POPULATION GEOGRAPHY
ISSN 0256-5331 Volume 47(2) December 2025

Micro-Level Population Forecasting and Built-up Area Modelling: Durