serious planning efforts.

5.3 The Baruipur Municipality, KMA

With KMC Ward 109 and Rajpur-Sonarpur Municipality brimming, Baruipur Municipality has started sharing the population pressure further down the E. M. Bypass. It is located 27 Km due south of Kolkata Metropolitan Authority (KMA), and going through rapid urban transformation by natural growth and migration. Southward extension of EM Bypass and rail connectivity of the area with the city core of Kolkata has resulted in rapid development of the area and influx of population.

Table 5.5: Decadal growth rate of population and number of household Baruipur Municipality

Year	Population	Number of Household	Decadal Growth rate (Population)
1991	37659	7201	-
2001	44964, 0.84 fold rise	9608, 0.74 fold rise	19.4
2011	53191, 0.85 fold rise	13403, 0.72 fold rise	15.5

While the decadal growth rate is 15.5% between 2001 and 2011 vide Table 5.5, built-up area is covering nearly 42.73% in 2020 (Fig. 4.12). According to the Baruipur Municipality sources, the projected population for the year 2031 is 72656. Ward by ward (Fig. 5.6) population size shows growth direction of Baruipur. Table 5.6 shows that the municipality's northernmost wards (1, 2, 13) are substantially more populated than the southern wards (7, 8, 9 and 16), which have an average population size of around 3000.

Population growth rate is the highest in the northern most ward (Ward 1) having 46.356% in between 2001 and 2011, while negative population growth can be seen in Wards 3 (-0.860%) and 17 (-3.203) which are centrally located with very high density. Ward 17 has very low population and mainly agricultural in character. Baruipur Railway Station is in Ward 3 and because of traffic congestion people trying to move outward. Population growth in Ward 4 indicate the movement of population outward (Table 5.5). In Ward 4, road is connected to Baruipur-Champahati Road. Though the road is important yet it is single-lane road.

The tendency to move outward from the core of Baruipur has caused expansion of built-up area to 60% (Fig. 4.18) in the horizon year 2040, In the horizon year agricultural land could go down to 4.5%, putting a telling pressure on Kolkata's food security. Thus, urbanisation not only changes the character of the lands but job pattern of the people which is presently noticed in KMC Ward 109. Increasing population indicates urban growth but the development should be a planned one instead of the present organic growth challenging infrastructural needs.

Table 5.6: Decadal growth rate - population and number of household Baruipur Municipality

Ward No.	Population		Population growth (%)	Population Density	
	2001	2011		2001	2011
1	2552	3735	46.356	37.79	45.29
2	3109	3820	22.869	69.97	80.30
3	2441	2420	-0.860	62.88	68.69
4	3017	3971	31.621	45.19	53.88
5	3166	3517	11.087	77.79	88.10
6	2775	3143	13.261	76.86	85.38
7	1849	2122	14.765	55.49	69.63
8	3236	3535	9.240	117.24	118.03
9	2035	2439	19.853	62.04	79.29
10	3837	4815	25.489	91.09	99.97
11	1929	2117	9.746	114.73	115.35
12	1990	2112	6.131	141.66	158.61
13	2849	3336	17.094	183.00	185.93
14	3459	3873	11.969	112.92	132.22
15	1936	1949	0.671	48.67	51.67
16	2860	3410	19.231	105.36	154.21
17	1873	1813	-3.203	71.86	107.56

The Government's decision to shift district headquarters of South 24-Parganas from Kolkata city-core to Baruipur led planning for providing facilities first, started four lane road expansion for 12km on the both side of Tolly's Nullah from Garia to Baruipur which connects Baruipur with Kolkata through Eastern Metropolitan Bypass that passed through KMC Ward 109, bridge construction across Tolly's Nullah and beautification of both sides of the canal have been done in 2009, that has been funded by Jawaharlal Nehru National Urban Renewal Mission Scheme (JNNURM) and Ganga Action Plan. Thus, led by the facilities laid by the government, people have started to live here and now it is halfway urbanised. Though the plan of shifting has not been implemented, beside connectivity, people already started to live here. People from Kolkata have started to shift here for low land price and ample land availability. Outsiders of Kolkata living far from the city liked to shift here for low rent and nearness of the city. Due to the availability of bigger plots of land at a cheaper rate, realtors have already procured large chunks land in Baruipur Municipality. According to "99 acres"[6] average property rate near the Baruipur railway station is ₹3530 per sq. ft. in 2024 which was around ₹2600 per sq. ft. in 2020. In the last 5 years property price in Baruipur has increased by 34.6%, whereas land price increased

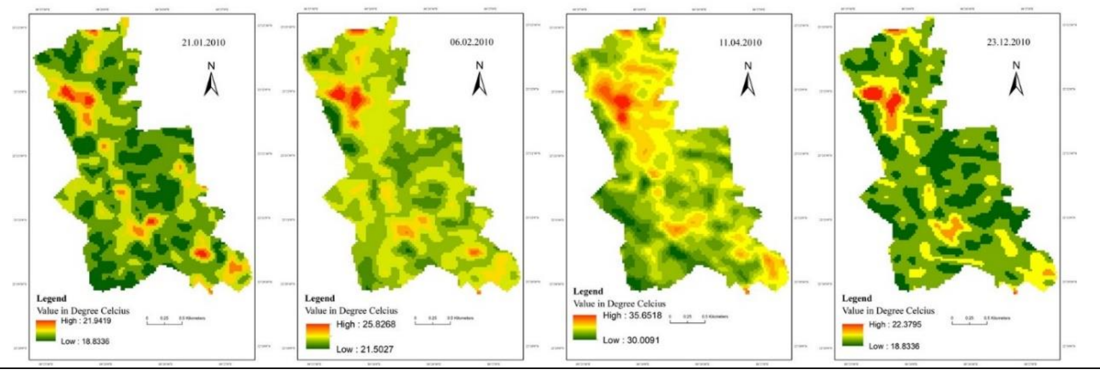
[6] https://www.99acres.com/property-rates-and-price-trends-in-baruipur-kolkata-south-prffid, checked on 13.11.2024 at 18:16

from ₹500 per sq. ft in 2020 to ₹1300 sq. ft. in 2024. Its connectivity by road and railways to the key towns of South 24 Parganas and Kolkata made the area attractive to the people and realtors. The regional road network stretches out in all directions and the area's suburban rail services serve the region's primary transit demand. It also handles the daily transport of fruits and vegetables to Kolkata and its neighbourhood.

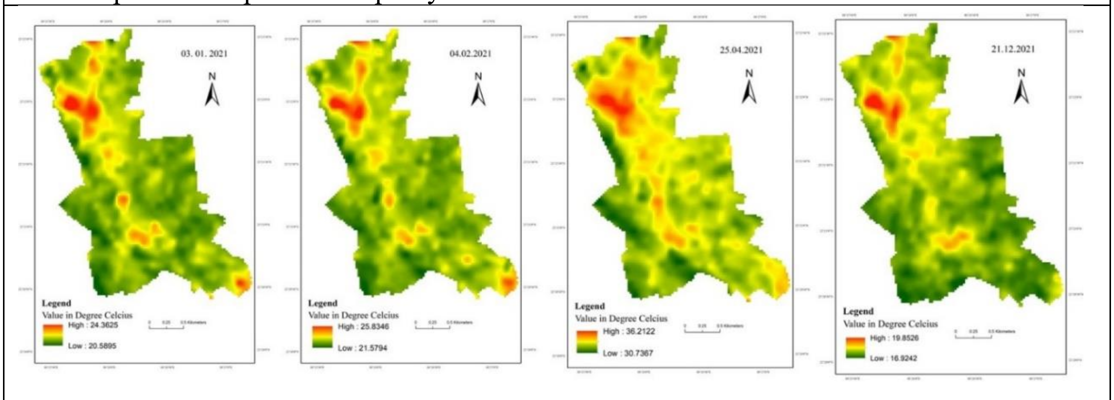
Though the E. M. Bypass and the State Highway, SH-1, are serving the area, presence of intermittent connecter/feeder roads at short gaps at the heart of the settlement causes traffic congestion during the morning and evening peak hours. During early morning hours the fruit vendors occupy SH-1 with street-side loading and unloading, thereby congesting the road. To avoid this nuisance, a flyover has come up but the problem still persists since the market exists at the approaches of the flyover and constrict them. The narrow 2-lane feeder roads connected to the SH-1 with open drains and no footpath only adds to the woe. With approximately 16% of the roads being kutcha (water bound macadam, WBM roads) and another 23% being brick roads, it becomes a mess in the months of monsoon while adding to the air pollution during rest of the year. The condition of the surface of the roads are poor due to lack of maintenance that reduces speed of the vehicles and renders the roads accident-prone and noisy.

Baruipur Municipality has a longitudinal expansion along the course of the river Adi Ganga once navigable and broad which people must have enjoyed earlier. As the river got silted, it lost its importance though. Presently rail and road network encourages people to live here. Though the river lost its importance, the linear shape of the study area still holds. Like KMC Ward 109, increasing built-up area and decreasing water body and vegetation would add to the LST at Baruipur. The raw data for LST for the years 2010 and 2021 are provided in Fig 5.8a and 5.8b and averaged in Fig. 5.8c, which shows that the area under 23ºC has increased. Adi Ganga (Tolly Canal) is passing through the western part of the canal. People litter the canal with solid waste and arrange for idol immersions post-festivity. Encroachment on the banks is another persistent problem. Directions of National Green Tribunal (NGT) in the order dated 30.05.2017 (legal case with Joydeep Mukherjee vs. the Chairman Pollution Control Board & Others) towards mitigation of the situation of Adi Ganga and Tolly's Nallah has helped in cleaning up the banks of the Tolly Canal and many encroachments have been removed. This has extended the areas with LST below 23ºC. However, due to the ongoing construction works, the area with LST in the 24-25ºC band has been extended, area above 26ºC has also increased in 2021. The episode of intervention by the NGT is a ray of hope that shows small, timely and well-planned interventions can harness the degradation effectively. Thus, urban agriculture in residential areas and roof-top cultivation might effectively harness the LST level.

LST maps of Baruipur Municipality 2010

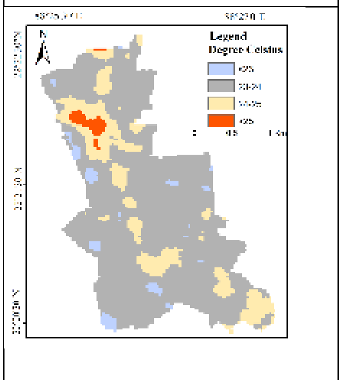


LST maps of Baruipur Municipality 2021

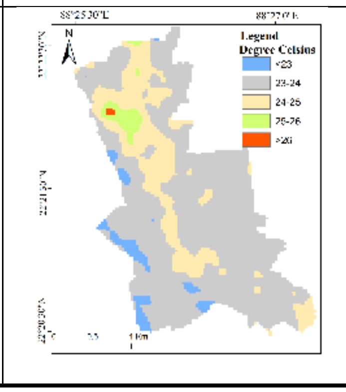


Figs. 5.8: LST maps of Baruipur Municipality during **a.** 2010 and **b.** 2021 from which average LST maps have been generated

2010



2021



Temperature (°C)	Year	
	2010	2021
< 23	16.03	24.71
23 - 24	479.51	435.40
24 - 25	102.80	132.79
25 - 26	9.93	14.58
> 26	0.00	1.00

Images used for generating average LST maps of Baruipur Municipality					
Image	Date of acquisition	Thermal Band	Image	Date of acquisition	Thermal Band
Landsat 5TM	21.01.2010	Band 6	Landsat 8	03.01.2021	Band 10
Landsat 5TM	06.02.2010	-Do-	Landsat 8	04.02.2021	-Do-
Landsat 5TM	11.04.2010	-Do-	Landsat 8	25.04.2021	-Do-
Landsat 5TM	23.12.2010	-Do-	Landsat 8	21.12.2021	-Do-

Fig. 5.8c: Average LST maps of Baruipur Municipality for the years 2010 and 2021(**Source**: Pal, et al., 2024)

The census reports of 2001 and 2011, summarised in Table. 5.7, reveals that along with the increase in total population, share of total-, main- and marginal workers have increased. Total worker increased from 32% to 36%, of which 30% are main workers and 2% marginal workers in 2001. However, in 2011, 33% of the population are main workers and 3% are marginal workers. Share of non-worker has reduced but still is alarmingly high. However, female marginal worker has increased from 0.3% in 2001 to 0.5% in 2011. The woman workforce is not exploited to the desired level.

Table 5.7: Break-up of working population in Baruipur Municipality during 2001 and 2011

Year	Total worker	Main worker	Total Marginal worker	Female Marginal worker	Non-worker
2001	14181, 32%	13356, 30%	825, 2%	263, 0.3%	30732, 68%
2011	19276, 36%	17374, 33%	1902, 3%	930, 0.5%	33852, 63%

Urban facilities attract people from its hinterland, resulting in rise in built-up area and reduction of vegetation and waterbody. Projections show if not controlled by the local government, in Baruipur the share of waterbodies will reduce from 6% in 2010 to 4% by 2040 while cropland will drop from 25.29% to 6%, thereby changing the vegetative land cover that would jeopardise the city's food security. However, the degree of urbanisation has not attained its height in the southern fringes of Baruipur as of now due to poor connectivity and dearth of other infrastructures and needs quick intervention for a planned upbringing and a promising future. Off late, population density is found to reduce in Wards 3 and 17, where the railway station and the super-speciality hospitals are housed and gradually relocating themselves in the wards on the eastern belt. With open drains, narrow road, scarcity of water due to depletion of ground water table and increased level of arsenic in ground water (Chaudhuri et al. 2019) – the problems will only proliferate without proper planning and regular assessment and upgrade to handle the pressure of predicted growth.

Information from HTML file generated by the model are shown in Tables A5.3 and A5.4, p.105, shows the driving variables for these changes should also be taken into consideration while planning. They are distance to built-up area (most influential), distance to vacant land, distance to vegetation, slope, distance to railway stations, distance to road, distance to health facilities, DEM, distance to railway lines, distances to workplaces and waterbody (least influential).

The condition of KMC Ward 109 is an alarm call to the planning authorities with very little vacant space for any efficient facility planning. It is now possible only to provide piecemeal solutions to some limited problems. However, it provides a lesson to follow and apply in the newer fringes subjected to rural to urban transformation.

5.4 KMC Ward 144

One such newer fringe area that has been selected for this study is KMC Ward 144 which had been under Joka I and Joka II Gram Panchayats till 2012 and included into KMC. Thus, since 2012 matters like health, solid waste management, street lighting, repair and maintenance of buildings and other existing assets, addressing water logging, drainage, and keeping watch on parks and water-bodies have come under the purview of KMC. Inclusion to KMC and linking by the metro railway project have paced up the real-estate business in Ward 144 attracting prospective realtors in acquiring land and gradually altering them into built-up area. However, the tram service through the Diamond Harbour road has been put to rest to allow for the pillars that would support the overhead metro railway track.

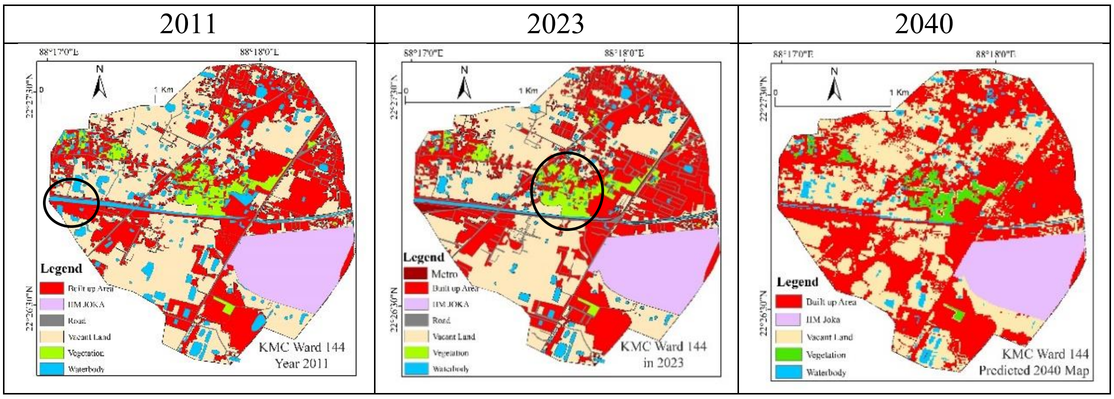
IIM Joka or IIM Calcutta, the ESIC Hospital and Diamond Park, one of the largest cooperative housing societies in West Bengal, are a few important establishments which act as centres of attraction. At its inception, the expansion was along the National Highway, NH12, which has gradually begun to pervade the entire ward. In 1961, during the inception of IIM, Joka, the entire area manifested agrarian land use, lying below the road level, prone to inundation (Shaw, 2024).

Earlier, in Fig. 4.25 and Fig. 5.8 growth forecasting map suggests that within 2040 the built-up area will cover 47.98% of total area of the ward. Alarming change will be noticed in the form of reduction of vegetation and waterbody and allied air pollution and rise in LST.

Table 5.8 Projected LU for KMC Ward 144 in percent

Classes	2011	2023	2040 (Projected)
Built-up area	21.96	39.14	47.48
Vacant land	48.71	39.37	33.78
Vegetation	9.32	4.40	2.92
Water body	8.13	5.10	3.82
IIM	11.87	11.87	11.87

Inclusion of Ward 109 within KMC took place in 1984 and in 2002 built-up area occupied 21.1% of the entire ward (Table 5.3), whereas Ward 144 has been incorporated to KMC in 2012 when the built-up area in 2011 has already reached 21.96% (Table 5.5). Situation of both the wards are very similar and in MLPNN model for Ward 109 the most influential variable has been found to be the Euclidian distance of vacant land for the base year 2010 while for Ward 144 the most influential variable is the Euclidian distance to vegetation. Between 2002 and 2040 built-up area increased from 21.2% to 74.7% in KMC Ward 109 (Table 5.4). Nearly the same situation is expected to happen for Ward 144 where it will shoot from 21.96 % in 2011 to 47.48% by 2040 (Table 5.8).



Figs. 5.9: Change of LU with special emphasis on waterbody filling and agricultural land conversion for KMC Ward 144

In Ward 109 urban expansion started along E. M. Bypass and while in Ward 144 it started along NH 12 formed by the merger of the-then NH 34 and NH 117 in 2010 before growing due west. Settlements overshadowing the already silting Churial Canal can be noticed over the years in Fig. 5.9 questioning the drainage of the ward under question. In ward 109 waterbody conversion has been drastic and its effects on LST has been profound. Rise in LST in the built-up and vacant lands have been noticed in Baruipur Municipality, while the immediate reduction in LST by the Tolly Canal looks very heartening. It was proposed to resettle people residing by the Churial Canal at Kolagachia resettlement zone (Fig. 5.10) which partly materialised but grossly backlashed due to smaller dwelling units and larger commuting distance from their workplace.

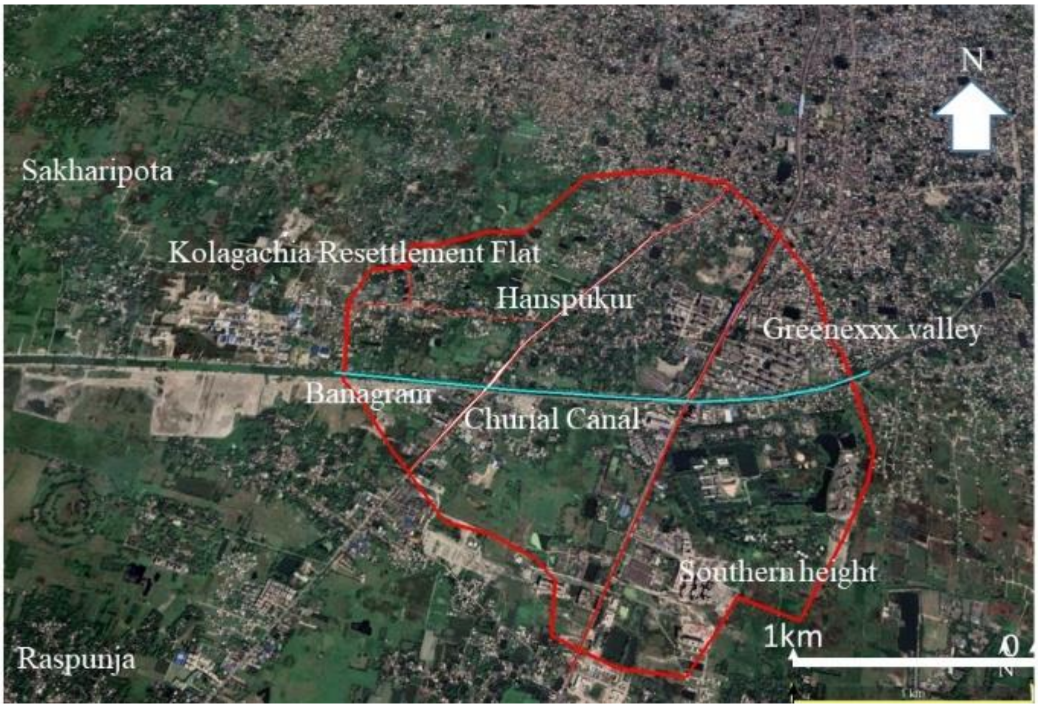


Fig. 5.10: Churial Canal and other points of KMC Ward 144 where agricultural lands are acquired and transferred by Government of West Bengal

The Genexxx Valley housing complex covering nearly 8 ha, at Diamond Park came up in 2012. Southern Height housing complex, spread over 0.84 ha, actually replaced agricultural land and some waterbody. Per sq. ft. value of the flats in Southern Heights is ₹6,859[7] whereas large plots which are few kilometres away from Ward 144 is being sold at ₹346/sq. ft. Similar to KMC Ward 109, big plots are first converted to housing complexes, while the smaller holdings might be infilled later.

Joka I and Joka II gram panchayats had a total population 29439 in 1991 (Table 5.9), 46461 in 2001 and 65147 in 2011 (Khatua, 2018; Chowdhury, 2020). Since the population in Joka I and II village panchayats were overshooting, they have been inducted within KMC in 2012. But since the Census reports of 2021 is still due, no official population count is available for KMC Ward 144.

Table 5.9: Population of Joka I and Joka II Gram Panchayat

	Total population	Growth rate (in %)
1991	29439	
2001	46461	57.82
2011	65147	40.22

As in other study areas it is expected that because of municipal facilities, transportation network, nearness of the city, population will increase and hand in hand vegetated land, waterbody, vacant land will reduce and affect environment. Information from the HTML file generated by IDRISI Selva [Table A5.5 and A5.6, Appendix-A5 p. 106] shows the driving variables responsible for these changes. They are distance to vegetation (most influential), distance to vacant land, distance to waterbodies, distance to roads, distance to built-up area, distance to metro railways, distance to schools, distance to workplaces, distance to hospitals, DEM and slope (least influential). In order to conduct an optimum planning, these factors should be taken into consideration so that a sustainable city life can be achieved.

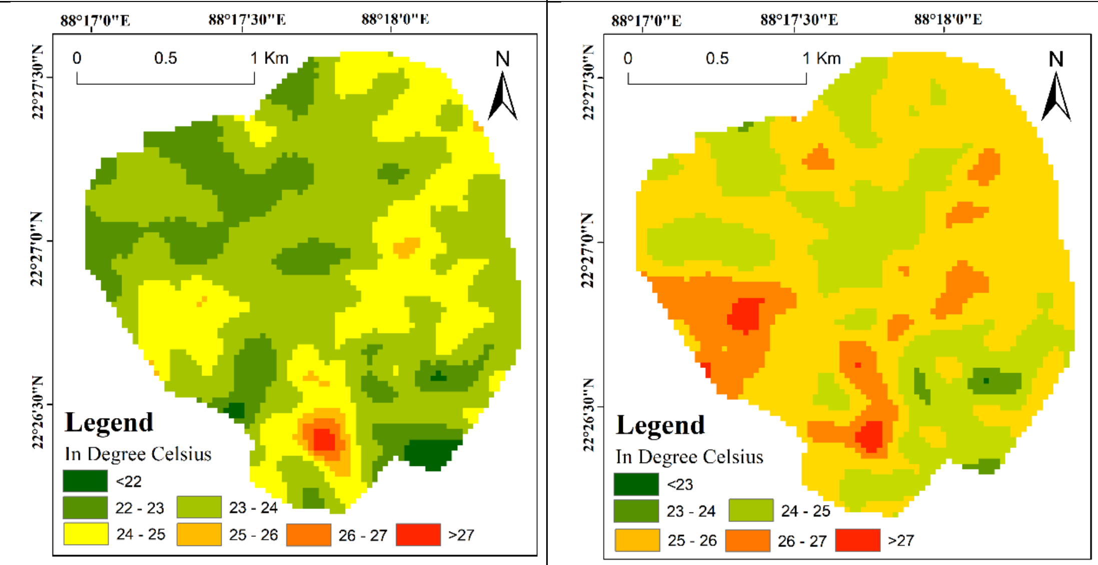
Reduction of vegetation cover and water body affects LST. Fig. 5.11 shows that both higher and lower both ranges of the temperature increased from 27.64°C (2010) to 28.354°C (2023) and from 21.30°C (2010) to 23.58°C (2023). In 2023 area mainly covered by 25-26°C had been below 23-24°C in 2010 (Fig. 5.11). The green patches of 23°C -24°C have replaced by yellow patches. Construction sites and sites changed from waterbody to vacant land (Fig. 5.9) are thereby changing their temperature status. Mainly construction sites are having highest temperature.

Fig 5.12 depicts the changes in land coverage of LST. It shows area below 23-24ºC reduced largely and 24°C -25°C and 25°C -26ºC have increased. In 2010 there was no area below 28ºC, but in 2023 temperature rose to 28ºC. It shows a total temperature increase over the area. There

[7] https://www.magicbricks.com/project-dtc-southern-heights-for-sale-in-kolkata-pppfs (checked on10.01.2025 at 02:48)

was no area below 22ºC in average. It means like other places temperature increase is gradually becoming predominant which indicates rapid urbanisation in the Ward.

2010	2023



List of raw images used to generate the average LST maps of KMC Ward 144					
Image	Date of acquisition	Thermal Band	Image	Date of acquisition	Thermal Band
Landsat 5TM	21.01.2010	Band 6	Landsat 9	09.01.2023	Band 10
Landsat 5TM	06.02.2010	-Do-	Landsat 9	10.02.2023	-Do-
Landsat 5TM	11.04.2010	-Do-	Landsat 9	07.04.2023	-Do-
Landsat 5TM	23.12.2010	-Do-	Landsat 9	21.12.2023	-Do-

Figs. 5.11: Average land surface temperature distribution in KMC Ward 144

In near future, the impact of urbanisation will aggravate, if its crisis and demand is not supported with the adequate infrastructural aid. Though the Government's aid in terms of improvement of environment and quality of life for citizens have been taken care of but application of them in accordance with LU changes is urgent.

Kolkata Environmental Improvement Program (KEIP) launched in 2002 (India: Kolkata Environmental Improvement Project, 2015) and Kolkata Environmental Improvement Investment Project (KEIIP) launched in 2014 (KEIIP's Commitment, 2014-2023, Ind: Kolkata Environmental Improvement Investment Program Tranche 1- Sewage and Drainage, 2014) are still operational with Asian Development Bank loan to improve the quality of life by providing sewerage, drainage, water supply to the KMC Wards 101 to 141 and other added areas of Kolkata (India: Kolkata Environmental Improvement Investment Program -Tranche 2, 2022) and yet waterbodies are receding.

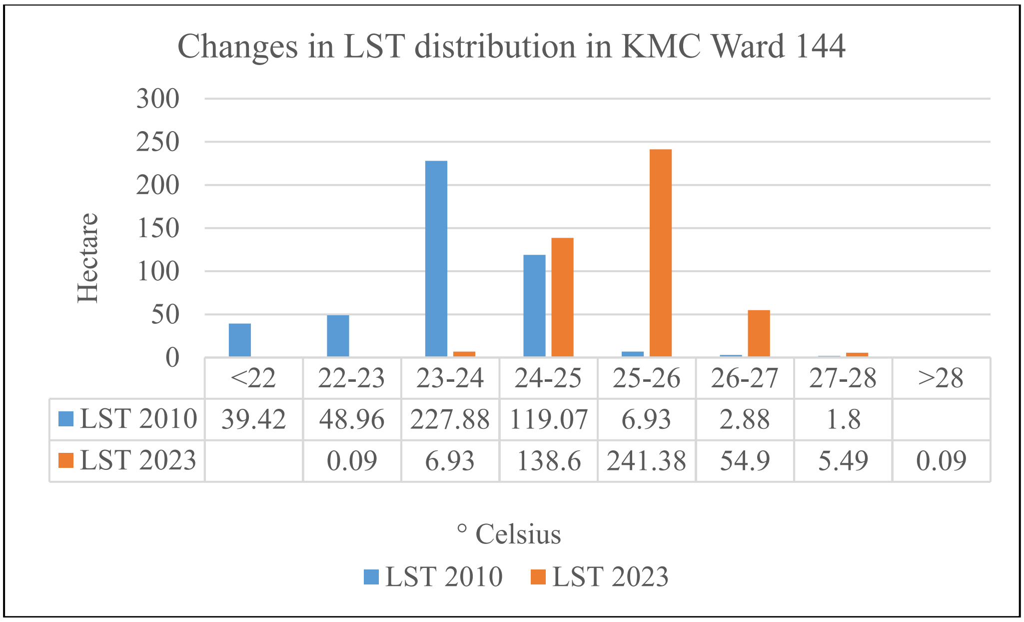


Fig. 5.12: Changes in LST distribution in KMC Ward 144

5.5 Comparison with Urban and Regional Development Plan Formulation and Implementation (URDPFI) Guidelines

The ministry of urban affairs and employment, Government of India, published Urban Development Plan Formulations and Implementation in 1996, has advanced guidelines to make a city and towns sustainable by generating enough resources with the help of State Town and Country Planning departments, urban development authorities, urban local bodies, schools of planning and various research institutions.

The research has provided a vision for 2040. Comparing the result with the guidelines would help to develop a sustainable planning for other likely areas. Table 5.10 shows the guidelines of URDPFI, 2014, where no minimal quantity for agricultural and waterbodies are prescribed.

According to URDPFI (Table 5.10), KMC Ward 109 could be fit in as a small town in 1991 with a population of 23271, but with 32.99 persons per hectare (pph) against stipulated 75-125 pph mark (Table 5.3). In the year 2011, it approached a medium city as the population became 64567 but the density was 91.55pph against stipulated 100-150pph and would turn to 102015 persons (projected) with 144.65pph in 2021 and may be counted as a full-fledged medium town. The centripetal movement of population from outskirt to city for job and centrifugal movement of population from city to outskirt for low land value, low cost of living and improved communication is responsible for changes in land use morphology in this ward. Progressively it became an urban area and part of KMC. KMC has also been forced to sprawl to accommodate its population and include this area. Thus the journey from rural to urban area can be seen with its widening gap between demand and resources and allied environmental degradation.

Table 5.11 shows that KMC Ward 109 has higher density of residential areas of 45.54% (321.19 ha). The facilities and vicinity attracts people and thus the residential areas are sprawling wider. Ground survey shows high rises in many spots. The residents of these high rises mainly depend on water of bore well. Big housing complexes do have water treatment plant of their own but standalone flats do not have that facility. Few congested slum areas are also present where no lay out plan for residential zone are available. Sufficient light and air in the buildings, soil water outlet, noise, dust and local hazard protection are lacking in these slums.

Table 5.10: URDPFI 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 5.11: 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	205.22
Recreational	0.45	3.2	**Total**	100	705.55

Though URDPFI has suggested there should be 4-5% commercial and 10-12% industrial land use but in the ward 109 they are only 3.32% (23.4 ha) and 0.12%. Government, semi-government offices, Government land, land for education and research purposes, medical and health purposes, social, cultural and religious purposes all come under public and semi-public land use category. Any large city should have 12-14% public and semi-public land but the ward 109 has only 2.13% public and semi-public land. As the said ward is part of a large city, it has a very low public and semi-public land. Lands for recreational purposes are also very low. So, one thing is very clear from the above scenario, facilities available in this Ward is not proportional to the population and residential areas.

Baruipur Municipality used to have 74 persons per hectare population in 1991 which rose to 103 persons per hectare in 2011. Thus, population density at Baruipur Municipality is leaping ahead like KMC Ward 109 (Table 5.6). Its journey from rural area to small town and gradually towards medium town is also affecting the LU pattern. Unplanned growth results in difficult state for sustainable development.

Table 5.12: LU distribution of Baruipur Municipality

Land use category	ha	%	Land use category	ha	%
Residential	309	54.4	**Transport and Communication**	59	10.4
Commercial	4	0.7	**Plantation**	76	13.5
Public and Semi-Public	6	1.1	**Agriculture**	38	6.7
Recreational	7	1.2	**Total**		100

(Source: Slum free city plan of action (SFCPoA)-Baruipur Municipality, 2014)

Baruipur Municipality is primarily a residential area (Table 5.12) as it matches with the URDPFI proposed guidelines having few industrial activities (clubbed with commercial area). Betel plantation, fruit and orchards, vegetable and crop cultivation in the southern and extreme western part of the municipality cover 13.5% and 6.7% of areas, which does not match URDPFI guidelines. Educational institutes and hospitals and health care centres cover 1.1% of area are under public and semi-public LU. Other than residential area a large part of land is utilised for agriculture and plantation purposes. It is essential to retain the local essence of a planning area and conserve its social diversity.

Table 5.13: Land use distribution of KMC Ward 144 for 2023

Land use category	ha	%	Land use category	ha	%
Residential	147.04	33.12	**Transport and Communication**	23.82	5.37
Commercial	4.47	1.01	**Plantation and Agriculture**	67.13	15.12
Industrial	4.47	1.01	**Water bodies**	39.9	8.99
Public and Semi-Public	58.33	13.14	**Vacant Land**	98.33	22.15
Recreational	0.45	0.10	**Total**	446.42	100

Further, Baruipur Municipality faces deficit in potable water supply as population keeps growing. Piped water supply is intermittent and is not available in every premises, so people depend on bore wells that often shows arsenic contamination (Chaudhuri et al, 2019) in the shallow tube wells. This contamination also effect cultivation.

Table 5.13 shows that KMC Ward 144 has also become predominantly a residential area where few industries are present. Establishments like IIM, Calcutta, dominates the public and semi-public area. Few renowned schools like the Kendriya Vidyalaya has been established here. Few temples are established here which attract a large number of people throughout the year.

However, the condition of the collector roads is not good and need very good planning to enliven them judiciously before getting saturated, so as to avoid the problems that are now too obvious in KMC Ward 109. Relocation and migration to well-connected outskirts is the driving force behind development of KMC Ward 144.

Table 5.14: Land use distribution of the three study areas for 2040

Land use category	Ward 109		Baruipur Municipality		Ward 144	
Built-up area	526.73 ha	74.68%	364.69 ha	60%	212.22 ha	47.54%
Vacant land	137.93 ha	19.56%	96.02 ha	16%	150.97 ha	33.82%
Vegetation	2.7 ha	0.38%	98.60 ha	16%	13.07 ha	2.93%
Waterbody	27.9 ha	3.96%	21.54 ha	3.5%	17.09 ha	3.83%
IIM					53.07 ha	11.83%
Agricultural land			27.92	4.5%		
Stadium and Open space	10.08 ha	1.73%				
	705.34 ha	100	608.77 ha	100	446.42 ha	100

The story remains the same. Bursting population pressure forces people to try and move outwards. Speculative private players use this force to develop facilities like hospitals and schools and often lay roads too in private endeavour to develop some fringe area with low land price as a centre of attraction for prospective takers, wherein other essential facilities (potable water, sewer lines, roads, organised open spaces, market, bank, post-office, transportation, etc.) continue to lack without an initial master plan.

Table 5.14 shows the scenario that might happen in the projected year 2040 for the three study areas if the growth spree goes unabated. Efforts must be on to abide by the distribution of space for all land uses mentioned in URDPFI 2014 for a sustainable future. To this end, proper planning and proper governance is essential at the inception to conserve resources and ensure physical and psychological wellbeing for the citizens. Existing policies like AMRUT (Atal Mission for Rejuvenation and Urban Transformation), JNNURM, (Jawaharlal Nehru Urban Renewal Mission), KUSP (Kolkata Urban Services for Poor) to instil these benefits, ensure potable water, treat and recycle waste water for managing urban greens. Vertical, terrace gardening and rain water harvesting can also be practiced to this end. Thus, a holistic solution is essential instead of piecemeal steps.

Appendix A5

The HTML files from Idrisi Selva

Table A5.1: HTML file generated by the model for KMC Ward 109 (final a)

a) Input Files			b) Parameters and Performance	
Sl	Variables	Description	Parameters	Performance
1	eveuroad_10_one_new	Evidence likelihood of Euclidian distance of roads,	Input layer neurons	10
2	slope_c10percent	Slope in percent	Hidden layer neurons	8
3	eveubuilt_10_one_new	Evidence likelihood of Euclidian distance of built-up area	Output layer neurons	6
4	eveuvac_10_one_new	Evidence likelihood of Euclidian distance of vacant land	Requested samples per class	48
5	eveuveg_10_one_new	Evidence likelihood of Euclidian distance of vegetated land	Final learning rate	0.0010
6	eveuwat_10_one_new	Evidence likelihood of Euclidian distance of waterbody	Acceptable RMS	0.01
7	railstn_eudcell10	Euclidian distance to rail stations	Iterations	20000
8	raileud_cell10	Euclidian distance to railways	Training RMS	0.1729
9	hospiall_eud	Euclidian distance to hospitals	Testing RMS	0.2104
10	workeud	Euclidian distance to workplace	Accuracy rate	84.14%
Training site file	one_109_Train_ change_to_built		Skill measure	0.8097

Table A5.2: HTML file generated by the model for KMC Ward 109 (final b)

Model	Accuracy (%)	Skill measure	Influence order	Model	Accuracy (%)	Skill measure	Influence order
With all variables	84.14	0.8097	N/A	Var. 6 constant	62.76	0.5531	2
Var. 1 constant	82.76	0.7931	9	Var. 7 constant	68.97	0.6276	3
Var. 2 constant	80.00	0.7600	6	Var. 8 constant	78.62	0.7434	4
Var. 3constant	79.31	0.7517	5	Var. 9 constant	80.69	0.7683	7
Var. 4 constant	62.76	0.5531	**1 (most influential)**	Var. 10 constant	82.07	0.7848	8
Var. 5constant	84.14	0.8097	10 (least influential)				

Table A5.3: HTML file generated by the model for Baruipur Municipality, KMA (final a)

a) Input Files			**b) Parameters and Performance**	
Sl. No.	Independent variable	Description	Parameters	Performance
1	eudroad20	Euclidian distance of road	Input layer neurons	11
2	eudhealth	Euclidian distance of health centres	Hidden layer neurons	9
3	eudrailstn	Euclidian distance of rail station	Output layer neurons	7
4	eveudwork	Evidence likelihood of Euclidian distance of workplace	Requested samples per class	1630
5	ev_eurail	Evidence likelihood of Euclidian distance of railway	Final learning rate	0.0001
6	evdem	Evidence likelihood of DEM		
7	eveudveg20	Evidence likelihood of Euclidian distance of vegetation	Acceptable RMS	0.01
8	slop	Slope	Iterations	10000
9	evluint10	Evidence likelihood of Euclidian distance of built-up area	Training RMS	0.1962
10	ev_euvac20	Evidence likelihood of Euclidian distance of vacant land	Testing RMS	0.1954
11	ev_eudwater20	Evidence likelihood of Euclidian distance of waterbody	Accuracy rate	84.33%

Table A5.4: HTML file generated by the model for Baruipur Municipality, KMA (final b)

a) Forcing a Single Independent Variable to be Constant							
Model	Accuracy (%)	Skill measure	Influence order	Model	Accuracy (%)	Skill measure	Influence order
With all variables	84.33	0.8171	N/A	Var. 6 constant	84.19	0.8155	8
Var. 1 constant	83.56	0.8082	6	Var. 7 constant	63.93	0.5792	3
Var. 2 constant	84.15	0.8151	7	Var. 8 constant	81.94	0.7893	4
Var. 3 constant	82.47	0.7955	5	**Var. 9 constant**	**42.72**	**0.3317**	**1 (most influential)**
Var. 4 constant	84.33	0.8171	10	Var. 10 constant	61.96	0.5561	2
Var. 5 constant	84.29	0.8167	9	Var. 11 constant	84.33	0.8171	11 (least influential)

Table A5.5: HTML file generated by the model for KMC Ward 144 (final a)

a) Input Files			b)Parameters and Performance	
Independent variable 1	eveudbuilt	Evidence likelihood of Euclidian distance map of built-up area	Input layer neurons	11
Independent variable 2	eveudhosp	Evidence likelihood of Euclidian distance map of hospital	Hidden layer neurons	8
Independent variable 3	dem	dem	Output layer neurons	6
Independent variable 4	slope	Slope	Requested samples per class	614
Independent variable 5	eveudvac	Evidence likelihood of Euclidian distance map of vacant land	Final learning rate	0.0005
Independent variable 6	eveudwater	Evidence likelihood of Euclidian distance map of water bodies	Acceptable RMS	0.01
Independent variable 7	eveuveg	Evidence likelihood of Euclidian distance map of vegetation	Iterations	10000
Independent variable 8	eveuwork	Evidence likelihood of Euclidian distance map of workplaces	Training RMS	0.2028
Independent variable 9	eveuroad	Evidence likelihood of Euclidian distance map of roads	Testing RMS	0.2013
Independent variable 10	eveumetro	Evidence likelihood of Euclidian distance map of metro railways	Accuracy rate	82.32%
Independent variable 11	eveuschool	Evidence likelihood of Euclidian distance map of schools	Skill measure	0.7878
Training site file	one_Train_to_built	Change to built-up area		

Table A5.6: HTML file generated by the model for KMC Ward 144 (final b)

Model	Accuracy (%)	Skill measure	Influence order	Model	Accuracy (%)	Skill measure	Influence order
With all variables	82.32	0.7878	N/A	Var. 6 constant	58.65	0.5038	3
Var. 1 constant	81.60	0.7792	5	Var. 7 constant	50.85	0.4102	1 (most influential)
Var. 2 constant	82.32	0.7878	9	Var. 8 constant	82.32	0.7878	8
Var. 3 constant	82.37	0.7885	10	Var. 9 constant	81.33	0.7759	4
Var. 4 constant	82.37	0.7885	11 (least influential)	Var. 10 constant	82.10	0.7852	6
Var. 5 constant	51.62	0.4194	2	Var. 11 constant	82.26	0.7871	7

Table A5.7: HTML file generated by the model for KMC Ward 109 (tuning 1a)

a) Input Files			b) Parameters and Performance	
Sl	Variables	Description	Parameters	Performance
1	eveudhosp_n	Evidence likelihood of Euclidian distance map of hospitals	Input layer neurons	10
2	ev_slope_percent_n	Evidence likelihood of slope in percent	Hidden layer neurons	8
3	evraileud_n	Evidence likelihood of Euclidian distance map of railways	Output layer neurons	6
4	evrailstn_n	Evidence likelihood of Euclidian distance map of rail stations	Requested samples per class	48
5	eveudbuilt10_n	Evidence likelihood of Euclidian distance map of built up area	Final learning rate	0.0010
6	eveudvac_10_n	Evidence likelihood of Euclidian distance of vacant land	Acceptable RMS	0.01
7	eveudscool_n	Evidence likelihood of Euclidian distance of school	Iterations	20000
8	eveudroad10_n	Evidence likelihood of Euclidian distance map of roads	Training RMS	0.2260
9	EVlikelhoodwork10	Evidence likelihood of Euclidian distance map of workplaces	Testing RMS	0.2468
10	eveudveg_10_n	Evidence likelihood of Euclidian distance map of vegetation	Accuracy rate	70.29%
Training site file	lcm_Train_change_to_Built	Change to built-up area	Skill measure	0.6435

Table A5.8: HTML file generated by the model for KMC Ward 109 (tuning 1b)

Model	Accuracy (%)	Skill measure	Influence order	Model	Accuracy (%)	Skill measure	Influence order
With all variables	70.29	0.6435	N/A	Var. 6 constant	39.13	0.2696	1 (most influential)
Var. 1 constant	70.29	0.6435	7	Var. 7 constant	70.29	0.6435	10
Var. 2 constant	69.57	0.6348	5	Var. 8 constant	68.84	0.6261	4
Var. 3 constant	70.29	0.6435	8	Var. 9 constant	50.72	0.4087	2
Var. 4 constant	70.29	0.6435	9	Var. 10 constant	69.57	0.6348	6
Var. 5 constant	67.39	0.6087	3				

Table A5.9: HTML file generated by the model for KMC Ward 109 (tuning 2a)

a) **Input Files**			**b) Parameters and Performance**	
Sl. No.	Independent variable	Description	Parameters	Performance
1	eveudhosp_n	Evidence likelihood of Euclidian distance map of hospitals	Input layer neurons	9
2	ev_slope_percent_n	Evidence likelihood of slope in percent	Hidden layer neurons	7
3	evraileud_n	Evidence likelihood of Euclidian distance map of railways	Output layer neurons	6
4	evrailstn_n	Evidence likelihood of Euclidian distance map of rail stations	Requested samples per class	48
5	eveudbuilt10_n	Evidence likelihood of Euclidian distance map of built up area	Final learning rate	0.0010
6	eveudvac_10_n	Evidence likelihood of Euclidian distance of vacant land	Acceptable RMS	0.01
7	eveudroad10_n	Evidence likelihood of Euclidian distance map of roads	Iterations	20000
8	EVlikelhoodwork10	Evidence likelihood of Euclidian distance map of workplaces	Training RMS	0.2428
9	eveudveg_10_n	Evidence likelihood of Euclidian distance map of vegetation	Testing RMS	0.2441
Training site file	lcm_Train_change_to_Built	Change to built-up area	Accuracy rate	71.52%
			Skill measure	0.6583

Table A5.10: HTML file generated by the model for KMC Ward 109 (tuning 2b)

a) Forcing a Single Independent Variable to be Constant							
Model	Accuracy (%)	Skill measure	Influence order	Model	Accuracy (%)	Skill measure	Influence order
With all variables	71.52	0.6583	N/A	Var. 5 constant	68.21	0.6185	4
Var. 1 constant	71.52	0.6583	6	Var. 6 constant	56.29	0.4755	1(most influential)
Var. 2 constant	70.86	0.6503	5	Var. 7 constant	73.51	0.6821	9 (least influential)
Var. 3 constant	71.52	0.6583	7	Var. 8 constant	59.60	0.5152	3
Var. 4 constant	71.52	0.6583	8	Var. 9 constant	58.94	0.5073	2

Table A5.11: HTML file generated by the model for KMC Ward 144 (tuning 3a)

a) Input Files			**b)Parameters and Performance**	
Independent variable 1	eveudbuilt	Evidence likelihood of Euclidian distance map of built-up area	Input layer neurons	11
Independent variable 2	eveudhosp	Evidence likelihood of Euclidian distance map of hospital	Hidden layer neurons	8
Independent variable 3	dem	dem	Output layer neurons	6
Independent variable 4	slope	Slope	Requested samples per class	614
Independent variable 5	eveudvac	Evidence likelihood of Euclidian distance map of vacant land	Final learning rate	0.0003
Independent variable 6	eveudwater	Evidence likelihood of Euclidian distance map of water bodies	Acceptable RMS	0.01
Independent variable 7	eveuveg	Evidence likelihood of Euclidian distance map of vegetation	Iterations	10000
Independent variable 8	eveuwork	Evidence likelihood of Euclidian distance map of workplaces	Training RMS	0.2094
Independent variable 9	eveuroad	Evidence likelihood of Euclidian distance map of roads	Testing RMS	0.2060
Independent variable 10	eveumetro	Evidence likelihood of Euclidian distance map of metro railways	Accuracy rate	80.75%
Independent variable 11	eveuschool	Evidence likelihood of Euclidian distance map of schools	Skill measure	0.7690
Training site file	one_Train_to_built	Change to built-up area		

Table A5.12: HTML file generated by the model for KMC Ward 144 (tuning 3b)

Model	Accuracy (%)	Skill measure	Influence order	Model	Accuracy (%)	Skill measure	Influence order
With all variables	80.75	0.7690	N/A	Var. 6 constant	58.58	0.5030	3
Var. 1 constant	80.91	0.7709	9	Var. 7 constant	55.62	0.4675	2
Var. 2 constant	80.75	0.7690	7	Var. 8 constant	80.75	0.7690	6
Var. 3 constant	80.91	0.7709	10	Var. 9 constant	79.92	0.7591	4
Var. 4 constant	80.97	0.7716	11 (least influential)	Var. 10 constant	80.58	0.7670	5
Var. 5 constant	50.63	0.4076	1 (most influential)	Var. 11 constant	80.80	0.7696	8

Chapter 6

CONCLUSIONS

6.1 Summary

This research has tried to assess the problems of fast urbanisation in the peripheral regions of KMA. Attempts have been made to map land use changes, analyse the changes, predict future LULC if the process continues uncontrolled till the horizon year 2040, and make recommendations that would assist in presently-absent micro level planning for each ward or similar rural-urban fringe areas that might be inducted into the municipal corporations in future, and review the situation. To this end three representative study areas, one nearly super-saturated, one at the intermediate state of growth and the last, beginning to transform only since 2012, have been selected for the case studies as representative samples to identify the problems and frame a set of recommendations.

For example, in 2021, as shown in Table 5.11, the residential area in KMC Ward 109 has become 45.54% exceeding the recommended 35-40% built-up area in URDPFI 2014 guideline for the Metro cities (Table 5.10). Space for transportation and communication is 12.29% against recommended 15 to 18%. These values are comparable, but the space for recreational activities (0.45% against recommended 20-25%) reflects the lack of physical activities among the residents and the degree of mental anxiety and agony of the residents. Fig.4.1 shows the roads in Ward 109 do not follow rectangular grids, whereby constrictions appear at the intersections, some being obtuse and others producing acute angles. Thus, the supply lines for potable water, and drains for storm water and sewerage disposal have to meander their ways. Addition of infrastructural facilities get technically difficult when these lines are not straight and mutually perpendicular, making them liable to leakage and choking. If the transformation goes unabated, the built-up area would go up to a precarious 74.68% by the horizon year 2040 (Table 5.14). Vacant land would recede from 64.37% in 1992 (Fig. 4.2) to 29.07% in 2021 (Table 5.11) and to 19.56% by 2040 (Table 5.14). This will have immense effect on land surface temperature since, simultaneously, vegetation is supposed to wilt up to a meagre 0.38% and waterbodies to 3.96%.

Fig. 4.11 reflects that the roads in Baruipur Municipality have developed organically without any prior plans. Extension of roads and construction of sewerage and water supply system in such condition would be a real challenge for the planners, highlighting the need of prior planning, land allocation and their conservation for future use. Specifically, the perishable products market of fruits and vegetables, on the either side of SH1, in the neighbourhood of the Baruipur Super-speciality Hospital causes severe bottleneck that is triggered at the early morning and prolongs indefinitely. This indicates a need of dedicated commercial spaces and allied storage space while dissociating them from the transportation facilities to avoid encroachment. In Baruipur, service roads are frequently found to terminate into the arterial road which decelerates the flow of thoroughfare traffic through SH1. Open drains by the road is also a menace at Baruipur, liable either to be filled up or pose problems of accident. In 2014, the share of roads was a meagre 10.4% against suggested 15-18% in URDPFI 2014.

Comparing Tables 5.10 and 5.13, the built-up area (33.12% in 2023) in KMC Ward 144 is found to have attained near-saturation (35-40%, URDPFI 2014) within 11 years of inducting from Gram panchayat to KMC. This percentage is expected to shoot up to 47.54% by 2040 if it goes unchecked. It may be noted that the metro service from Joka to BBD Bag is not yet functional and the Joka-Majherhat service does not help the commuters. Thus, when the metro service would become fully functional, chances are very high that it would boost the building industry further and likely to overshoot the predicted value if not regulated. KMC Ward 144 too has very little recreational space, and the planners must pay immediate attention to this to provide activity centres for physical and mental boost of the residents across all ages. With some degree of vacant land and waterbodies available presently in bigger parcels, there is still scope to plan the roads, drainage, sewer system and recreational activities if taken up immediately.

Thus, it is observed that there are certain common and certain specific problems observed in the three study areas and, generally speaking, this would be true for any ward studied in detail. For example, the meandering lanes and markets overpowering the arterial roads is a problem specific to Baruipur, whereas, the pressure of multiple private Hospitals, with their staffs, patients and their attendants seeking permanent and temporary stays, and hospital waste disposal, etc., are specific problems of KMC Ward 109, and so on. Thus, the suggestions for remediation would comprise of certain general recommendations and certain specific ones that can be managed only by specific planning of any ward. However, at an aggravated state, such solutions are piece meal and hence planning at inception is essential.

6.2 Problems

Overall, the following problems have been noticed in the three study areas:

1. The built-up areas are spreading unabated while vegetation, arable and open land, and waterbodies are retreating precariously.
2. Land surface temperature (LST) is on the rise in built-up areas and their denuded neighbourhoods and receding waterbodies. Lack of plantations too has direct bearing with LST, food security and deteriorating air quality index with elevated particulate level and increased noise pollutions, while receding waterbodies worsen LST and pond ecosystem niches.

3. Roads, usually insufficient and of irregular width, are being encroached by the road side markets to hinder traffic flow and cause accidents. Footpaths are lacking or being encroached.
4. Choked drains and encroached canals supplemented with filling up of natural waterbodies have added to waterlogging woes during the monsoons. Often drains are uncovered, thereby susceptible to be filled in with debris and prone to accidents.
5. Quite often markets conflict with road in absence of earmarked storage space and parking lots.
6. Existing share of organized open space for recreation is no match with recommended values and open spaces for recreation, socializing, physical activities and play grounds are lacking.
7. Roads are insufficient, often not linearly aligned and multiple neighbourhood roads lead directly to the arterial roads instead of terminating to a service road parallel to the arterial road that collects traffic from the service roads at appropriate intervals.
8. Cross roads close to grade separators cause congestion.

The process of urbanisation is rather dynamic and worsen day by day for immediate individual benefits unless carefully nurtured and regularly inspected and cared for a systemic alleviation. To this end it is essential to plan the neighbourhoods in micro-level following certain guidelines and recommendations. URDPFI guidelines, 2014[1] by the Ministry of Urban Development, Government of India can be followed along with the globally accredited 17-point Sustainable Development Goals (SDGs)[2] by the United Nations. Vis-à-vis, this research comes up with certain recommendations in Article 6.3 following the observations made locally through this research that may be accounted to address the problems of rapid transformations noticed in the fringes of Kolkata Municipal Area.

6.3 Recommendations

On the basis of availability of data and resources, local and regional level predictive model, like this research work, will help in anticipating immediate and low investment planning other than long term and holistic one, by visualising the present and future scenario in cities growth and growing demand. Integration of historical records with real time inputs and scenario simulations will support sustainable development. To this end, having present and some horizon year LU projections, and associated change maps would become beneficial.

For efficient management of the peripheral wards and the rural-urban fringe units the following recommendations are deemed important, which are being classified into two groups: a set of low investment imminent solutions, followed by a set of inception level recommendations, involving bigger budget, primarily applicable for a well-managed planning of a new inclusion where availability of bigger chunks of land parcels make planning easier, phased, and more comprehensive:

[1] https://mohua.gov.in/upload/uploadfiles/files/URDPFI%20Guidelines%20Vol%20I(2).pdf
[2] https://sdgs.un.org/goals

A. The low investment plans that could be implemented at any point of time to ease out the existing problems to induce some degree of relief:

    1. Potable water should be collected and treated from surface water sources conserving the ground water and simultaneously control the menaces of arsenic poisoning and ground subsidence. In this context, saving treated water by two means could be practiced. Gravity taps at public places and ball valves in overhead water reservoirs are simple means of saving overflowing of precious treated water. Levying a token water tax could add to citizen's awareness.
    2. If the growth of built-up LU goes unabated, the future of East Kolkata Wetland is bleak which has a direct bearings with waste water reclamation, the lake bio-diversity and overall LST of the city gradually heading towards being a heat island. Waterbodies are extremely important and must be cared for.
    3. Conserving natural water bodies without lining them and replacing hardscapes with trees and grasses can restore pond-side ecosystems that supports insects, butterflies, dragonflies, damselflies and birds. Further, it would take care of restoring LST inside the city limits. Developing organised open spaces around the waterbodies would be even better.
    4. Building lined drains with proper slopes, covering them within the city limits, cleaning them at regular intervals and desilting the drainage canals outside the city limits, where they are unlined, can take care of monsoon waterlogging. It is essential to safeguard the canals from human encroachment for quicker drainage. A satellite image assisted contour map for the present state of waterlogging is essential for planning the ideal future scheme.
    5. Replenishment and addition to the fallen trees during cyclone Amphan wherever possible is recommended with local fruiting trees having deep tap roots so as to improve city's air quality by arresting particulates and absorbing noise pollution in addition to reducing top soil erosion. This would also contribute positively to avian bio-diversity.
    6. Social forestry, landscaping and urban agriculture could breathe an air of well-being and peace while bringing down the ambient in a big way. Planning to plant set of different flowering trees that would bloom round the year in sequence, could be a comfort for eyes and minds.
    7. Play fields for the kids and walking tracks for the grown-up people have wilted up gradually and needs restoration. In densely populated wards, open spaces being scarce, indoor games like table tennis, basketball, badminton, swimming, and martial arts, etc., can be planned, while in the low-density wards with relatively more open spaces, outdoor games can be thought of. This would enhance social bonding and provide a healthier pack of citizens. Diabetes and obesity are two menaces that could thus be trained for the otherwise sedentary population.
    8. In the constricted intersections with impaired visibility, roadside convex mirrors can be planned to view the transverse traffic flow and avoid delays and accidents.
    9. It is important to avoid bottlenecks in the straight reaches of the road too for smooth flow of traffic. Street-side parking and vending are two root-causes that needs to be addressed with

interaction and relocating them. Prohibitive parking charges could inflict a social change while adding to the government exchequer.

10. Looking into the poor state of woman employment, vocational training for the women is essential which would add to the economic standards at the household level and must be taken up as a priority by the Indian and the State Governments as well as the NGOs. Women literacy and empowerment would can contribute to abating environmental degradation in a big way.

B. Inception-level and big-budget recommendations:

Phased micro planning at each ward level with GIS tools is essential to ease off the specific crisis they possess following certain broad guidelines, as listed below.

11. In the newer and less dense localities, the neighbourhood could be planned such that facilities like markets, organised open spaces for social gathering and a library, primary health facilities, banks and other such facilities are within the walking distance to create a cleaner, quieter and interactive neighbourhood with an aim to introduce the same gradually in the denser wards during future demolition and reconstructions.
12. If an arterial road serving a congested ward has parallel service roads along it, as in case of E. M. Bypass through Ward 109, rectangular grids of roads might be implemented to connect the locality to the service road and let the service road connect to the arterial road in a straight reach equidistant from two consecutive bus stops where merger to the mainstream fast flow can take place with minimum weaving conflict. A fast, unhindered flow produces minimum pollution and simultaneously the health of flexible pavements is retained for a longer period since the detrimental intermittent braking and acceleration is thus minimised. Contrastingly, an arterial road can pass through the heart of a newly planned low-density ward, from which radiating roads can enter and serve the neighbourhoods like the leaf-veins.
13. At-grade roads have lower maintenance requirement than the grade separators, while effective dispersal plan for the traffic at the touch-down point for grade separated fast corridors define the success of the costly grade separated installations. Thus, the approaches to the grade separated stretches must be planned in detail for a successful project. The congested situation at the Park Circus intersection and its remediation may be referred to following the commissioning of the Rabindra Sadan-Park Circus flyover necessitating multiple flanks to dissipate the crowd towards E. M. Bypass and Sealdah railway station through AJC Bose Road.
14. The percent of built-up area need to be reduced through high-rises thus expanding the green expanse all around following the recommendations of URDPFI 2014.
15. Grade separations in the form of flyovers and underpasses are costly projects by themselves and maintenance is equally costly compared to at-grade roads. Thus bringing jobs and

neighbourhoods closer can have multipurpose benefits. Bicycles can curb the demand of automated two-wheelers, four-wheelers and transit modes as well as paratransit modes of travel.

16. Metro railway services are now being extended to connect N S C Bose International Airport, Sealdah railway station, Kolkata railway station, B. B. D. Bag and Howrah railway stations and also connect Dalhousie to Esplanade and southern fringes and reconnect to Salt Lake and Airport to produce a complete circuit. Now radial road connections from the core to the Metro railway stations as well as from the fringes to the Metro Stations can create an efficient transportation network to eliminate overall congestion in and around Kolkata. These two proposals of minimizing the travel demand and providing an efficient connectivity can take Kolkata to a glorious future, with better air quality index.
17. Planned marketplaces with adequate parking and storage spaces away from the arterial roads can be a remedy to congestion of the type visible in Baruipur. It is a trend noticed in the suburban railway stations that the vegetable and fish markets grow around the station approach so that the commuters access them on their way back. Before relocating them, the end users must be taken into confidence, since if a remedy to congestion is achieved, the users will be the first to be benefitted.
18. Adding benefits to some selected locations would attract crowd from long distance. Thus, the benefit is gradually lost under population pressure intending to avail these facilities. Instead, if the facilities are evenly distributed, no single facility would seem a priority for people, easing out the pressure.
19. The planners must attempt to stick to a specified population density and share of built-up area with respect to the area being planned. The URDPFI Guideline, 2014 recommendations may be adhered to. KMC specified floor area ratio (FAR)[3] must be adhered to for airy and sunny dwelling units and brighter office places.
20. The seventeen-point sustainable development goal (SDG) must be taken into consideration while planning.
21. Open minded deliberations must be hold on technical observations, political, sociological and citizens' experiences so as to attain a brighter future ultimately.
22. A planner can select a few sets of remedial regulations and compute and assess alternative scenarios (Chakraborty and McMillan 2018) for the horizon year with each such constraints to identify the most efficient regulations for a holistic planning approach towards a sustainable future.
23. Finally, public-private partnership could be a solution for financial aids, but the government must persuade the financers to uphold public interests as the foremost priority.

[3] https://www.kmcgov.in/KMCPortal/downloads/Building_%20Rules2009.pdf

6.4 Scope for Future Work

The recommendations from this research and similar other research works may be used to produce micro-level development plans for each ward and peri-urban neighbourhoods for a sustainable future and strictly abided by. Each planning zone has its own speciality, plus points and adversities that require specific attentions. Detail LU maps must be prepared to docket them before developing a plan to envision the ward 20 to 25 years hence. Thereafter it is essential to aggregate all such infrastructural requirements to compile a 'Perspective Plan' to integrate the entire KMC as a single system and execute the plan in five year phases. Thus, the long-term, policy-oriented 'Perspective Plan' is dissociated into a set of medium-term 5-year 'Development Plans'. Thereafter, the micro-level 'Annual Plans' follow for effective resource mobilization for 'Plans of Projects/Schemes' to be executed each year.

Top-down and bottom-up assessments of the situation must be done at regular intervals for any noticeable aberrations or emerging problems and plan for their remediation to let the system function smoothly over the time.

6.5 Concluding Remarks

This research found rapid urbanisation without micro-level a-priori planning affects the urban functioning critically and hence a detail work-up is essential to forecast and assess the future and implement regulatory norms to abate any unsustainable turn with intermittent supervision.

REFERENCES

1. Ab Ghani, N. L., Siti, Z., Abidin, Z., Zamani, M., & Abiden, Z. (2011). Generating transition rules of cellular automata for urban growth prediction. *International journal of geology*. 5 (2).

2. Abdelkarim, A. (2023). Monitoring and forecasting of land use/land cover (LULC) in Al-Hassa Oasis, Saudi Arabia based on the integration of the Cellular Automata (CA) and the Cellular Automata-Markov Model (CA-Markov). *Geology, Ecology, and Landscapes*. 9 (1).

3. Aburas, M. M., Ramli, M. F., Ho Y., & Ashaari, Z.H. (2015). A review: of land suitability analysis for urban growth: by using the GIS_Based Analytic Hierarchy process. *Asian journal of applied sciences*. 3 (6).

4. Adam, H. E., Csaplovics, E., & Elhaja, M. E. (2016). A Comparison of pixel-based and object-based approaches for land use land cover classification in semi-arid areas, Sudan. *IOP conf.series: Earth and environmental sciences.* 37 012061.

5. Aithal, B. H., Vinay, S., & Ramchandra, T. V. (2018). Simulating urban growth by two state modelling and connected network. *Modelling earth systems and environment.* 4(4).

6. Ali, S. A., & Ahmed, A. (2019). Forecasting MSW generation using artificial neural network time series model: a study from metropolitan city. *SN Appl. Sci.* 1(1338).

7. Almeida, C.M.D., Batty, M.., Monteiro, A.M. V., Camara, G., Soares-Filho, B.S., Cerqueira, G.C., & Pennachin, C.L. (2003). Stochastic cellular automata modelling of urban landuse dynamics: empirical development and estimation. *Computers, Environment and Urban Systems*. 27(5.

8. Anderson, J.R., Hardy, E.E., Roach, J.T., & Witmer, R.E. (1976). A landuse and land cover classification system for use with remote sensor data. *Geological survey professional paper*. 964.

9. Azabdaftari, A., & Sunar, F. (2024). Predicting urban tomorrow: CA- Markov modeling and district evolution. *Earth Science Informatics*. 17 (4.

10. Baqa, M. F., Chen, F., Lu, L., Qureshi, S., Tariq, A., Wang, S., Jing, L., Hamza, S. & Li, Q. (2021). Monitoring and modelling the patterns and trends of urban growth using Urban Sprawl Matrix and CA-Markov model: A case study of Karachi, Pakistan. *Land*. 10 (7).

11. Barranco, R. R., Silva, F. B., Herrera, M. M., & Lavalle, C. (2014). Integrating the MOLAND and the urban atlas geo-databases to analyse urban growth in European Cities. *Journal of map & geography libraries.* 10(3), 305-328.

12. Basu, K., Roy, S. S., & Ray, R. (2024). An analytical study of urban expansion on the impacts of land use-land cover dynamics- A case study on Barasat Sub-division, North 24 Pargana, *IJRES*. 12, 246-262

13. Bera, D., Das Chatterjee, N., Mumtaz, F., Dinda, S., Ghosh, S., Zhao, N., Bera, S., & Tariq, A. (2022). Integrated influencing mechanism of potential drivers on seasonal variability of LST in Kolkata Municipal Corporation, India. *Land.* 11 (9). 1461.

14. Bharath, A. H., Vinay, S., & Ramchandra, T. V. (2016). Agent based modelling urban dynamics of Bhopal, India. *Journal of Settlement and spatial planning*. 7(1).1-14.

15. Bhatta, B. (2009). Analysis of urban growth pattern using remote sensing and GIS: a case study of Kolkata, India. *IJRS*. 30 (18), 4733-4746.

16. Bhatta, B. (2010). Analysis of Urban Growth and Sprawl from Remote Sensing Data. *Advances in geographic information science.*

17. Bhatta, B. (2012). Urban growth analysis and remote sensing – a case study of Kolkata, India 1980 – 2010, https://www.amazon.com/Urban-Growth-Analysis-Remote-Sensing-ebook/dp/B00A9YGOW0

18. Biswas, M., Banerjii, S., & Mitra, D. (2020). Land-use-land-cover change detection and application of Markov model: A case study of Eastern part of Kolkata. *Environment, Development and Sustainability.* 22 (5).

19. Biswas, S., & Ghosh, S. (2022). Estimation of land surface temperature in response to land use/land cover transformation in Kolkata city and its suburban area, India. *International Journal of Urban Sciences.* 26 (4).

20. Buyadi, S. N. A., Wan Mohd, W. M. N., & Misni, A. (2014). Quantifying green space cooling effects on the urban microclimate using remote sensing and GIS techniques. *FIG Congress*.

21. Census of India. (1991). District census handbook. *Village and town wise primary census abstract*. District Kolkata series 20. West Bengal.

22. Census of India. (2001). District census handbook, *Village and town wise primary census abstract.* District Kolkata series 20. West Bengal.

23. Census of India. (2011). District census handbook. *Village and town wise primary census abstract.* District Kolkata Series 20. West Bengal.

24. Chakraborty, A., & McMillan, A. (2018). GIS and Scenario Analysis: Tools for Better Urban Planning. *Comprehensive Geographic Information Systems*. 2. 371–380. doi:10.1016/b978-0-12-409548-9.09649-4

25. Chaudhuri, P., Aitch P., & Dutta A. (2019). Determination of arsenic concentration in ground water and its effects on children: a case study of Sonarpur and Baruipur Block, South 24-Parganas, West Bengal. *Journal of Global Resources.* 6 (01). 134-140.

26. Cheng, c., Xing, Z., Ye, L., Yang, J., & Xie, Z. (2024). Characteristics and influencing factors of landscape pattern gradient transformation of small-scale agroforestry patches in mountain cities. *Sustainability*. 16(15).

27. Chowdhury, A. (2020). Comparative study of state level and city level responses to urbanisation and peri-urbanity in West Bengal and Assam.

28. Clarke, K. C., Hoppen, S., & Gaydos, L. J. (1996). Methods and techniques for rigorous calibration of a cellular automaton model of urban growth. *Environment and planning B: Planning and design.* 24. 247-261

29. Congalton, R. G. (2001). Accuracy assessment and validation of remotely sensed and other spatial information. *International journal of wild land fire*. Vol 10.

30. Congalton, R. G., & Green, K. (2019). Assessing the accuracy of remotely sensed data: principles and practices. 3rd Ed. *CRC Press*.

31. Congalton, R. G. & Green, K. (2009). Assessing the accuracy of remotely sensed data: principles and practices, 2 Ed., *CRC Press*, p.56.

32. Crooks, A., Castle, C, & Batty, M. (2008). Key challenges in agent-based modelling for geo-spatial simulation. *Computers, Environment and Urban Systems*. 32. 417-430. https://doi.org/10.1016/j.compenvurbsys.2008.09.004

33. Cruze-Bello, G. M., Galeana-Ptzana, J. M., & Gonzalez-Arellano, S. (2023). Urban growth in peri-urban, rural and urban areas: Mexico City. *Building & cities*. 4(1). https://doi.org/10.5334/bc.230

34. Das, P., & Angadi, D. (2020). Land use- land cover (LULC) transformation and its relation with land surface temperature changes: a case study of Barrackpore subdivision, West Bengal, India. *Remote Sensing Applications: Society and Environment.* 19, 100322, https://doi.org/10.1016/j.rsase.2020.100322

35. Das, S., & Sarkar, R. (2021). Land use using multi-temporal remote sensed imagery and landscape metrics: a sub-catchment level study of the Bhagirathi-Hugli River, West Bengal, India. *GSDEO*. 012003. doi:10.1088/1755-1315/1164/1/012003.

36. Deng, J., Wang, K., Hong, Y., & Qi, J. G. (2009). Spatio-temporal dynamics and evolution of land use change and landscape pattern in response to rapid urbanization. *Landscape and urban planning*. 92(3-4). 187-198.

37. Dinda, S., Chatterjee, N. D., & Ghosh, S. (2021). An integrated simulation approach to the assessment of urban growth pattern and loss in urban green space in Kolkata, India: a GIS based analysis, *Ecological Indicators*. 121. 10178.

38. Dolui, S., & Chakraborty, S. (2023). Forecasting the effects of urban expansion on the agricultural and forest landscape using MLPNN-Markov Chain Model in Greater Guwahati Metropolitan area, India, *Agriculture and Climatic issues in South Asia: Geospatial applications.* CRC Press.

39. Dousari, A. E. a., Mishra, A., & Singh, S. (2023). Land use land cover change prediction and urban sprawl prediction for Kuwait metropolitan region, using multi-layer perceptron neural network (MLPNN). *The Egyptian Journal of Remote sensing and Space science*. 23. 381-389.

40. Dupuy, S., Tormos, T., & Laine, G. (2012). OBIA for combining LiDAR and multispectral data to characterize forested areas and land cover in a tropical region. *Proceedings of the 4^th^ (GEOBIA)*.

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

42. Eastman, R. (2009). Idrisi Taiga Guide to GIS and Image Processing. Clark Laboratories. *Clark University.*

43. Eastman, J. R. (2020a). TerrSet liberaGIS: Geospatial Monitoring and Modeling Software manual (Version 20.0). *Clark University*.

44. Eastman, J. R. (2020b), TerrSet liberaGIS: Geospatial Monitoring and Modeling Software tutorial (Version 20.0). *Clark University*.

45. Engelen, G., Lavalle, C., Barredo, J., Meulan, M. V., & White, R. (2007). The Moland modelling framework for urban and regional land-use dynamics. *The Geojournal Library*. 90. https://doi.org/10.1007/978-1-4020-5648-2_17.

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

47. Gandhi, S. I., & Suresh, V. M. (2012). Prediction of urban sprawl in Hyderabad city using spatial model. Remote sensing and GIS techniques. *International journal of scientific research*. 1(2).

48. Garg, S. K. (1977). Water Supply Engineering. *Khanna Publishers*. New Delhi.

49. Gaube, V., & Remesch, A. (2013). Impact of urban planning on household's residential decisions: an agent-based simulation model for Vienna. *Environmental modelling & software*. 45. 92-103.

50. Ghosh, A. (2016). Changing of landuse/ land cover patterns of Arambagh municipality in last two decades by using remote sensing and GIS technique. *IJSR*. 5(10).

51. Gonzalez-Mendez, M., Olaya, C., Fasolino, I., Grimaldi, M., & Obregon, N. (2021). Agent-based modelling for urban development planning based on human needs. Conceptual basis and model formulation, land use policy. 101. 105110

52. Government of West Bengal. (2009). The Kolkata Gazette. Registered No. *WB/SC-247, No. WB (Part-1)/009/SAR-320.*

53. Guo, Y., Jiao, L., Sun, Y., Zhang, H., Liu, Z, & Xu, G. (2024). A novel urban population-land coupling simulation model: Integrating spatial equilibrium and macro-micro strategies. *International Journal of Applied Earth Observation and Geoinformation*. 132.

54. Gupta, A., & Malik, I. H. (2021). Dynamics of land use and land cover change in Salt Lake City, Kolkata, West Bengal. *Annals of the Romanian Society for Cell Biology*. 25 (4).

55. Hakim, A. M. Y., Baja, S., Rampisela, D, A., & Arif, S. (2021). Modelling land use/land cover changes prediction using multi-layer perceptron neural network (MLPNN): a case study in Makassar city, Indonesia. *International journal of Environmental studies*. 78 (2).

56. Halder, A., Khatun, N., Dutta, A., & Satpati, L. (2022). Anthropogenic interventions and urban hydro-geomorphic hazards in Kolkata, India. *Anthropogeomorphology*. 495-523.

57. Halder, S., Chatterjee, U., Bhattacharya, S., Paul, S., Bindajam, A. A., Mallick, J., & Abdo, H. G. (2024). Peri-urban dynamics: assessing expansion patterns and influencing factors. *Ecological Processes.* 13. article no. 58.

58. Hardin, P. J., Jackson M. W., & Otterstrom SM. (2007). Mapping, measuring, and modeling urban growth. *Geo-spatial technologies in urban environments. (2nd ed.). Springer.*

59. Hasan, S., Shi, W., Zhu, X., Abbas, S., & Khan, H.U.A. (2020). Future Simulation of Land Use Changes in Rapidly Urbanizing South China Based on Land Change Modeler and Remote Sensing Data. *Sustainability*. 12 4350.

60. Hasnine M, & Rukhsana. (2023). Spatial and temporal analysis of land use and land cover change in around Kolkata city, India, using geospatial technique. *Journal of the Indian Society of Remote Sensing*. 51 (4). https://doi.org/10.1007/s12524-023-01669-1

61. Hua, L., Tang, L., Cui, S., & Yin, K. (2014). Simulating urban growth using the SLEUTH model in a coastal peri urban S district in China. *Sustainability*. 6 (6). https://doi.org/10.3390/su6063899.

62. Huang, J., Wu, Y., Zhan, Y., & Cui, W. (2015). An integrated approach based on Markov Chain and cellular automata to simulation of urban land use changes. *Applied mathematics and information sciences.* 9(2). 769-775.

63. Jack, T. V. (1996). Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes. *Journal of clinical epidemiology*. 49 (11). 1225-1231.

64. Jafari, M., Majedi, H., Monavari, S. M., Alesheikh, A, A., & Zarkesh, M. K. (2016). Dynamic Simulation of urban expansion through a CA-Markov model case study: Hyrcanian region, Gilan, Iran. *European journal of Remote Sensing*. 49. 513-523.

65. Jamal, S., & Ali, B. (2023). Determining urban growth in response to land use dynamics using multilayer perceptron and Markov chain models in a metropolitan city: past and future. *Environmental Development and Sustainability.* 27(1).

66. Jantz, C. A., Goetz, S. J., & Shelley, M. K. (2003). Using the SLEUTH urban growth model to simulate the impacts of future policy scenarios on urban landuse in the Baltimore-Washington metropolitan area, *Environment And Planning B: Planning And Design*, 31(2), pages 251-271.

67. John, B., Das, S., & Das, R. (2020). Effect of changing land use scenario in Kolkata Metropolitan on the variation in volume of runoff using multi temporal satellite images. *Indian Chem Soc*. 97. 555-562.

68. Jensen, J. R. (2015). Introductory digital image processing: a remote sensing perspective. (4th Ed.). Pearson education.

69. Karah, A., Koch, J. A. M., & Wimberly, M, C. (2024). Understanding urban growth modeling in Africa: Dynamics, drivers and Challenges. *Cities*. 146(2).

70. Khatua, S. (2018). Municipalization and 'Core-Ing' of the peri-urban: case study of a newly added area in the Indian city of Kolkata. *International journal of social science and economic research*. 3(08).

71. Kim, J. M., Park, J. S., Lee, C. S., & Lee, S. G. (2022). Predicting of urban expansion using convolutional LSTM network model: the case of Seoul metropolitan area, Korea. *ISPRS Annals of Photogrammetry Remote sensing and Spatial Information Sciences*. X-4/W3-2022.

72. Kumar, V., & Agarwal, S. (2022) Urban modelling and forecasting of landuse using SLEUTH model. *International Journal Of Environmental Science And Technology*. 23(06).

73. Landis, J. R., & Koch, G. G. (1977). The Measurement of Observer Agreement for Categorical Data. *Biometrics*. 33(1).

74. Lea, J. (2024), Cloud-based remote sensing with Google Earth Engine Fundamentals and Applications. *Springer*. E-book

75. Lepers, E., Lambin, E., Janetos, A., Defries, R., Achard, F., Ramankutty N., & Scholes, R. (2005). A synthesis of information on rapid land cover change for the period 1981-2000. *Bioscience*. 55(2).

76. Li, X., & Yeh, A.G.O. (2000). Modelling sustainable urban development by the integration of constrained cellular automata and GIS. *Int. J. Geographical Information Science*. 14(2).

77. Li, X. & Yeh, A.G.O. (2004). Analyzing spatial restructuring of landuse patterns in a fast growing region using remote sensing and GIS. *Landscape and Urban Planning*. 69 (4).

78. Lillesand, T., Kiefer, R. W., & Chipman, J. (2015). Remote sensing and image interpretation. 7th Ed.

79. Liu, J., & Mason, P. J. (2016). Image processing and GIS for remote Sensing, 2nd Ed. John Wiley and Sons.

80. Lynch, P, Blesius, L, & Hines, E. (2020). Classification of urban area using multispectral indices for urban planning, *Remote Sensing*, 12 (15).

81. Mahata B, Sahu, S. S., Sardar, A., Rana, L., & Maity, M. (2024). Spatiotemporal dynamics of land use/land cover (LULC) changes and its impact on land surface temperature: A case study in New Town Kolkata, eastern India. *Regional Sustainability*. 5(2).

82. Maithani, S. (2009). A Neural Network based Urban growth Model of an Indian city. *J. Indian Soc. Remote Sensing.* 37.

83. Maity, S., G. Lal., & Srivastava. (2020). Assessment of land surface temperature of Kolkata Urban Agglomeration, West Bengal, India, *Aayushi International Interdisciplinary Research Journal*.80.

84. Majumder, S. (2020). Assessment and Detection of land cover changes in the southern fringe of Kolkata using remotely sensed data. *Geography Environment Sustainability*. 13(4). https://DOI-10.24057/2071-9388-2020-65

85. Majumder, S., & Sivaramakrishnan, L. (2020). Mapping of urban growth dynamics in Kolkata Metropolitan area: a geospatial approach. *Urbanisation and Regional Sustainability in South Asia*. Springer international publishing.

86. Majumder, S., & Sivaramakrishnan, L. (2015). Patterns of land use in and around Kolkata city: a spatio-temporal analysis. *Indian cartographer*. 35.

87. Mallick., J., Kant, Y ., & Bharath, B. D. (2008). Estimation of land surface temperature over Delhi using Landsat-7 ETM+. *J. Ind. Geophys. Union*. 12(3).

88. Masoudi, M., Richards, D. R., & Tan, P. Y. (2024), Assessment of the influence of spatial scale and type of land cover on urban landscape pattern analysis using landscape metrics. *Journal of Geovisualization and Spatial Analysis*. 8.

89. Mawjoud, A. A., & Jamel., M. G. (2016). Using the analytical hierarchy process and GIS for decision making in rural highway route location. *International Journal Of Civil Engineering And Technology*. 7(2).

90. Mcgarigal, K. (2015). FRAGSTATS Help.

91. Mcgarigal, K., Cushman, S. A., & E. Ene. (2012). FRAGSTATS, Version 4.0: Spatial Pattern Analysis Program for Categorical and Continuous Maps. *Computer software program produced at the University of Massachusetts*. Amherst.

92. McGarigal, K., & Marks, B. J. (1995). Fragstats: Spatial pattern analysis program for quantifying landscape structure. *U. S. Department of Agriculture.*

93. Mithun, S., Sahana, M., Chattopadhyay, S., Chatterjee, S., Isla, J., & Costache. R., (2022). Comparative framework for spatially explicit urban growth modeling for monitoring urban land-use efficiency and sustainable urban development (SDG 11.3.1): a study on Kolkata Metropolitan Area, India. *Geocarto International*. 37(27).

94. Mohammadi, M., Sahebgharani, A., & Malekipur, E. (2013). Urban growth simulation through cellular automata(CA), Analytic hierarchy process (AHP), GIS; Case study of 8th and 12th municipal districts of Isfahan. *GeographiaTechnica*. 08(2).

95. Mohibul, Sk., Siddiqui, L., Siddqui, M. A. Masood, Sarif, N. (2022). Spatio-temporal analysis of land use/Land cover change using STAR method in Kolkata Urban Agglomeration. *Challenges of Disasters in Asia*.

96. Mosadeghi, R., Warnken, J., Tomlinson, R., & Mirfenderesk, H. (2015). Comparison of Fuzzy-AHP and AHP in a spatial multi-criteria cedision making model for urban land-use planning. *Computers, Environment and Urban Systems*. 49. http://dx.doi.org/10.1016/j.compenvurbsys.2014.10.001

97. Mukherjee, J. (2017). The Chairman Pollution Control Board & Ors, Item No. 3, dated 30.05.2017, List on 18.9.2017, https://www.casemine.com/judgement/in/5b17d5644a932678010076bb, Copied on 28.12.2024 at 17.50

98. Mukherjee, S., Bebermeier,W., & Schutt, B. (2018). An overview of the Impacts of land use land cover changes (1980-2014) on urban water security of Kolkata. *Land*. 91(7).

99. Mundiya C. N., & Aniya, M. (2005). Analysis of landuse/cover changes and urban expansion of Nairobi city using remote sensing and GIS, *International journal of remote sensing*. 26(13).

100. Mustaqum, M, & Islam, W. (2023). Multitemporal analysis of land use/land cover changes and landscape fragmentation in Murshidabad district of West Bengal, India, *Current World Environment*. 18(2).

101. Nasiri, V., Darvishefat, Rafiee, R., Shirvany, A., & Hemat, M. A. (2017). Land use change modeling through an integrated Multi-Layer Perceptron Neural Network and Markov Chain analysis (case study: Arasbaran region, Iran). *J. For. Res*. 30. https://doi.org/10.1007/s11676-018-0659-9

102. Nilsson, K., Pauleit, S., Bell, S., Aalbers, C., & Nielsen, T. S. (2013). Peri urban futures: Scenarios and models for land use change in Europe, *Springer*.

103. Nimbarte, N., Sainis, S., & Balamwar, S. (2022). Analysis of greenness in urban cities using supervised and unsupervised classification. *Advances In Intelligent Systems And Computing.* Computational vision and bio-inspired computing.

104. Noviani, R., Ahmad., &Marfuah, I. N. (2023). Spatial patterns analysis of land use changes using spatial metrics in the peri-urban area of Surakarta city 2023. *IOP conference series: Earth and environmental science*. 1314 (1).

105. Novin, M. S., & Khosravi, F. (2017). Simulating urban growth by emphasis on connective routes network (case study: Bojnourd city). *The Egytian Journal of Remote Sensing and Space Science*. 20, 31-40,

106. Oguez, H., Modelling urban growth and land use/land cover change in the Houston metropolitan area from 2002-2030, Texas A & M University, 2004.

107. Omar, N. Q., Sansui, S. A., Hussin, W. m. W., Samat, n., Mohammed, K. S., 2014, Markov-CA model using analytical hierarchy process and multi-regression technique. IOP Conf. Series: Earth and Environmental science. 20(1).

108. Pal, R., Niyogi, A. G., & Niyogi, J. G. (2024). Spatio-temporal dynamics of LULC in Baruipur Municipality around South Kolkata. *Journal Of Institute Of Town Planners*. 21(2).

109. Patil, V. D., Sankhua, R. N., & Jain, R. K. (2012). Analytic hierarchy process for evaluation of environmental factors for residential land use suitability. *IJCER*. 2(7).

110. Pijanowski, B. C., Brown, D. G., Shellito, B. A, & Manik, G.A. (2002). Using neural networks and GIS to forecast landuse changes: A Land Transformation Model. *Computers, Environment And Urban Systems.* 26(6).

111. Rahaman, M., Dutta, S., Sahana, M., Das, D. N. (2018). Analysing urban sprawl and spatial expansion of Kolkata urban agglomeration using geospatial approach. *Applications And Challenges Of Geospatial Technology*. Springer.

112. Ramchandra, T, V, Aithal, B. H., & Sowmyashree, M. V. (2014). Urban structure in Kolkata: metrics and modelling through reo-informatics. *Appl Geomat*. 6.

113. Ramchandra, T.V., Aithal, B.H., Vinay, S., Joshi, N. V., Kumar, U., & Rao, K.V. (2013). Modelling urban revolution in greater Bangalore, India. *30th annual symposium on space science and technology*.

114. Ramchandra, T.V., Bharath, A. H., & Durgappa, S. D. (2012). Insights to urban dynamics through landscape spatial pattern analysis. *International Journal of Applied Earth Observation and Geoinformation*. 18.

115. Ramrez-Aguilar, E. A., & Sauza, L.C. L. Urban form and population density: Influences on urban heat island intensities in Begota, Colombia. *Urban Climate*. 29.

116. Rohit, B. G. (2022). Urban growth modeling and assessment using agent – based model

117. Rwanga, S. S., & Ndambuki, J. V. (2017). Accuracy assessment of land use/ land cover classification using remote sensing and GIS. *International Journal of Geoscience*. 8(4).

118. Saaty, T. L. (1980). The analytic hierarchy process. *McGraw Hill*.

119. Saha, G., Das, S., Tikle, S., & Shit, P. K. (2024). Spatial-temporal changes of urban sprawl, LULC and dynamic relationship between land surface temperature (LST) and bio-physical indicators: A study of Kolkata Municipal Corporation, West Bengal. *Geospatial Practices in Natural Resources management*.

120. Saha, P., Mitra, R., Chakraborty, K., & Roy M. (2022). Application of multilayer perceptron neural network Markov chain model for LULC change detection in the Sub-Himalayan North Bengal. *Remote Sensing applications: society and environment*. 26(1).

121. Sahalu, A.G. (2014). Analysis of urban land use and land cover changes: A case study in Bahir Dar, Ethiopia. *Masters Program in Geospatial Technologies*.

122. Sahana, M., Hong, H., & Sajjad H. (2018). Analyzing urban spatial patterns and trend of urban growth using urban sprawl matrix: a study on Kolkata urban agglomeration. *India Science Of The Total Environment*.

123. Sahin, E., Iban, M. C., & Bilgilioglu, S. S. (2024). Remote sensing enabled urban growth simulation overlaid with AHP-GIS based urban land suitability for potential development in Mersian Metropolitan area, Turkiye. *Applied Science*. 14(8).

124. Samat, N., Mahamud, M. A., Tan, M. l., Tilaki, M. J. M., & Tew, Y. L. (2020). Modelling land cover changes in peri-urban areas: a case study of George Town Conurbation, Malaysia. *Land*. 9 (10).

125. Sang, L., Zhang, C, Yang, J., Zhu, D., & Yun, W. (2011). Simulation of land use spatial pattern of towns and villages based on CA-Markov model. *Mathematical and Computer Modelling*. 54(3-4).

126. Saxena, A., & Jat, M. K. (2019). Capturing heterogeneous urban growth using SLEUTH model. *Remote Sensing Applications: Society And Environment*. 13. https://doi.org/10.1016/j.rsase.2018.12.012

127. Selmy, S. A. H., Kucher, D. E., Mozgeris, G., Moursy, A. R. A., Jimenez-Ballesta, R., Kucher, O. D., Fadl, M. E., & Mustafa, A. A. (2023). Detecting, analysing, and predicting land use /land cover (LULC) changes in Arid regions using landsat images, CA_Markov Hybrid model and GIS techniques. *Remote Sensing*. 15 (23).

128. Shan, J., Alkheder, S., & Wang, J. (2008). Genetic algorithms for the calibration of cellular automata urban growth modelling. *Photogrammetric Engineering & Remote Sensing*. 74 (10).

129. Shaw, A. (2015). Inner-city and Outer-city Neighbourhoods in Kolkata: Their Changing Dynamics Post Liberalization. *Environment and Urbanization ASIA*. 6(2).

130. Shaw, A. (2024). Managing India: The idea of IIMs and its changing contexts. *Routledges*. 1^{st} Ed.

131. Shi, X., Matsui, T., Haga, C., Machimura, T., Hashimoto, S., & Saito, O. (2021). A scenario- and spatial-downscaling-based land-use modelling framework to improve the projections of plausible future: a case study of the Guangdong-Hong-Kong-Macao Greater Bay Area, China. *Sustainable Science*. 16(5).

132. Shoyama, K., Matsui, T., Hashimoto, S., Kabaya, K., Oono, A., & Saito, O. (2018). Development of land-use scenarios using vegetation inventories in Japan, *Sustainability Science.* 14(1).

133. Shuvo F.K., & Janssen, P. (2013). Modelling informal settlements using a hybrid automata approach. *Proceedings of the 18th international conference on computer-aided architectural design research in Asia (CAADRIA 2013)*.

134. Sietchiping, R. (2000). Understanding informal urban patterns by integrating geographical information system (GIS) and Cellular Automata (CA) modelling, *1st International Conference on Systems Thinking in Management*.

135. Silva, E. A., & Clarke, K. C. (2002). Calibration of the SLEUTH urban growth model for Lisbon and Porto, Portugal. *Computers, Environment And Urban Systems*. 26(6).

136. Simwanda, M., Murayama, Y. (2017). Integrating geospatial techniques for urban landuse classification in the developing sub-Saharan African city of Lusaka, Zambia. *ISPRS International Journal of Geoinformation*. 6(4).

137. Soffianian A., & Nadoushan, N. A. (2010). Modelling urban changes using geomod model inArak, Iran. *Conference: 3rd International conference on cartography and GIS.*

138. Solecki, W. D., Pope. C., Rosenzweig, G., Chopping, M., Goldberg, R., & Polissar, A. (2004). Urban heat island and climate change: An assessment of interacting and possible adaptations in the Camden, New Jersey region. *NJDEP*.

139. Story, M., & Congalton, R. (1986). Accuracy assessment: a user's perspective. *Photogrammetric Engineering and Remote Sensing*. 52(3).

140. Subedi, P., Subedi, K., & Thapa, B. (2013). Application of a Hybrid Cellular Automaton-Markov (CA-Markov) Model in land-use change prediction: A case study of Saddle creek drainage basin, Florida. *Applied Ecology And Environmental Sciences*. 1(6).

141. Sudhira, H. S., Ramachandra, T. V., Raj, K. S., & Jagdish, K. S. (2003). Urban growth analysis using spatial and temporal data. *Photonirvachak, Journal of the Indian Remote Sensing*. 31(4).

142. Sudhira, H. S., Ramchandra, T.V., Jagadish, K.S. (2004). Urban sprawl: metrics, dynamics and modelling using GIS. *International Journal of Applied Earth Observation and Geoinformation*. 5(1).

143. Suganth, S., Elango, L. (2020). Estimation of groundwater abstraction induced land subsidence by SBAS technique. *J. Earth Syst. Sci*. 129(46).

144. Taha, L. G. E. (2014). Assessment of urbanization encroachment over Al-Monib island using fuzzy post classification comparison and urbanization metrics. *The Egyptian Journal Of Remote Sensing And Space Science*. 17(2).

145. Thapa, R. B., Murayama, Y. (2010). Drivers of urban growth in the Kathmandu valley, Nepal: Examining the efficacy of the Analytical Hierarchy Process, *Applied Geography*. 30(1).

146. Thomas, R. W. (1981). Information statistics in geography, Geo abstracts. *University of East Anglia*.

147. Town and Country Planning Organization. (2016). Urban and regional development plan formulation and implementation (URDPFI) guidelines, 2014. *Centre for science and environment workshop on "Need for better assessment tool: Time to deliberate" Session IV-Land use planning and management.*

148. Tsagkis, P., Bakogiannis, E., & Nikitas, A. (2023). Analysing urban growth using machine learning and open data: An artificial neural network modelled case study of five Greek cities. *Sustainable Cties And Society*. 89.

149. 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 Multi-Layer Perceptron Neural Network-based Markov Chain model. *Sustainability*. 13(2).

150. Wolfram, S. (1983). Statistical Mechanics of Cellular Automata, Reviews of Modern Physics. 55.

151. Wu. Y., & Feng. J. (2017). Development and application of Artificial Neural Network. *Wireless Personal Communications*. 102 (5).

152. Xiaoqing, S., Mengmeng, W., Yajing, S., Qi, F., Jingwei, X., Weina, Z., Guosong, Z., & Zhifeng, W. (2020). Urban vacant land in growing urbanisation: an international review. Journal of Geographical Sciences. 30(4).

153. Xu, T., Gao, J., Coco, G., & Wang, S. (2020). Urban expansion in Auckland, New Zealand: a GIS simulation via an intelligent self-adapting multiscale agent-based model. *International Journal of Geographical Information Science*. 34 (11).

154. Xu, X., Zhang, J, Zhou, X. (2008). Modeling urban land use changes in Lanzhou based on artificial neural network and cellular automata. *Proceedings of SPIE - The International Society Of Optical Engineering.*

155. Yaghoobi, M., Vafaeenejad, A., Moradi, H., & Hashemi, H., (2022). Analysis of Landscape Composition and Configuration Based on LULC Change Modeling. *Sustainability.* 14(20).

156. Yang, L., Xian, G., Klaver, J.M., & Deal B. (2003). Urban land cover change detection through sub-pixel imperviousness mapping using remotely sensed data. *Photogrammetric Engineering & Remote Sensing*. 69 (9).

157. Yeh, A. G., O., & Li, X. (2001). Measurement and monitoring of urban sprawl in a rapidly growing region using entropy. *Photogrammetric Engineering & Remote Sensing*. 67 (1).

158. Zare, P., Leao, S., Gudes, O., & Petit, C. (2024). A simple agent-based model for planning for bicyclists' movements in urban environment. *Computers, Environment and Urban Systems*.108.

159. Zhang, J., Wu, D., Zhu, A., & Zhu, Y. (2023). Modelling urban expansion with cellular automata supported by urban growth intensity over time. *Annals of GIS*. 29 (3).

160. Zhang, Z. (2018). Multivariate time series analysis in climate and environmental research. *Springer.*

161. Zhou, Y., Varquez, A. C. G., Kanda, M. (2019). High-resolution global urban growth projection based on multiple applications of the SLEUTH urban growth model. *Scientific Data*. 6.

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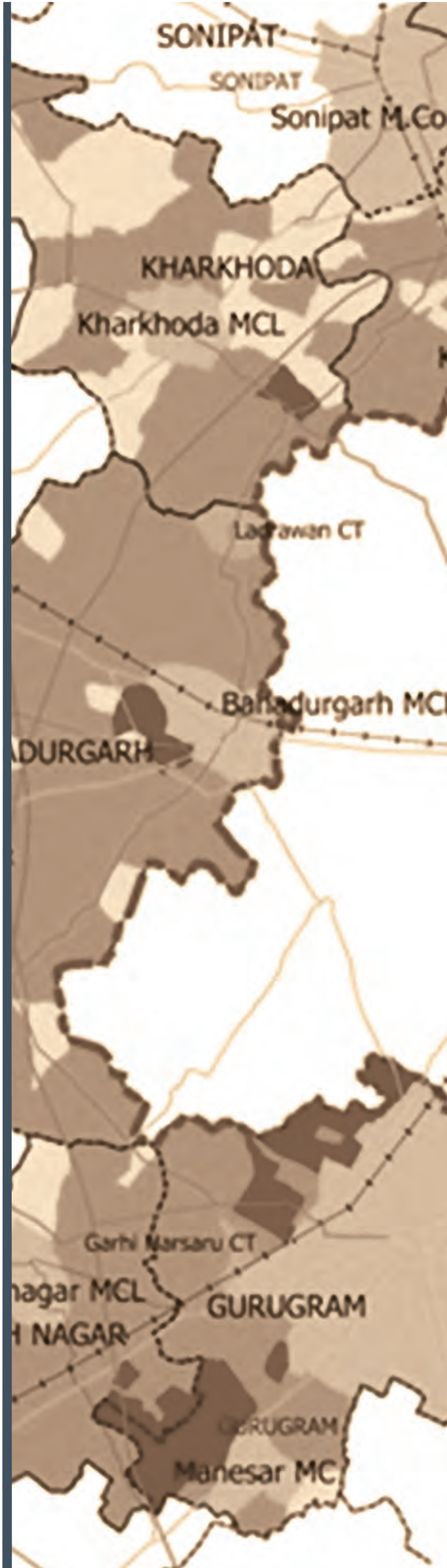

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Integrating Green Infrastructure for Resilient Cities
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Developing Blue-Green Infrastructure
Uncovering the Impacts of Land Use Change

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Editorial

Rapid urbanization has been a global phenomenon, with more than half of the global population living in the urban settlements. As per the estimates of United Nations, nearly 70 percent of the world population is expected to live in the towns and cities by 2025. Consequent to the rapid urbanization, the cities are facing the challenges of rapid urban sprawl, housing shortage, infrastructural deficiencies, environmental degradation, etc. The municipal bodies are starved of finances for development, maintenance, and management of basic amenities. Climate change has worsened the conditions under the present ways and patterns of development. International and national agencies are on the task to suggest mitigation strategies for better quality of life in the future cities.

Prof. Veena Garella has made comprehensive efforts to gather information on the impacts of climate change on the urban growth and infrastructural aspects of human habitat. She has taken different aspects, as viewed/ expressed by experts and institutions, to deliver what is required to be done to make the quality of life in the future cities conducive.

In the paper titled 'Peri-Urbanisation in National Capital Region of Delhi - A Spatial Temporal Analysis', Sunil and Dr. Sanjukkta Bhaduri have viewed that there is no consensus on the methodology to delineate the peri-urban area. They have attempted to review the delineation process of the rural urban fringe and have also attempted to delineate the same in the National Capital Region of Delhi. Factors like distance from metropolitan centres, transport infrastructure and commercial & industrial centres, as points of attractions/opportunities, have been analyzed to assess their relative importance in the delineation of the peri-urbanization in the NCR of Delhi. The research reveals that every fifth settlement in the NCR is peri-urban. Distance from the commercial and industrial centres and transport infrastructure were found to be important causative factors towards peri-urbanization.

Ruma Pal, Dr. Arup Guha Niyogi, and Dr. Jayita Guha Niyogi in their paper titled 'Spatio-temporal Dynamics of LULC in Baruipur Municipality around South Kolkata' have identified that urban sprawl of Kolkata is mostly directed southward i.e. towards the Baruipur municipality. The objective of their research is to monitor the efforts to replace the pockets of water bodies, greeneries, orchards and crop fields with built up facilities resulting in fragmented land use that would need longer haul to connect them to end-users. They have recommended facility planning approach to enhance local accessibility and reduce travel instead of a unified hierarchical neighbourhood.

In the third paper titled 'An Assessment of Relationship Between Industrialization and Urbanization in Bhiwadi Region of Rajasthan: A Spatio-Temporal Analysis' Vinod Kumar, Vikas Rawat, Veena Sanadhya, and M.S. Negi have tried to examine the relationship between industrialization and the urbanization process in Bhiwadi industrial area. Indicators such as capacity of workers, trends in urban population, industrial status, and the extent of built-up or infrastructure areas were studied. Normalized difference built-up index (NDBI) was used to identify the changes in the land use and land cover for two decades i.e. 2000 to 2020.

The fourth paper by Hasna P. on the topic 'Eco Tourism Concept: A Case for Ottappalam - Shoranur Region' is an attempt to appreciate the eco-tourism initiatives for the Ottappalam-Shoranur region towards sustainable environmental, social, and economic development along with livelihood empowerment. The research reflects that the region under study has many unutilized tourism potentials such as scenic beauty in the backdrop of the Nila River and tangible and intangible heritage, but lack of infrastructure facilities and publicity, improper management of tourist destinations, no tourism development plan have left the region unattended. The research opined that sustainable tourism planning should be done for the region.

Himani Gautam, Varsha Khetrapal Kumar in their paper titled 'Integrating Green Infrastructure for Resilient Cities: A Review Paper' have opined that green infrastructure (GI), a network of natural and semi-natural features integrated into urban areas, is pivotal in building resilient cities. Their research aims to investigate the role of GI in building resilient cities, exploring the multifaceted contributions of nature-based solutions in enhancing urban resilience to environmental, social, and economic challenges. It explores GI's role in urban resilience, tackling rapid urbanization and climate change impacts through case studies. Further, it explores GI principles and components like parks, green roofs, and permeable pavements, emphasizing their benefits. The research concludes that a holistic approach to building urban resilience based on GI is important to address a fuller range of ecosystem disturbances and disasters to create outcomes that develop urban sprawl's environmental and ecological benefits.

In the paper titled 'Assessment and Optimization of Solid Waste Disposal Practices in Srinagar, Garhwal: The Sustainable Approach for Himalayan Region' Anjali Naik, Jyoti Yadav, M. S. Negi, K. S. Bisht have delved into the solid waste disposal practices within the Himalayan region of Srinagar, Garhwal, with a focus on evaluating waste generation rates and types as a primary objective. The research also aims to assess the effectiveness of waste management strategies and formulate sustainable approaches for infrastructure development in hilly terrains. Their analysis reveals that municipal solid waste management in Srinagar is ineffective, marked by poor segregation and handling practices, including the disposal of collected waste in open landfills without employing scientific methods. The research recommends setting specific objectives and deadlines, defining roles and responsibilities for local government entities, nonprofit organizations, and the Srinagar Municipal Authority, allocating sufficient funding, and ensuring proper transportation and disposal of municipal solid waste.

The seventh paper on 'Integrating Waste Management into Urban Planning: Production of Bioethanol through Acid Hydrolysis and Fermentation Using Municipal Organic Waste of Indore City' by Dr. R. N. Singh and Neha Gour has pointed that urban planning is essential for tackling the pressing issue of fossil fuel depletion and fostering sustainable energy solutions. It presents that bioethanol production from municipal organic waste (MOW) is a viable alternative, particularly in cities like Indore, where significant quantities of organic waste are generated. They have suggested that integrating bioethanol production from MOW into urban planning strategies offers multiple benefits, including improved waste management, reduced greenhouse gas emissions, enhanced energy security, and economic development, hence advancing towards a cleaner and greener energy future.

The paper titled 'Developing Blue-Green Infrastructure in Megacities of India: Case of Delhi & Mumbai' by Somya Gupta, Garima Sarwan and Ishani Garg addresses the Blue-Green Infrastructure (BGI) concerns in four major cities i.e. Mumbai, Copenhagen, Delhi, and New York City to evaluate their efforts in promoting sustainable urban development. The research attempts to identify common themes in BGI development across the cities, such as community engagement, multi-stakeholder collaboration, and institutional support. However, it also highlights the unique challenges faced by each city in implementing BGI. The study contributes to the emerging literature on urban resilience and sustainable development, providing insights into the design, implementation, and management of BGI in diverse urban contexts.

The last paper of the volume title 'Uncovering the Impacts of Land Use Change: A Case Study of Open/ Green Areas Converted to Commercial Areas in Bathinda City, Punjab' have expressed that expansion of various activities has put increased pressure on cities to build more spaces. They assessed the spatio-temporal variations in land use and their impact along one of the major commercial streets of Bathinda, Punjab, between 2002 and 2022. Their research reveals that the commercial areas along the mall road have increased at the expense of shrinking green and open areas. These alterations in land use have increased impervious surface coverage, resulting in water logging issues, putting more pressure on the existing road capacity, and causing a loss of sense.

Ashwani Luthra, Ph.D.
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Spatio-Temporal Dynamics of LULC in Baruipur Municipality around South Kolkata

Ruma Pal[1], Dr. Arup Guha Niyogi[2], Dr. Jayita Guha Niyogi[3]

Abstract

Being restricted in the East and West, and saturated along the North, the urban sprawl of Kolkata is mostly directed southward – towards the Baruipur municipality, altering its original role of being a major source of fruits and vegetables catering Kolkata. The objective of this study is to monitor any efforts to replace the pockets of water bodies, greeneries, orchards and crop fields with built-up facilities resulting in fragmented land use that would need longer haul to connect them to end-users, which calls for additional travel-related congestion and pollution load; instead a unified hierarchical neighbourhood facility planning is recommended to enhance local accessibility and reduce travel. Multi-temporal images of Baruipur are analysed by FRAGSTATS to generate landscape-level and class-level metrics and study splitting and land fragmentation. Shannon's entropy and Land Surface Temperature are used to show the direction of sprawl and gradual rise of temperature. There could be other factors that may be studied as well. This methodology could help planners to keep constant vigil and intervene at the right point of time.

1. INTRODUCTION

Development and urbanisation of countries bring gradual changes in national landscape (Henderson, J. V., and Wang, H.G., 2007). Increasing settlement density, (McGranahan, G. and Satterthwaite, D., 2014), conversion of land from non-urban to urban uses (Weith, T., et al, 2021) mark urbanisation. Urbanisation effects landscape-structure and pushes rural/urban fringes outward (Weng, Q., 2019). It involves economic growth and development in urban and regional areas (Chaolin, G., 2019, Nguyen, H. M., and Nguyen, L. D., 2018). But urbanisation and development need sustainability (Simon, D., 2008). Developments due to urbanisation beyond the limits of the city-municipalities and spilling of population from the cities into the peripheral areas lead unplanned development (Shilpa, S. J., 2021). Unplanned urban growth brings land use changes, which results into losses in agricultural land (Maheshwari, B., et al., 2014), water bodies (Mitra, D., and Banerji, D., 2018), forest land (Ancha, P. U., 2021), etc. Government officials and city planners need to know the current scenario of land uses for the better management of problems and planning. Spatio-Temporal urban growth and sprawling pattern can be monitored (Megahed, Y. et al., 2015, Pham, M. H. et al., 2010) and predicted (Megahed, Y. et al., 2015) using remote sensing data (Getu, K., 2021). Supervised classification technique helps in quantitative analysis of remote sensing data where segmentation of spectral bands assist into classification of ground cover classes (Richards, J. A., 2012) and Maximum Likelihood Classifier (MLC) method helps in land use classification to detect LULC changes (Singh, K. T., et al., 2022). Shannon entropy measures LU change pattern outlining urban sprawl (Chong, C. H., 2017). To scale the entropy value, relative entropy is used by researchers to understand the urban growth pattern (Bhatta, B., and Giri, B., 2012). The statistical programme FRAGSTATS measures the urban growth, composition of LUs (Pham, M. H., et al, 2010) and estimates the changes

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of landscape pattern (Borana, S. L., et al., 2017). Many researchers studied urban morphology to understand the direction of urban development with the help of landscape indices (Jia, Y., et al., 2019, Getu, K., 2021, Keita, M.A., 2021).

LULC changes have various facets of effects on environment such as on LST (Jiang, J., and Tian, G., 2010), water balance (Schilling, K. E., et al, 2008), climate (Duveiller, G., et al., 2020) etc. Urban growth causes increase in local land temperature (Kanga, S., et al., 2022) and affects environment from local to global level (Turner, B. L., et al., 1994). The structural change in LULC in urban areas intensifies LST. Solecki, W. D., et al., 2004, examined the urban heat island effect at Camden, (Mallick, J., et al., 2008) worked on LST in Delhi, (Wongsai, N., et al., 2017) worked on Phuket Island. Scientists (Buyadi, S.N.A., et al., 2014) have worked on the cooling effect of parks by measuring the temperature difference in and outside a park depending on landscape. Urban green-spaces could reduce the high radiant temperature of the surrounding developed areas.

Many researchers have analysed the planned and unplanned peripheral growth of a city as a whole (Jat, M. K., et al., 2008), whereas some researchers have delved on smaller administrative unit (Herold, M. et al., 2003). Urban dynamics regarding large scale changes for LULC depend on nature of land use (LU) and intensity of growth (Ramchandra, T. V., 2012) from the smaller unit.

Kolkata, more than 300 years old (Chakraborty. S., and Shiva. J., 2022), is experiencing peripheral urban growth in south-eastern part of the Kolkata Municipal Corporation (KMC) (Mehebub, S., 2018). It has diverse nature of urban growth for urban core and rural periphery part (Mithun, Sk., 2016). KMC outskirts manifest certain striking characteristics but they are seldom studied. Baruipur municipality, a metropolitan outfit of the city of Kolkata, is situating in such a peripheral part of south-eastern fringe of Kolkata Metropolitan Area (KMA). To mitigate this gap of studies, the Baruipur municipality, located 27 km away from the heart of Kolkata on the south-eastern expansion corridor and still having room for expansion, has been chosen to study the immediate impact of urban expansion. The locational uniqueness of Baruipur municipality in the proximity of urbanised Kolkata on the northern side and backward Sundarban (Ghosh, U., 2018), on the southern side (68 km by road) make the area important. Spatial pattern of urbanisation shows relatively more urbanisation towards its northern part while the eastern and southern boundaries of the study area remain less urbanised.

With the southward extension of the Eastern Metropolitan (EM) bypass, accessibility of Baruipur has increased and rate of urbanisation has flourished at a faster pace engulfing the open spaces. Increase in built-up spaces and unplanned development in and around the municipality area has rendered Baruipur into a suburb of Kolkata. Development of such a peripheral area, developed to support KMC and presently under the impact of metropolitan expansion around KMC, currently suffers from loss of vegetation and water body, population increase and land surface temperature rise.

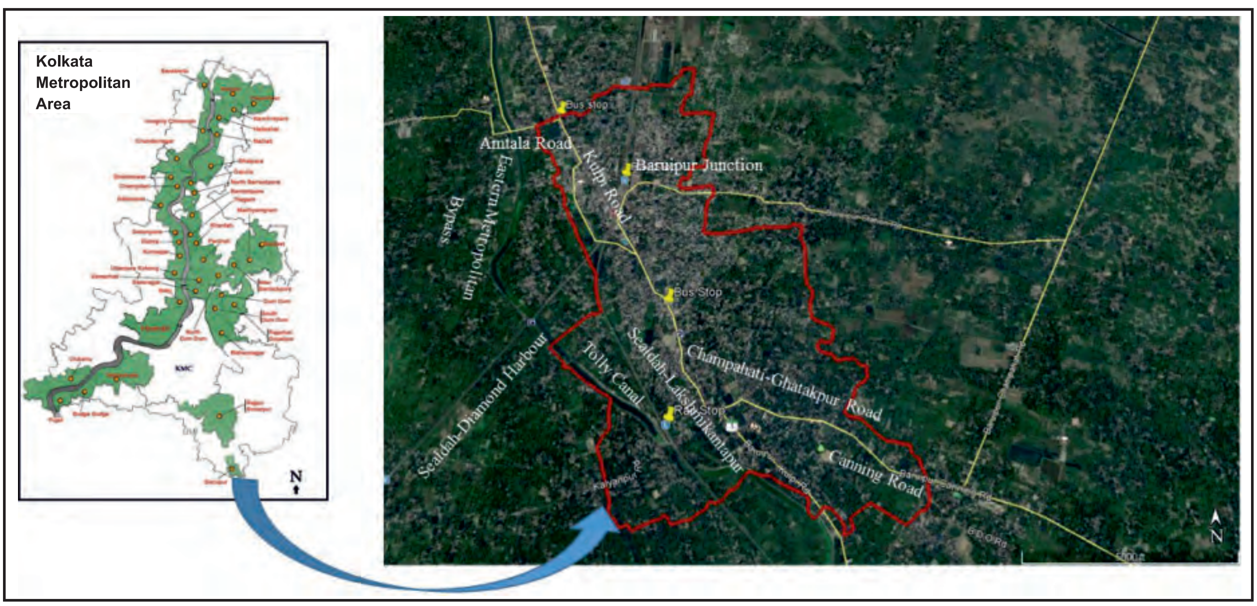
Lot of literature is available on change detection studies, however, studies on Baruipur are scanty. In this study, a freeware, FRAGSTATS, has been used to identify the splitting and land fragmentation using freely available high-resolution data that has been manually digitized and manually classified as well. A relationship on loss of vegetation and water body to LST has been drawn. The study area is also unique since this South Kolkata neighbourhood had drawn attention in recent times as substitute for Alipore district headquarters to Kolkata, as a prospective metro centre and as a prospective recipient of metro services. Urban growth pattern, direction of sprawl, land surface temperature, splitting and fragmentation of land use at Baruipur has been studied for a period of thirty years.

2. DATABASE AND METHODOLOGY

In step I, with the help of remote sensing data and GIS, study area is delineated. In step II, changes in LULC are detected. In step III, Shannon's entropy, class level and landscape level metrics are computed. These provide the urban growth pattern of the study area. Step IV studies the effect of urbanisation by deriving population and household maps from census data and LST scenario.

Baruipur municipality, divided into 17 wards, is located 27 kilometres south of Kolkata, West Bengal, India. It is located in between 22°39'N to 22°33'N latitude and 88°42'E to 88°46'E longitude, approximately and positioned at the extreme southern side of KMA on the banks of Tolly's canal. Baruipur is connected to Kolkata by Kulpi Road via EM Bypass. Other significant roads include Canning Road radiating from the south-eastern extremity and Amtala Road radiating from the north-western extremity (figure 1).

Figure 1: Study Area



Baruipur Junction railway station is connected to Sealdah railway station; one of the three major railway stations of KMA, located 25 kms away, by more than 80 pairs of suburban Electric–Multiple-Unit trains (https://indiarailinfo.com/station/map/baruipur-junction-brp/7850?tt=0). The railway station, situated at the intersection of Sealdah-Diamond Harbour and Sealdah-Lakshmikantapur sections of suburban railway lines, serves Baruipur and its surrounding areas. Accessibility provided by the Metro rail service, located within 7 km, is also a point of attraction of development of this area. Thus, connectivity of this area has drawn attention of the common people and the real estate builders alike. It is believed that an extension of metro rail, namely Airport-Kavi Subhas link upto Baruipur connecting Netaji Subhas Chandra Bose International Airport, Kolkata, approximately 34 km away (https://indiarailinfo.com/station/map/baruipur-junction-brp/7850), will further escalate the attraction potential and growth of Baruipur.

The present research uses multi-spectral and multi-temporal images, census data and field survey data as input. Multi-temporal satellite images of Landsat 5 Thematic Mapper™ for the years 1991, 2001, 2010, 2011 and Landsat-8 Operational Land Imager Thermal Infrared Sensor (OLI_TIRS), 2021, are downloaded from United States Geological Survey (USGS) Earth Explorer (https://earthexplorer.usgs.gov) official website.

Table 1 shows the detailed specifications of used satellite data. All the images, administrative maps, collected from administrative offices were registered in UTM, Zone 45 and WGS 84.

Table 1: Detailed Specifications of Imageries Used Here

Image	Date of Acquisition	Spectral Band	Thermal Band	Cell Size
Landsat 5 TM	02.02.1991	1,2,3,4,5,7		30m
	12.01.2001	1,2,3,4,5,7		-Do-
	24.01.2011	1,2,3,4,5,7		-Do-
	21.01.2010	2,3,4,5	Band 6	(120m) 30m
	06.02.2010	2,3,4,5	-Do-	-Do-
	11.04.2010	2,3,4,5	-Do-	-Do-
	23.12.2010	2,3,4,5	-Do-	-Do-
Landsat 8	03.01.2021	4,5,3,6	Band 10	(100m) 30m
	04.02.2021	4,5,3,6	-Do-	-Do-
	25.04.2021	4,5,3,6	-Do-	-Do-
	21.12.2021	4,5,3,6	-Do-	-Do-
	04.02.2021	1,2,3,4,5,6,7,8,9		30m

Image processing, subsetting (extracting a smaller area from a larger image) and supervised classification (categorizing pixels with supervised technique), accuracy assessment has been done in ERDAS Imagine 2014. Supervised classifications of Baruipur municipality, extracted from the downloaded images, for the years 1991, 2001, 2011 and 2021, has been conducted considering three classes – built-up area, vegetation and water body. In this municipality, fruit orchard and vegetable farming are very important landuse, and green area can be identified round the year.

Though vectorisation is time consuming and costly, still it is the most accurate way of data extraction of land use (McGargical, K., and Marks, B.J., 1995). In supervised classification, misclassification of pixels creates problem. Hence, this technique has been avoided for detail study. LULC maps for 2010 and 2020 have been generated by digitisation in ArcMap 10.2.1 for change detection with the help of freely available google earth images having high resolution new and historical image data. Thereafter, the data is being exported to ArcGIS as a.kml file and converted to.shp file. These maps classify agricultural land separately which give a detailed accurate picture of the municipality that helps in future policy delineation.

To compute Shannon Entropy, Fishnet (creating grid of any size) of rectangular cells, along with IDs have been generated in ArcGIS. Entropy and relative entropy values are computed for every cell. These values are incorporated in the map on the basis of their identification numbers (IDs). These maps reflect the growth pattern of Baruipur.

Yeh and Li (Yeh, A. G., Xia, and Li, X., 2001) used Shannon's entropy to measure the extent of urban sprawl. After extracting the built-up area, the ward has been divided into four parts taking the centroid of the ward area. Then Shannon's Entropy has been calculated to measure the degree of concentration or dispersion of built-up area among n (n=4) zones. It is calculated by

$$H_n = -\sum_i^n P_i * ln(P_i) \quad (1)$$

Here is the proportion of the variable (built-up area) in the ith zone (i= individual zone) and n is the total number of zones. The value of entropy ranges from 0 to 1. If the distribution is compact, the entropy value will be 0 or near zero. Mosammam (Mosammam, H. M., et, al., 2017) worked on relative Shannon Entropy, where,

$$H_n = -\sum_i^n P - ln(P_i) / ln n. \quad (2)$$

Relative or Normalized Shannon's entropy value is used to scale the entropy value from 0 to 1. If closer to 0, distribution is compact and if closer to 1, it implies a dispersed distribution or sprawling.

Classified raster data helps in analysing the landscape metrics at class level and landscape level with the help of open-source statistical software FRAGSTATS. It has been used to quantify the LU structure (McGargical. K. and Marks, B.J., 1995). Changing LU-structure results in changing landscape metrics (Sertel, E., et al, 2018). FRAGSTATS provides the fragmentation status, (Siti Yasmin, Y., and Muhammad, A. M., 2019) of the landscapes which helps in analysing the sprawling pattern of the area. To quantify landscape structure, classified raster data transferred to Geotiff format to use it in FRAGSTATS and.fcd files are prepared. Landscape metrics are calculated to understand the fragmentation of the built-up area expansion (Mithun, Sk., 2016, Herold M., 2003). The details of landscape metrics are provided in table 2.

Table 2: Property of Metrics

Metrics	Description	Units	Range
Class Level Metrics			
CA – Class Area	The sum of the areas of all urban patches, that is, total urban area in the landscape	Hectares	CA>0, no limit
NP - Number of Patches	The number of urban patches of each class.	None	NP≥1, no limit
LPI- Largest Patch Index	The area of the largest patch of every class		Percent
Precent Land - Percentage of Landscape	Sum of all patch areas divided by total landscape area multiplied by 100.	Percent	0< percent LAND≤100
Landscape Level Metrics			
SPLIT - Splitting Index	Total landscape area squared divided by the sum of patch area squared, all patches in landscape	None	1≤SPLIT≤number of cells in the landscape squared
LPI - Largest Patch Index	Percent of landscape of the largest patch	Percent	0<LPI≤100
NP- Number of Patches	Number of patches in the landscape	None	NP≥1, without limit, NP=1 when landscape has only 1 patch
TE- Total Edge	Sum of lengths of all edge segments involving the corresponding patch type	Meters	TE≥0, without limit

The derived landscape metrics helped in quantifying the spatial pattern of the Baruipur municipality. Quantified land use pattern and their changes over time, calculated from the images would help the planners. Eight metrics were considered. Class level metrics include CA, LPI, percent LAND, NP and landscape level metrics include SPLIT, LPI, NP and TE. CA and total area of the landscape becomes equal when entire image comprises a single patch. LPI shows the patch with which the landscape is covered, NP shows number of corresponding patch types. At landscape level SPLIT equals to 1 when landscape is covered by a single patch. SPLIT increases as the landscape is maximally divided. It means every cell will become a patch. LPI becomes 100 at landscape level when largest patch embraces the total landscape. It shows the dominance of class type in the area. NP does not show distribution of patches but shows fragmentation. TE includes landscape boundary area covering the edges. It shows the sum of the lengths of all edges in the landscape.

Census data of the population and number of households at the ward level has been accounted here to understand the relationship between changes in population and urban expansion.

Images of nearly same dates with 0 percent cloud cover have been used to extract LST and accounted to understand the changing temperature pattern in Baruipur. The thermal bands for Landsat 5 TM cells are resampled and cells of 120m are transformed into 30m. Same thing happened for Landsat 8 data. Cells of Thermal band of Landsat 8 are resized into 30m from 100m. Cloud cover increases temperatures at the surface of the earth by absorbing and trapping heat, released by the surface of earth, on it. Monsoons are also avoided as cloud cover distorts the thermal effect. No atmospheric correction was performed since the images used are cloud-free at the time of acquisition (Deng, C., et al, 2013).

LST is the radiative skin temperature of the land derived from solar radiation. Using the radiance rescaling factors provided in the metadata file, digital numbers of the images are converted to top of atmosphere radiance (at sensor) considering the thermal bands of the particular images. To calculate LST, formulae 1, 2 and 3 shown below have been adopted (Ayanlade, A., et al., 2021):

$$L_{\lambda} \frac{\left(LMAX_{\lambda} - LMIN_{\lambda}\right)}{\left(QCALMAX - QCALMIN\right)} \times \left(DN - QCALMIN\right) + LMIN_{\lambda} \quad (3)$$

Here, $L\lambda$ = Spectral radiance at the sensor

$LMAX\lambda$ = Spectral radiance scaled to in QCALMAX (Watts/(m^2 * sr* µm))

$LMIN\lambda$ = Spectral radiance scaled to in (Watts/(m^2 * sr* µm))

QCALMAX = Maximum quantized calibrated pixel value in DN

QCALMIN = Minimum quantized calibrated pixel value

The radiance is expressed as the top of atmosphere brightness temperature (in Kelvin) using the thermal constants provided in metadata file

$$TB \frac{K_2}{L_n\left(\frac{K_1}{L_{\lambda}} + 1\right)} \quad (4)$$

Where, TB = At-satellite brightness temperature in Kelvin (K)

$L\lambda$ = Spectral radiance in (Watts/ (m^2 * sr* µm))

K_1 and K_2 = Band specific thermal conversion constant from the metadata

Conversion of temperature from Kelvin to degree Celsius,

TC = TB - 273.15 (5)

In ArcToolbox, all calculations are done in Map Algebra. 8 individual images of nearly the same dates have been taken for the year 2010 as 4 cloud-free images of 2011 of the same period could not be gathered. 4 images of each set of 2010 and 2021 are averaged as individual image of any particular season do not satisfy the explanation of temperature change. Availability of more cloud-free images would give much better results. But unavailability of data from USGS became a constraint. Temperature distribution has been calculated in Microsoft Excel.

3. RESULTS AND DISCUSSION

KMC has grown linearly along the east bank of River Hooghly in the north-south direction. The northern part of KMC is near saturation because of its earlier unplanned urban growth. Westward expansion of KMC is negated by the presence of River Hooghly and the Ramsar site of East Kolkata Wetland stops legal eastward growth. Northbound expansion is delimited by the presence of settlements along the railway corridors. But the population density along the railway corridor to the southeast was low and presently show tremendous growth potential. Improved connectivity and expansion of the Metro Railway have paced this growth rate.

The built-up area of KMC has been progressing along the State Highway 1 (SH1), West Bengal, along Southeast towards Baruipur area and beyond. Analysed satellite maps for LULC for the years 1991, 2001 and 2011 clearly manifest this south-bound urban sprawl. The numeric outcomes of the change detection maps are provided in the form of transition matrix provided in table 3, showing the transitions from 1991 to 2001 and 2001 to 2011. The most prominent changeover happened from water body and vegetation to bare surface.

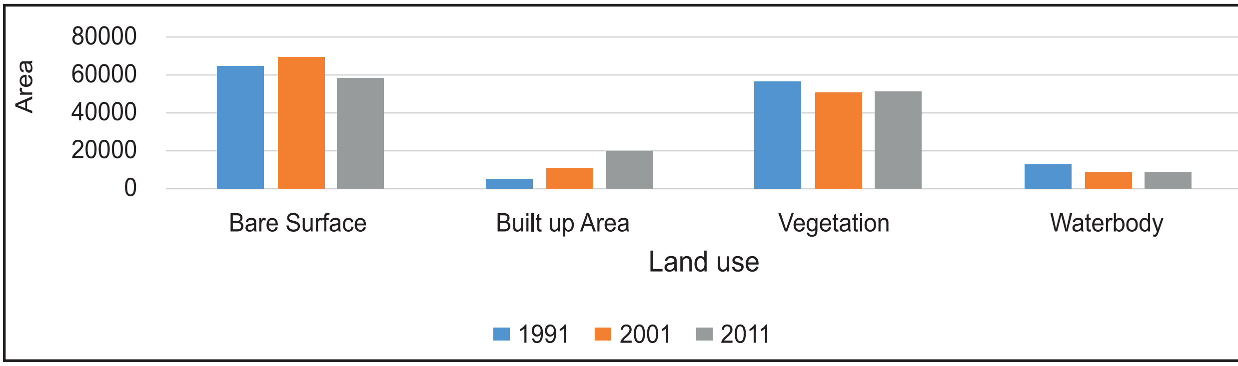
Table 3: Transition Matrix in Percentage Showing Land Conversion of KMC's South-Eastern Part from 1991 to 2001 and 2001 to 2011

		Land-Cover at Time 2001					Land-Cover at Time 2011			
Land-Cover in 1991	Nature of Land Cover	Bare Surface	Built Up Area	Vegetation	Water Body	Land-Cover in 2001	Bare Surface	Built Up Area	Vegetation	Water Body
	Bare Surface	83.28	5.71	9.65	1.36		74.83	10.22	12.57	2.37
	Built up Area	0.37	99.41	0.12	0.11		1.37	97.82	0.54	0.27
	Vegetation	19.07	2.11	75.22	3.6		9.47	5.15	83.32	2.06
	Waterbody	41.05	5.78	11.77	41.4		17.56	7.24	13.77	61.4

Table 3 may be interpreted thus, considering the first four terms in the first row, of the 100 percent of bare surface available in 1991, 83.28 percent remains bare in 2001, 5.71 percent has been converted to built-up area, 9.65 percent has been transformed into agricultural land and the remaining 1.36 percent was converted to water body.

KMC is expanding in area beyond its existing boundary and major push is reflected towards south which is reflected in the landuse distribution (figure 2). In these three time periods the main conversion of land is observed from water bodies to bare land that implies the scope for further conversion to more urban uses. Expansion of built-up area

Figure 2: Landuse Distribution in between KMC and Baruipur in Hectare (1991 - 2011)



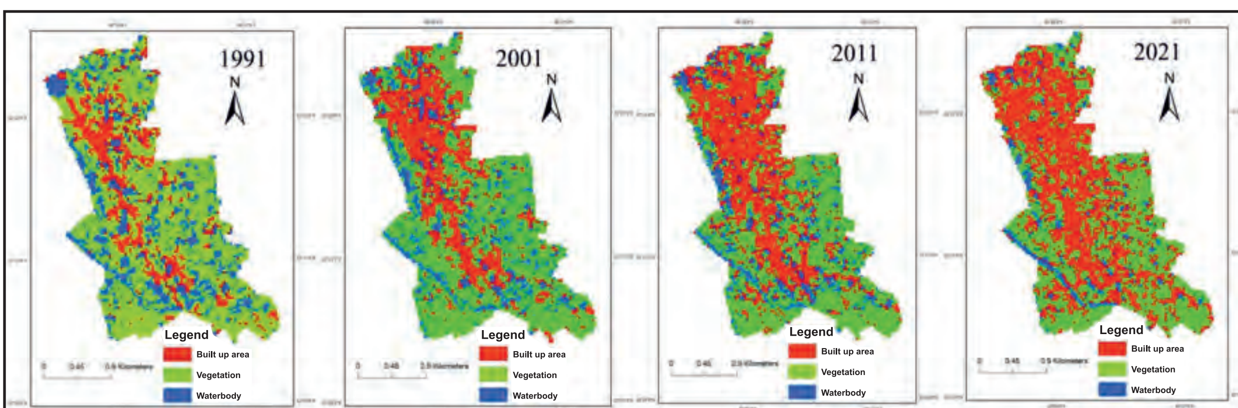
along SH1 or Baruipur-Kulpi Road towards south should be noticeable.

A large part of the area is covered by agricultural lands which coalesce with vegetation. Hence, increase in the share of vegetation is observed. Thus, bare surface has been considered as a landuse category instead of agricultural land.

Urban expansion of KMC towards south, conversion of bare surface, water bodies and vegetation into built-up area is quite evident. Since Baruipur is located on this path of expansion, its urban growth pattern, as a peripheral area of KMC, definitely needs to be studied.

Transformation of crop-fields to built-up areas is being noticed in many places. However, Baruipur claims special attention since it has been a potent source of vegetables and fruits that are being supplied to Kolkata and its neighbourhood. The transformation of agricultural lands to built-up areas has not only changed the job pattern, but, set the food supply chain in jeopardy and a challenge for the planners. From figure 3, distribution of lands in Baruipur Municipality shows that the built-up area has increased from 16.58 percent in 1991 to 47.70 percent in 2021 and water body and vegetation have decreased.

Figure 3: LULC Map of Baruipur - 1991, 2001, 2011 and 2021



	Area in Percentage			
Classes	**1991**	**2001**	**2011**	**2021**
Built-up area	16.58	27.60	38.88	47.70
Vegetation	61.57	53.30	47.20	45.00
Water Body	21.85	19.10	13.92	07.30

Accuracy assessments on the basis Google Earth imageries for the years 2001 and 2011 have been done. They are of 97 percent and 98 percent respectively. For 2001 and 2011 overall Kappa statistics are 0.9819 and 0.9819 respectively.

The change detection map in figure 4A shows main conversion from vegetation land to built-up area (yellow patch) which is noteworthy. Reduction in water body has considerable detrimental effect on the local environment of the study area. Spatial metrics have been derived for built-up area from these classified images to determine changes in spatial structure and monitor urbanisation.

Figure 4: Change Detection Map of Baruipur, Urban Growth of Baruipur

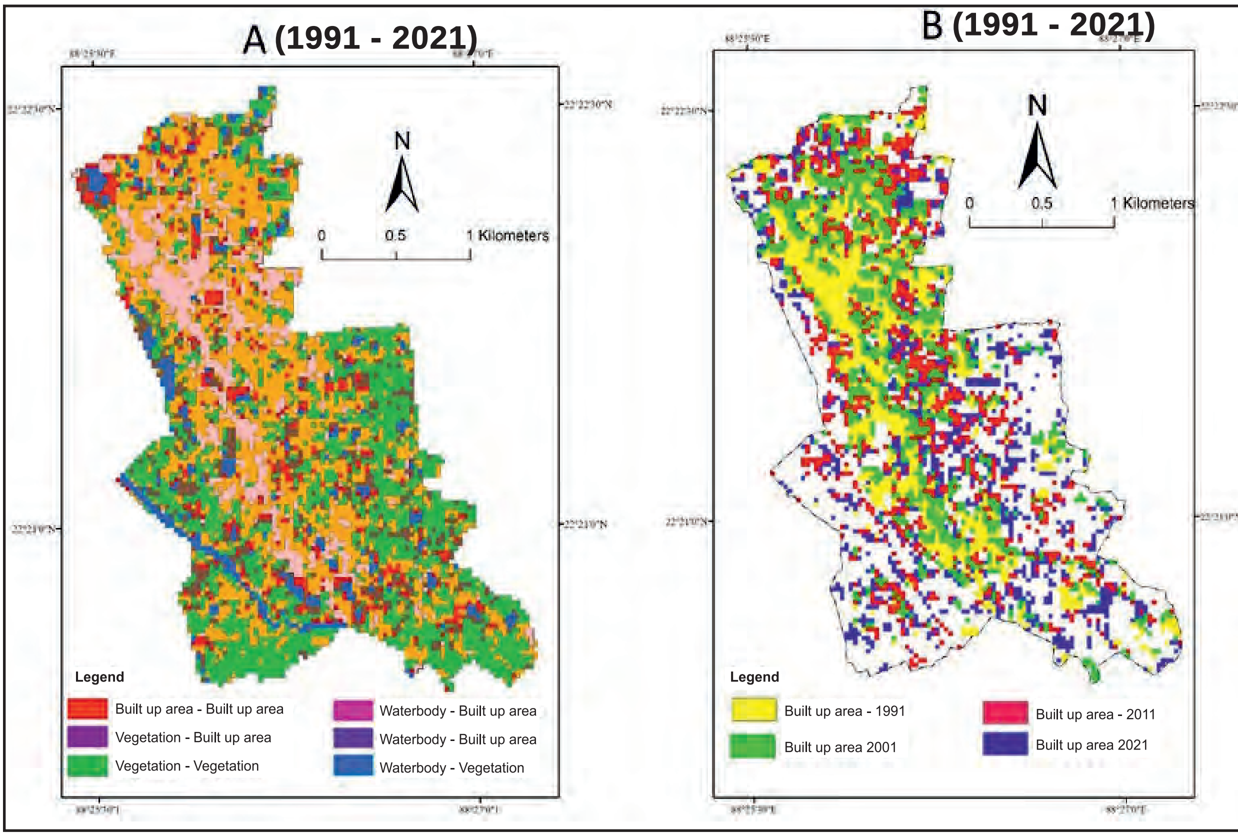
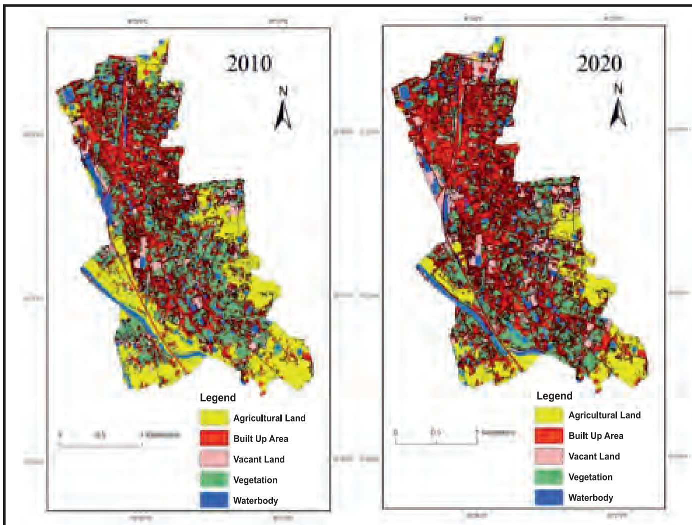


Figure 4B shows this urban growth between 1991 and 2021. Yellow colour denotes the distribution of built-up area in 1991. Northern part of the municipality is gradually getting saturated. Expansion of the built-up area by infilling and fragmenting the vegetation cover can be seen in north to south direction. The reason behind these changes or increment of urban space is the population increase and government planning. In the Comprehensive Mobility Plan, KMC, 2001-2025, Baruipur has been decided to be a Trans Metro City System where population has been projected at 3.0 million in 2025. To manage this population various plans have been taken for Baruipur, such as construction of flyover, extension of EM Bypass up to Baruipur, area wide traffic management and operation system, etc.

Extension of EM Bypass to Baruipur played a big role in providing a high-speed traffic corridor in the south to establish better accessibility in the south-eastern part of KMA and its adjoining vast hinterland. This road has helped in the movement of vehicles for the passengers and perishable commodities such as fruits, vegetables and milk, etc.

Detailed land use distribution maps of 2010 and 2020 have been prepared (figure 5) to ascertain the situation of vegetation. Since the maps are prepared manually by digitisation, vacant land, agricultural land and vegetation have been categorised separately. The problem of mixing of vegetation with agricultural land has been circumvented here. Landuse distribution shows that agricultural land, vegetation and vacant land have decreased in 2010 and 2020.

Figure 5: Land Use Map of Baruipur, 2010 and 2020



Land Use	2010	2020
Built Up Area	33.59	42.73
Vegetation	23.32	19.14
Vacant Land	11.68	10.80
Water Body	6.13	4.99
Agricultural Land	25.29	22.34

Note: Figures are in percent

Impact of vegetation loss and water body shrinkage on urbanisation have been studied in many places. In China, expanding urban areas are facing loss of vegetation (Zhang, Z., et. al., 2023); in Mexico, level of urbanisation is effecting plant communities (Meléndez-Jaramillo, E., et. al., 2023). Adverse impact of urbanisation on water body depletion (Beura, D., 2017), contamination and pollution (Vani, M., and Kamraju, M., 2016) have researched. Spatio-temporal changes in built-up area and subsequent conversion or encroachment upon vegetation and water body (Mitra, D., and Banerji, S., 2018) causes environmental degradation. Along with change detection, edge density, patch index, land fragmentation of the lands has been studied here that make the paper unique from others.

The yellow patches in the outer fringe of Baruipur Municipality and green patches in the central and southern part have steadily receded. But built-up area has increased from 33.59 percent in 2010 to 42.73 percent in 2020. Small patches of water bodies are shrinking.

Shifting of occupation towards non-agricultural activities (Mallik, G., 1990), increase in population (Census of India), southward expansion of KMC, urbanisation at the periphery are the root causes of this reduction in agricultural land.

The pattern of urbanisation can be understood by Shannon's entropy. The value calculated for Shannon entropy ranges from 0.00 to 0.17 for the grids 0 to 12. The value of built-up area for every grid (table 4) shows urban growth pattern. Values of the entropy ranges from 0 to 1. Here equals to 12 as area is divided into 12 grids. Other than grids 5, 8, 9, 11 and 12, relative entropies are close to zero, which indicates that the distribution of built-up area is compact at individual grid level. Half way mark of is considered as threshold.

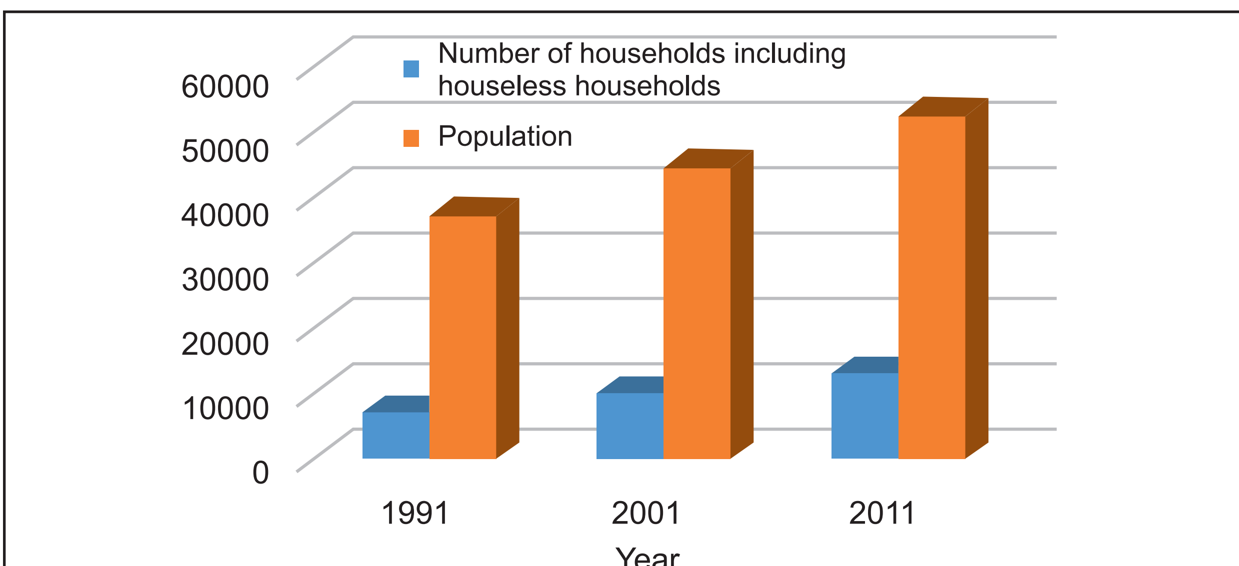
Table 4: Year Wise Relative Shannon Entropy

	Year Wise Relative Entropy					Year Wise Relative Entropy			
ID	**1991**	**2001**	**2011**	**2021**	**ID**	**1991**	**2001**	**2011**	**2021**
0	0.000	0.000	0.000	0.003	7	0.007	0.013	0.013	0.014
1	0.048	0.051	0.060	0.077	8	0.089	0.094	0.100	0.148
2	0.065	0.065	0.070	0.090	9	0.052	0.138	0.140	0.154
3	0.023	0.049	0.050	0.057	10	0.026	0.039	0.039	0.046
4	0.003	0.003	0.010	0.028	11	0.092	0.095	0.096	0.142
5	0.133	0.141	0.150	0.168	12	0.087	0.102	0.110	0.125
6	0.079	0.069	0.070	0.087	Total	0.833	0.859	0.908	1.139

Here is 1.11. Half of is equal to 0.55. Grids 9, 5, 11 and 12 locating in the central and northern part of Baruipur shows higher relative entropy value though below half way mark of threshold. The relative entropy value is lower in 1991 and increased to 2021. This indicates gradual urban growth in the area. Values show a compact and homogenous central part that has extended northward. Increased entropy values indicate increase in built-up area and expansion of urban sprawl. Overall entropy values for the whole municipality confirm a compact distribution of built-up area at grid level. But as time progresses, dispersed growth at Municipality level becomes evident. Total entropy value at municipality level shows that it is always sprawling as the total entropy value is always higher than the half-way mark of and crosses the upper limit of, i.e., 1.1. Calculated Shannon's entropy for built-up area definitely confirms that the urban growth is highly dispersing from 1990 to 2021 and need proper management to achieve sustainable development.

Figure 6 shows population growth and number of households from 1991 to 2011 in Baruipur. From 1991 to 2001 and from 2001 to 2011, the population growths were 19 percent and 18 percent, respectively. Whereas from 1991 to 2001, the increase of number of households including houseless households were 40 percent and 31 percent. Increasing number of population and household along with

Figure 6: Population and Number of Households in Baruipur



increasing entropy level indicate the horizontal growth of Baruipur. Since this municipality is located in the fertile agricultural land, this horizontal growth of the municipality needs to be monitored and properly managed, so that the area would not lose its characteristics.

Increasing entropy value shows that the area is developing and gradually expanding mainly because of real estate sector other than locational effect. Metric analysis at spatio-temporal scale helped in understanding the concentration, dispersion, fragmentation of built-up areas and other land uses mathematically. The result of FRAGSTATS at Class and Landscape level has been portrayed in eight metrics in figure 7A and 7B and a quantitative description of composition and arrangement of urban settings and growth has been shown in table 5.

Figure 7: Metrics: A. Class Level Metrics B. Landscape Level Metrics

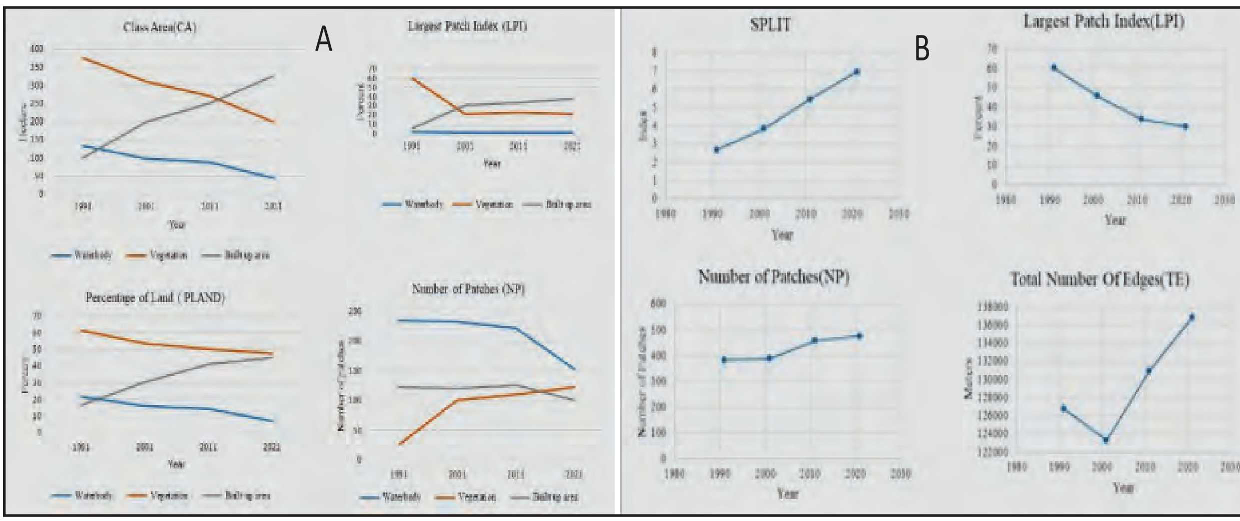


Table 5: Class Level and Landscape Level Metrics of Baruipur Municipality Showing Pattern of Landscape Changes

Class Level Metrics									
	1991	2001	2011	2021		1991	2001	2011	2021
CA					LPI				
Waterbody	133.11	97.92	88.11	44.19		2.2311	1.5514	1.5071	1.3298
Vegetation	375.03	311.12	270.72	200.26		60.36	21.52	22.90	21.72
Built Up Area	100.98	200.08	250.29	325.67		5.69	30.83	33.80	38.08
Percent Land					NP				
Waterbody	21.85	16.07	14.46	7.25		234	232	221	153
Vegetation	61.57	53.60	50.44	47.49		26	101	111	123
Built Up Area	16.58	30.33	41.09	45.26		123	120	126	101

Landscape Level Metrics

Year	SPLIT	NP	TE	LPI
1991	2.71	383	126810	60.36
2001	3.84	389	123330	45.83
2011	5.44	458	130920	33.80
2021	6.95	477	136810	30.07

CA shows the composition of the landscape. Table 5 shows that from 1991 to 2021, CA of built-up area increased while vegetation and water body have decreased. Percent land shows that the built-up area has increased from 16.58 percent in 1991 to 45.26 percent in 2021. Area under water body and vegetation has decreased from 21.85 percent to 7.25 percent and from 61.57 percent to 47.49 percent respectively. To accommodate has the increased population built-up area has increased. LPI represents the dominance. In 1991, the dominant class was vegetation. It had 60.36 percent LPI in 1991 and turned to 21.71 percent in 2021. In case of built-up area it was 5.69 percent in 1991 and became 38.07 percent in 2021. The vegetation was containing 26 NP at class level in 1990 which increased to 123 in 2021. It means fragmentation occurred for vegetation (LPI decreased). But in case of water body, NP decreased, representing lower CA. LPI of water body decreased due to filling and sometimes due to fragmentation of water bodies. Hence, number of water bodies are getting lesser and gradually replaced by built-up area at class level. Due to fragmentation, NP at class level increased mainly for vegetation. Due to urban expansion NP for built-up area increased.

SPLIT increases as the NP increases (Jaeger, J. A. G., 2000). Increment of SPLIT index at landscape level (table 5) with an increasing trend (figure 7B) more than threefold proves fragmentation of the area by scattering of patches. New built-up areas are added and vegetation areas are fragmented. SPLIT Index increased from 2.71 to 6.95 between 1990 and 2021. Along with NP at class level, TE, representing the increase of length of edges at landscape level, indicates porosity and fragmentation of the area. TE becomes zero when landscape has no edge, which means single patch will cover the entire area. The porous spaces are supplying areas for built-up purposes. Infilling of built-up areas makes the area more compact with urban space. Hence NP at class level of built-up area is reducing. LPI is the percentage of landscape that largest patch has. It approaches 0, when largest patch in the landscape gets smaller. Here patch size of the vegetation is getting smaller as LPI is decreasing from 60.36 (1991) to 21.72 (2021).

At class level LPI of built-up area is increasing and landscape level LPI is decreasing. This incident proves the losing dominance of vegetation and water body to built-up area. This confirms the urban expansion from 1991 to 2021. This happened mainly because of low land value, availability of larger land holdings, improved transportation, etc.

Fragmentation measuring the landscape division performs an important role in understanding the process of landscape degradation resulting in environmental and socio-economic change.

Figure 8: Shannon Entropy for Baruipur Municipality, from 1991 to 2021

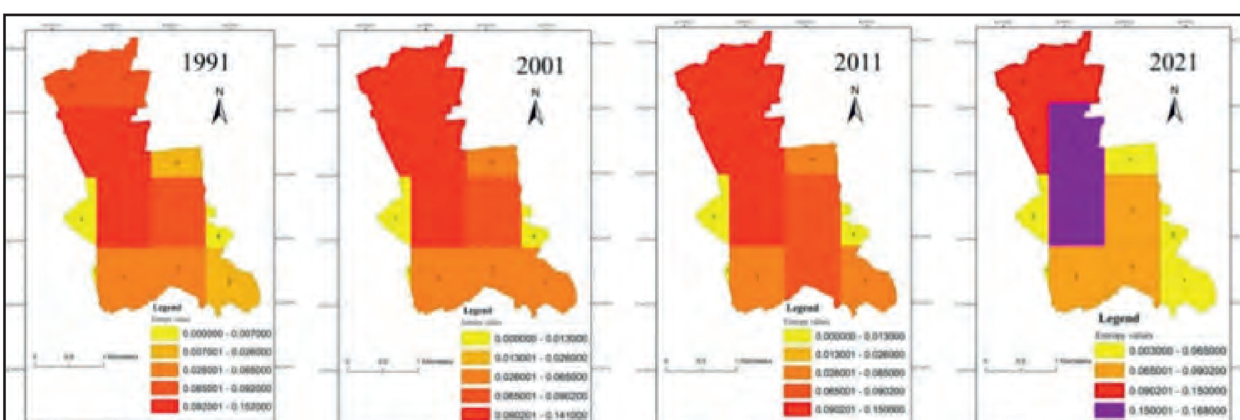


Figure 8 shows central Baruipur municipality had high entropy value as transportation junction of Baruipur lies here. This gradually extended to northward. In 2021, grid 6 and 10 show growth. Urban growth is higher in the north than the south. Gradually it extends southward.

Figure 9A shows that in 2001 the minimum population density of Baruipur was 37-44 persons per hectare which rose to 45-48 persons per hectare in 2011. Maximum density also rose from 142-183 persons per hectare to 183-186 persons per hectare. In wards 1, 3 and 14 population density rose from 142-183 persons per hectare in 2001 to 183–186 persons per hectare in 2011 (figure 9B). In 2001, under 142–183 persons per hectare were present in wards 1, 13, 17, 3, 14, 11 and 15. Household density has also been increased between 2001 and 2011.

Figure 9: Density Maps of Baruipur Municipality

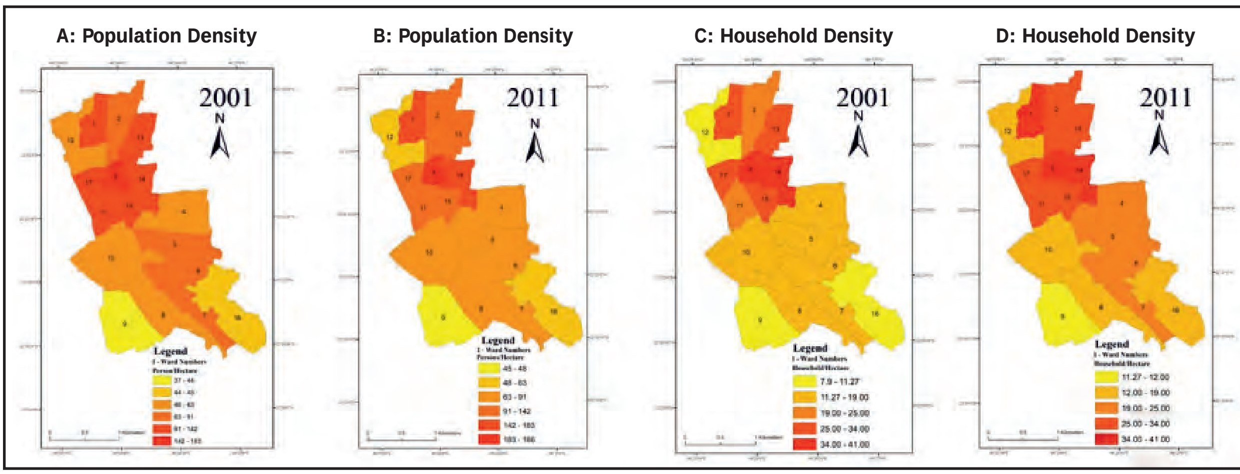


Figure 9 shows that ward 9 has the lowest density (population and household) since it mainly has agricultural land still its density is increasing. In case of ward 12, due to proximity to EM Bypass population and household density (figure 9C and 9D) increased, showing transformation of vacant lands into built-up areas. Same happened in ward 16 where too large amount of vegetated land has been converted into built-up area. This southward expansion is following the transportation network. Census reports along with eight metrics are showing spatio-temporal urban growth, all emphasizing urbanisation in Baruipur municipality, as well as a fragmented landscape because of urban expansion. Due to good connectivity of road wards 5 and 6 show increased household density with same range of population density (though population density increased). Champahati-Ghatakpur road is connecting Baruipur-Kulpi Road or SH1 with Baruipur Canning Road and SH3. This road connectivity helps in supply of perishable and non-perishable items to city. Ward 3 has the highest density for both the cases. It is due to the availability of all the facilities of road, railway station, and healthcare, etc.

As a result of built-form and artificial land coverage expansion, urban area experiences spatial variation of LST at micro level which contribute to the urban heat island effect to any city or area (Morabito, M., et al, 2016). LST is the surface temperature of the ground under the pixel scale with different fraction of surface type as different surface materials have different thermal properties. Present study searched the effect of urbanisation on LST in the said municipality. Images for two years 2010, 2021 have been taken.

Figure 10 and 11 are showing the LST maps of Baruipur for the years 2010 and 2021. Figure 12, derived from figure 10 and 11, shows the average LST maps for the years 2010 and 2021. Temperature interval taken is 1°C. Same degree difference for both the years 2010 and 2021 is maintained, however, the maximum LST varied.

Figure 10: LST Maps of Baruipur, 2010

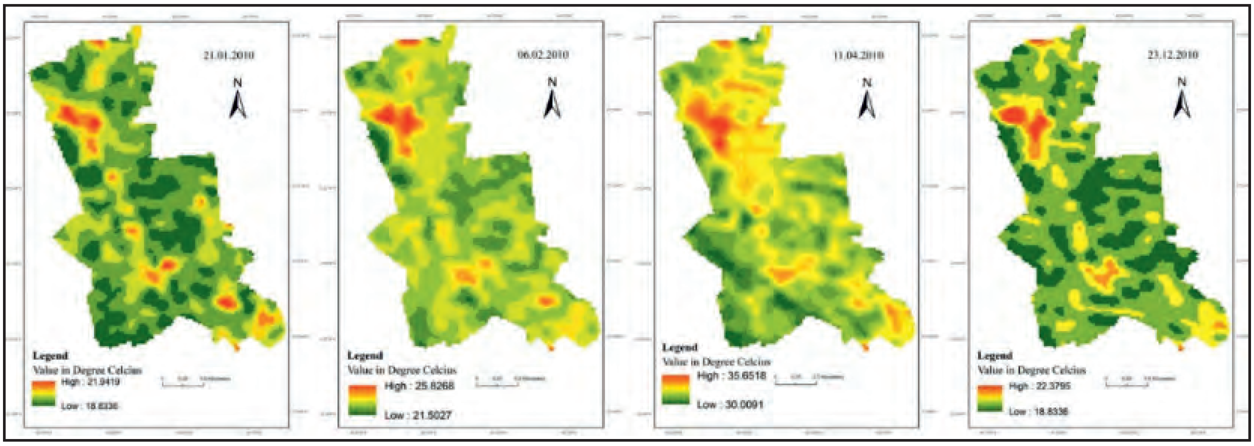
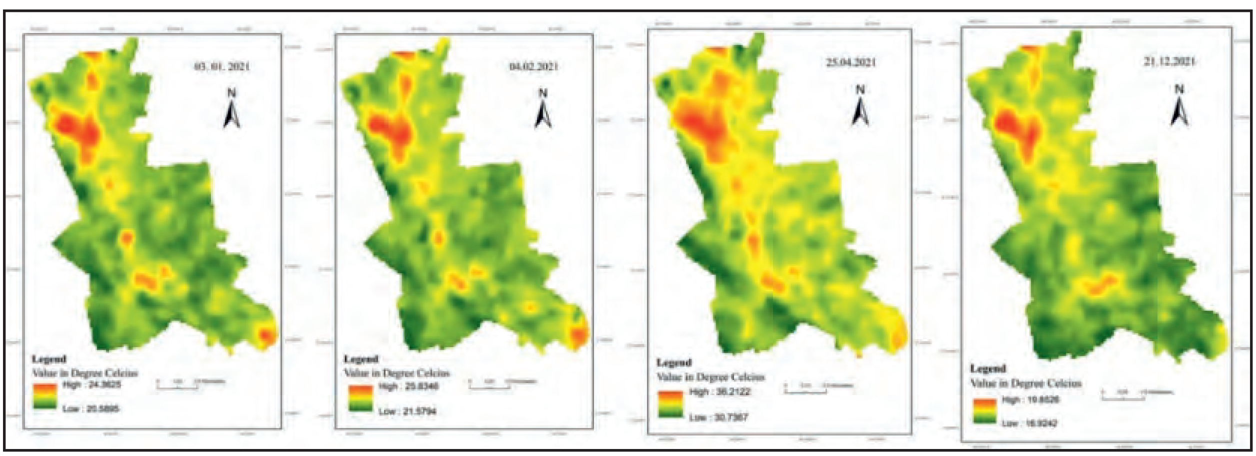


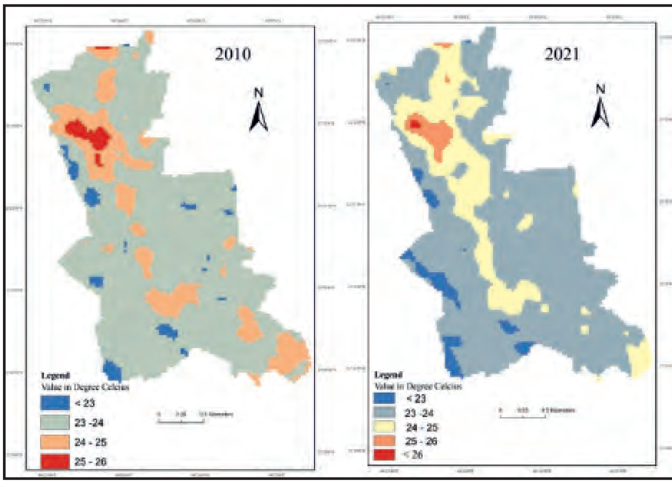
Figure 11: LST Maps of Baruipur, 2021



In figure 12 increase of yellow patch proves that the area covering temperature 24°C - 25°C has increased. The high temperature areas are covering the transportation features, large commercial areas, bare surfaces. Scene centre time is at 4.30 am GMT or 10.00 am. Hence, the LST calculated from the images are not the maximum temperature of the day. The area under 25° C to 26 ° C has increased. In 2010 the maximum temperature was 25.8 ° C. But in 2021 the maximum temperature rose to 26.4° C. A bare surface is present in this patch. The temperature can be controlled by planting trees along the boundary of the plot. The area under 25° C to 26 ° C is highly urbanised. This triangular area is covered by road and railway network. Dark coloured asphalt roads emit high temperature, release heat into the atmosphere and contribute to the LST.

A linear relationship is already found by the researcher between road development and increasing LST (Sameh, K. A., et al, 2022). In 2021 area under 22° C to 23 ° C has increased. This area mainly covers the part of Adi Ganga or Tolly Canal which is polluted by people, and its banks are illegally encroached. After

Figure 12: Average LST maps of Baruipur and Distribution of LST from 2010 to 2021 in Hectare 2010 and 2021



Temperature (^{0} Celsius)	Year	
	2010	2021
< 23	16.03	24.71
23 - 24	479.51	435.40
24 - 25	102.80	132.79
25 - 26	9.93	14.58
> 26	0.00	1.00

National Green Tribunal's (NGT) direction canal has been cleaned and illegal constructions are removed. The bench instructed Kolkata Police to be on surveillance (Times of India, 2017). Thereafter, the zone of under 23 ^{o}C has grown and that within 23^o C to 24 ^{o} C has shrunk, showing an efficient way to systematically combat urban heat.

4. CONCLUSION

The study shows a southward push of KMC resulting in fast urban growth and development of Baruipur municipality. Land fragmentation and undesirable filling of land parcels by built-up area, shrinkages of waterbodies and unwanted occupancies have been noticed. Increment of LST affects ecology, precipitation and humidity, etc., and needs to be monitored on a regular basis.

The three decisions, first, to shift the district headquarter from Alipore to Baruipur, secondly, the proposal to convert Baruipur into a Metro Centre by 2025, and finally, a plan to extend metro rail to serve Baruipur, has attracted various infrastructural facilities, that is transforming Baruipur into an attraction centre. Though, the first proposal was withdrawn, it triggered land acquisition by the realtors in various pockets. Fragmented availability of space hinders proper planning of facilities, which in turn forces more distance to be travelled, more congestion, fuel consumption and pollution load.

Following Atal Mission for Rejuvenation and Urban Transformation (AMRUT) policies is essential for sustainable development. Further, the following recommendations may be adopted:

Through proper hierarchical neighbourhood facility planning, establishment of compatible land uses with increased accessibility could be the primar y goal.

Adding to urban landscape, rain water harvesting, kitchen garden, and roof top cultivations be practised to create a cooler microclimate, as corroborated by the case of rejuvenating Tolly canal.

The agrarian land use must be relocated to barren lands and introduce improved agricultural techniques to substitute the supply of fruits and vegetables for the city.

Conservation of space earmarked for future infrastructural development must be planned on priority.

Continuous public sensitization and public-private joint governance is an efficient way of conserving the open spaces retained for future use and controlling air, water, noise and thermal pollution by keeping strict vigil on the waterbodies and greeneries too.

Limitation: This study has only observed the effect of LU changes on LST. Other environmental components such as rate of precipitation, ground water level, arsenic level and socioeconomic factors could have been studied. Overlaying the distribution of LST maps on LU maps and finding out the hotspots at micro-level will help in better planning.

REFERENCES

Ancha, P. U., Verinumba, I., Jande, J. A., and Abakpa, S. O., 2021, Assessment of the impact of urbanisation on forest resources in Otukpo local Government area Benue state, Nigeria, Journal of research in forestry, wildlife and environment, http://www.ajol.info/index.php/jrfwe

Ayanlade, A., Aigbiremolen, M, I., Oladosu, O, R., 2021,Variations in urban land surface temperature intensity over four cities in different ecological zones, Scientific reports, nature portfolio, 11:20537, https://doi.org/10.1038/s41598-021-99693-z

Beura, D., 2017, Depletion of water bodies due to urbanisation and its management, IERJ, Vol 3, Issue 6

Bhatta, B., Giri, B., 2012,Urban growth of Kolkata from 1980 to 2040: a remote sensing perspective, UGC sponsored state level seminar, Geographical appraisal of the city of joy's environmental wellbeing,

Borana, S. L., Yadav, S. K., Paihar, S. K., 2017, Analysis of urban sprawl pattern of Jodhpur city using landscape metrics, International Journal of Current Research, Vol 9, 11, 60392 – 60396,

Buyadi, S. N. A., Wan Mohd, W. M. N., Misni, A., 2014,Quantifying green space cooling effects on the urban microclimate using remote sensing and GIS techniques, FIG Congress, https://www.researchgate.net/publication/325170196

Chakraborty. S., and Shiva. Ji., 2022, A sustainable approach for the urban sprawl of Kolkata (Circa 1690-2020), In 19th International conference on Humanizing work and work environment, HWWE 2021, 1 December 2021 through 3 December 2021, Guwahati, http://raiith.iith.ac.in/id/eprint/9499

Chaolin, G., 2019,Urbanization: processes and driving forces, Science China earth sciences, 1351-1360, https://doi.org/10.1007/s11430-018-9359-y

Chong, C. H., 2017, Comparison of spatial data types for urban sprawl analysis using Shannon's entropy, A thesis University of South Carolina,

Deng, C., Wu, C., 2013, A spatially adaptive spectral mixture analysis for mapping subpixel urban impervious surface distribution, Remote sensing of environment, 2013, http://dx.doi.org/10.1016/j.rse.2013.02.005

District Census handbook, South twenty four parganas, 2011, Census of India, West Bengal, Series 20, Part XII-A

District Census handbook, South twenty four parganas, Village & Town directory, 2001, Census of India, West Bengal, Series 20, Part A & B

District Census handbook, South twenty four parganas, 1991, Census of India, West Bengal, Series 26, Part XII-A

Duveiller, G., Caporaso, L., Abad-Vinas, R., Perugini, L., Grassi, G., Arneth, A., Cescatti, A., 2020,Local biophysical effects of land use and land cover change: towards an assessment tool for policy makers, Land use policy, 91, 104382, https://doi.org/10.1016/j.landusepol.2019.104382

Getu, K., Bhat. H. G., 2021, Analysis of spatio-temporal dynamics of urban sprawl and growth pattern using geospatial technologies and landscape metrics in Bahir Dar, Northwest Ethiopia, Land use policy, 109, 105676

Ghosh, U., Bose. S., Brahamchari. R., 2018, Sundarbans living on the edge: climate change and uncertainty in the Indian Sundarbans, STEPS working paper 101.

Henderson, J. V., Wang, H.G., 2007, Urbanisation and city growth: The role of institutions, regional science & urban economics, 37, 283-313, doi:10.1016/j.regsciurbeco.2006.11.008.

Herold, M., Goldstein, N. C., Clarke, K. C., 2003, The spatiotemporal form of urban growth: measurement, analysis and modelling, Remote sensing of environment, doi:10.1016/S0034-4257(03)00075-0

Jaeger., J. A. G., 2000, Landscape division, splitting index, and effective mesh size: new measures of landscape fragmentation, Landscape Ecology, 15: 115-130

Jat, M. K., Garg, P. K., Khare, D., 2008, Modelling of urban growth using spatial analysis techniques: a case study of Ajmer city (India), International journal of remote sensing, DOI: 10.1080/01431160701280983

Jia. Y., Tang. L., Xu. M., Yang. X., 2019, Landscape pattern indices for evaluating urban spatial morphology – a case study of Chinese cities, Ecological indicators, 99, 27-37 https://doi.org/10.1016/j.ecolind.2018.12.007

Jiang, j., and Tian, G., 2010, Analysis of the impact of land use/ land cover change on Land Surface Temperature with remote sensing, Procedia Environmental science, International society for environmental information science 2010 annual conference (ISEIS), 571-575, doi:10.1016/j.proenv.2010.10.062

Kanga, S., Meraj, G., Johnson, B. A., Singh, S. K., PV Naseef, M.m., Farooq, M., Kumar, P., Marazi, A., Sahu, N., 2022,Understanding the linkage between urban growth and land surface temperature-a case study of Bangalore city, India, Remote sensing, https://doi.org/ 10.3390/rs14174241

Maheshwari, B., Purohit, R., Malano, H., Singh, V. P., Amerasinghe, P., 2014, Challenges and opportunities for peri-urban futures, In Book: The security of Water, food energy and liveability of cities, DOI:10.1007/978-94-017-8878-6_1

Mallik, G., 1990, Differential urban development in the south-eastern fringe of Calcutta metropolitan district a case study of Baruipur and Rajpur municipality, Thesis paper, University of Calcutta

Mallick., J., Kant, Y., Bharath, B. D., 2008, Estimation of land surface temperature over Delhi using Landsat-7 ETM+, J. Ind. Geophys. Union, July, Vol 12, No. 3, 131-140

McGargical. K., Marks, B.J., 1995, FRAGSTATS: Spatial pattern analysis program for quantifying landscape structure, United states department of agriculture, Pacific northwest research station, General technical report

McGranahan, G., and Satterthwaite, D., 2014, Urbanisation concepts and trends, Human settlements working, paper, IIED, http://pubs.iied.org/10709IIED

Megahed, Y., Cabral, P., Silva, J and Cactano, M., 2015, Land Cover Mapping Analysis and Urban Growth Modelling Using Remote Sensing Techniques in Greater Cairo Region –Egypt, ISPRS International journal of Geo-information, 4, 1750-1769, doi:10.3390/ijgi4031750

Mehebub. S., Haoyuan, Hong., Haroon, Sajjad., 2018, Analysing urban spatial patterns and trend of urban growth using urban sprawl matrix: A study of Kolkata urban agglomeration, India, Science of total environment, 628-629, 1557- 1566,

Meléndez-Jaramillo, E., Sánchez-Castilo, L., Martinez, M. T. de J. S., Sánchez-Reyes, U. J., 2023, Vegetation changes along an urbanisation and atmospheric pollution gradient in Mexico, Nature Conservation, 54:179-202, DOI: 10.3897/natureconservation.54.110257

Mithun, Sk., Chattopadhyay, S., Bhatt, B., 2016,Analysing urban dynamics of metropolitan Kolkata, India by using landscape metrics, Papers in applied geography, DOI: 10.1080/23754931.2016.1148069

Mitra, D., Banerji, D.., Urbanisation and changing waterscapes: a case study of New Town, Kolkata, West Bengal, Applied geography, 2018, https://doi.org/10.1016/j.apgeog.2018.04.012

Morabito, M., Crisci, A., Messeri, A., Orlandini, S., Raschi, A., Maracchi, G., Munafo, M., 2016, The impact of built-up surfaces on land surface temperatures in Italian urban areas, Science of the total environment, Vol 551-552, page 317-326, https://doi.org/10.1016/j.scitotenv.2016.02.029

Mosammam. H. M., Nia, J. T., Khani. H., Teymouri. A., Kazemi, M., 2017, Monitoring land use change and measuring urban sprawl based on its spatial forms The case of Qon city, The Egyptian Journal Of Remote sensing and Space Sciences, 20, pp.103-116.

Pham, M. H., Yamaguchi, Y., Bui, T. Q.,, 2010, A case study on the relation between city planning and urban growth using remote sensing and spatial metrics, Landscape and urban planning, 100, 223-230, doi:10.1016/j.landurbplan.2010.12.009

Ramchandra, T. V., Aithal, B. H., Sanna, D. D., Insights to urban dynamics through landscape spatial pattern analysis, International journal of applied earth observation and geoinformation, 2012, doi:10.1016/j.jag.2012.03.005

Richards, J. A., 2012, Supervised classification techniques, remote sensing digital image analysis, 247-318

Sameh, K. A., Macro, A. J., Antonio, J., Zhenhua, Z., Elsayed, S. M., Amr, A. H., Ahmed, A. E., Mohamed, K. A., Mahmoud, A. A., Laurence, J., Past and future impacts of urbanisation on land surface temperature in Greater Cairo over a 45 year period, The Egyptian journal of remote sensing and space sciences, 2022, https://doi.org/10.1016/j.ejrs.2022.10.001

Schilling. K. E., Jha. M. K., Zhang. Y., 2008, Gassman P. W., Wolter. C. F., Impact of land use and land cover change of the water balance of a large agricultural watershed: Historical effects and future directions, Water Resources Research, Vol 44, https://doi.org/10.1029/2007WR006644

Sertel, E., Topaloglu, R. H., Salli, B., Algan, I. Y., Aksu, G. Al, 2018,Comparison of landscape metrics for three different level land cover/ land use maps, International Journal of Geo-information, 7, 408, doi:10.3390/ijgi7100408

Shilpa. S. J., Planning strategies for the development of urban fringe of Trivandrum city: A case of Kazhakkoottam, Internationl journal of science and research, Vol10, Issue 7, July 2021.

Simon. D., Urban environments; Issues on the peri-urban fringe, Annu. Rev. Environ. Resource. 2008, 33:167-85

Singh, K. T., Ingh, N. M., Devi, T. T., 2022, A remote sensing, GIS based study on LULC change detection by different methods of classifiers on Landsat data, Innovative trends in hydrological and environmental systems, Lecture notes in civil engineering, Conference paper, 107-117

Siti Yasmin, Y., Muhammad, A. M., 2019, Evaluating spatial pattern among forest types in peninsular Malaysia using FRAGSTATS, SSPub

Solecki, W. D., Pope. C., Rosenzweig, G., Chopping, M., Goldberg, R., Polissar, A., (2004), Urban heat island and climate change: An assessment of interacting and possible adaptations in the Camden, New Jersey region, NJDEP.

Turner, B. L., Meyer, W. B., Skole, D. L., 1994, Global land-use/land-cover change: towards an integrated study, Royal Swedish academy of sciences, http://www.jstor.org/stable/4314168.

Vani, M., and Kamraju, M., 2016, Impact of urbanisation on lakes: A case study of Hyderabad, Journal of urban and regional studies, vol 5, no.1

Weith, T., Barkmann, T., Gaasch, N., Rogga, S., Strau, C., Zscheischler, J., 2021, Sustainable land management in a European context: a co-design approach, Sept 2020, Book, Springer ISBN: ISBN 978-3-030-50841-8, Chapter 5. DOI:10.1007/978-3-030-50841-8

Weng. Q., 2019, Impacts of urbanisation on land surface temperature and water quality, Techniques and methods in urban remote sensing, 267 – 306.

Wongsai, N., Wongsai, S., Huete, A.R., 2017, Annual seasonal extraction using the cubic spline function and decadal trend in temporal MODIS LST data, remote sensing, 9, 1254, http://dx.doi.org/10.3390/rs9121254

Yeh, A. G., Xia, Li, X., 2001, Measurement and monitoring of urban sprawl in a rapidly growing region using entropy, Photogrammetric Engineering & Remote Sensing, Vol. 67, No. 1, pp.83-90.

Zhang, Z., Zhao, W., Liu, Y., Pereira, P., 2023, Impacts of urbanisation on vegetation dynamics in Chinese cities, Environmental Impact Assessment Review, 103, 107227, https://doi.org/10.1016/j.eiar.2023.107227

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Comprehensive Mobility Plan, 2001-2025, Kolkata Metropolitan Area. chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://kmda.wb.gov.in/upload_file/file_doc/COMPRIHENSIVE_MOBILITY_PLAN.pdf (seen on 30.08.2023 at 17:54)

Times of India, 2017, https://timesofindia.indiatimes.com/city/kolkata/ngt-orders-central-agency-to-locate-missing-adi-ganga-links/articleshow/56841715.cms, seen at 12.09, 01.09.2023

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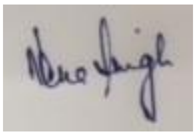
This is to certify that a research paper titled ***Multi-layer perceptron neural network and Markov chain model for urban growth prediction – A micro-level case study*** jointly authored by **Ruma Pal, Research Scholar, Department of Civil Engineering, Prof. Arup Guha Niyogi, Dept. of Civil Engineering, and Prof. Jayita Guha Niyogi, Dept. of Architecture, at Jadavpur University,** has been accepted for publication in **Vol. 47, NO. 1, June 2025** issue of the journal **Population Geography (ISSN 0256-5331), a UGC-CARE listed journal.** Ms **Ruma Pal** is the corresponding author.



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From the Editor's Desk

In the first issue of 2025, the *Population Geography* journal features articles focused on various aspects of population, as diverse in thematic connotation, subject treatment, and focus areas as possible. These articles examine the attributes and activities of specific groups of people across different regions of the country. Some studies utilise secondary data, particularly Census data, which is limited to the year 2011.

A study examines the performance of political parties in an assembly constituency in Haryana, as well as the transactional and non-transactional factors that influence voter behaviour. In any election study, it is crucial to understand the elements that shape voting behaviour.

An article explores interstate labour migration to South India, highlighting that younger migrants seek employment, while the labour force is trending towards seasonal and informal work. Another study on Mysuru city examines the impact of migration on individual well-being, suggesting that understanding these dynamics can help policymakers and migrants tackle challenges and promote urban growth and integration.

An analysis of 20 community development blocks in Puruliya district reveals that agricultural workers are increasingly diversifying into non-agricultural jobs. Despite challenges, this trend holds promise for generating resources and creating jobs, which could potentially improve living standards in the rural economy.

One study highlights disparity in maternal healthcare access in Punjab, particularly among scheduled castes, and calls for improved education and outreach. Another one from West Bengal shows higher undernutrition rates in Scheduled Tribe children, underscoring the need for targeted education and better healthcare access.

An assessment of rapid urbanisation in a peripheral area of the Kolkata Metropolitan Corporation (KMC) focuses on changes in land use and predicts trends up to 2040. It highlights the need for detailed micro-level planning, phased implementation, conservation of designated spaces, and continuous monitoring to mitigate negative impacts.

Highlighting disparities in development levels in the Jalpaiguri and Alipurduar districts, a comprehensive approach to human resource development is essential, emphasising the need for proactive measures and diagnostic plans to achieve balanced regional development at the grassroots level.

Haryana has experienced a significant increase in the number of higher education institutions, including colleges and universities, particularly since 1991, largely due to private investment. However, some districts still lack these educational institutions.

An article explores everyday Hinduism and local sacred sites, highlighting that Hindu householders often visit these places throughout their lives. A survey in five villages in Haryana suggests that understanding grassroots Hinduism is crucial for grasping how the religion is practised by the masses in India.

Lastly, we deeply appreciate the reviewers' support in this endeavour. Their keen insights, interventions and timely delivery are gratefully acknowledged and appreciated.

Nina Singh

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CONTENTS

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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

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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

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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.

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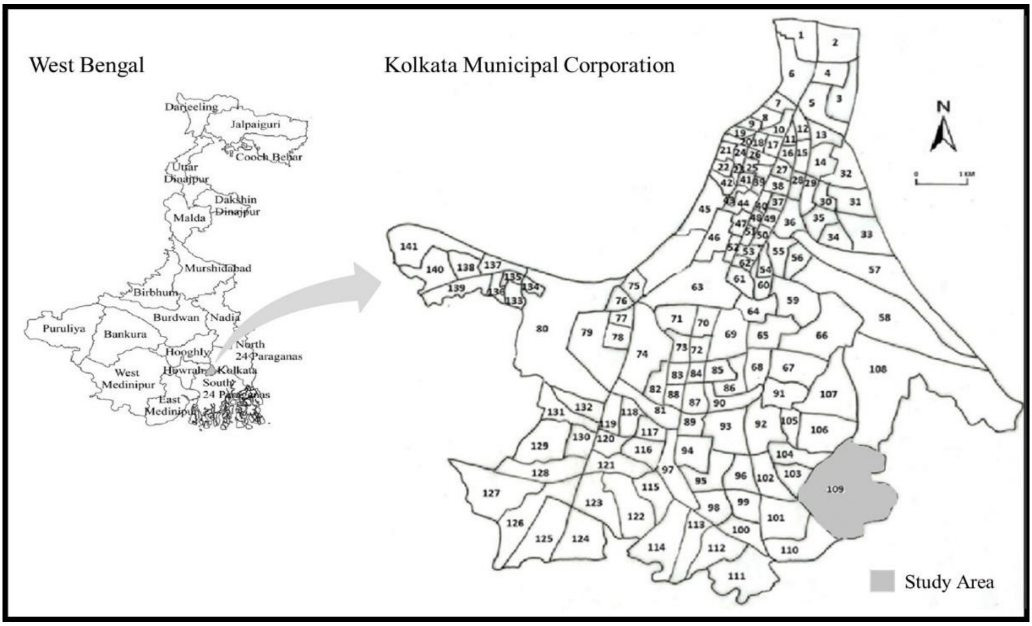
Figure 1

Location map, Ward 109, Kolkata Municipal Corporation

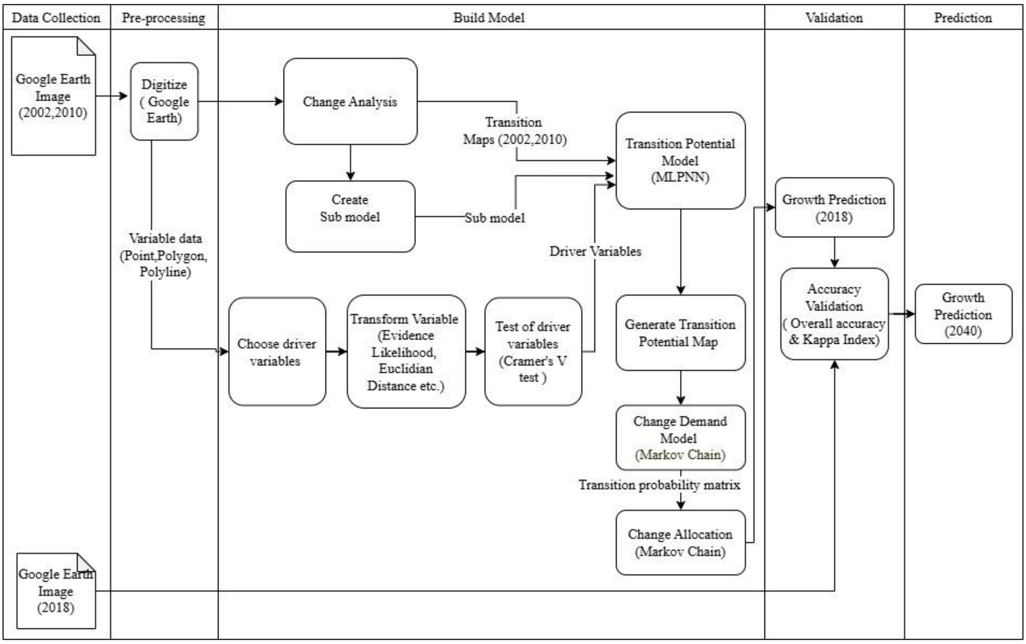


For land planning, the LCM is a method for predicting changes in land use. It maps future change scenarios using historical land cover change maps and empirically models the relationship between land cover transitions and explanatory variables (Eastman & Toledano, 2017).

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

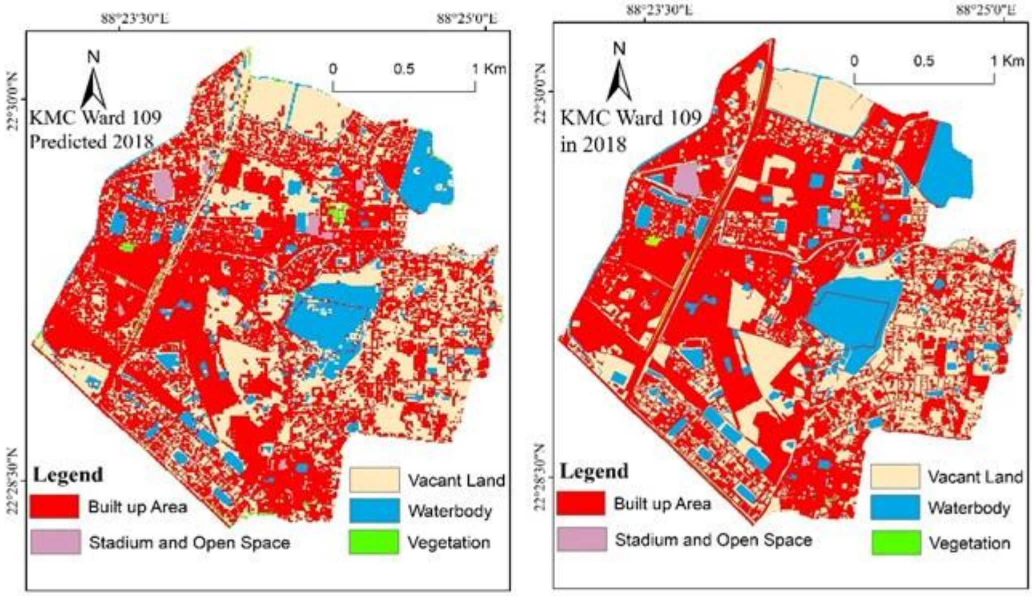


Table 5

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

		Reference data						
Classified data		Built-up area	Vacant land	Water body	Vegetation	Stadium and Open Space	Total	User's accuracy
	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%		

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

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

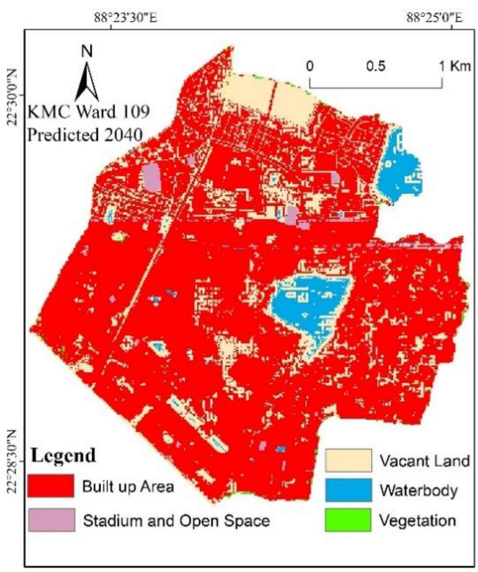
Accuracy assessment (Table 5) shows the model's acceptability. Hence, after validation, forecasting was done for the year 2040 (Fig. 4).

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

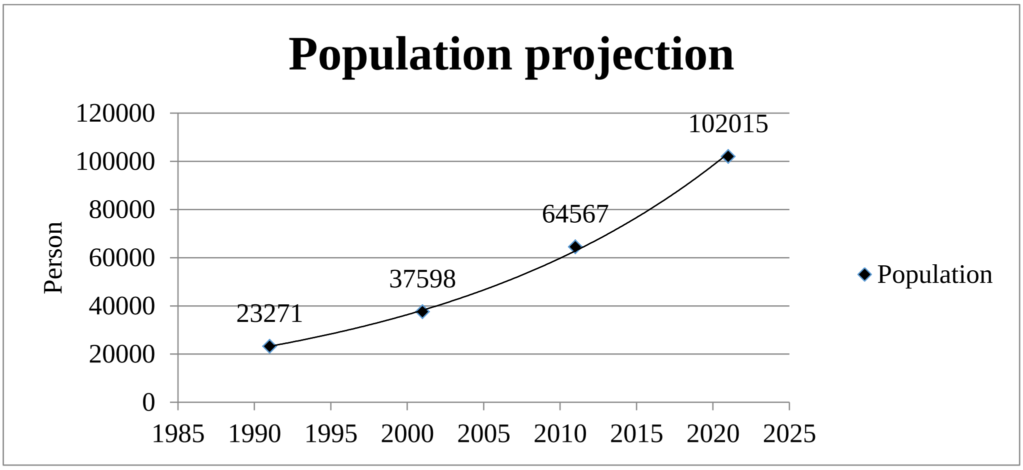
Predicted Land Use of 2040 for KMC Ward 109



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

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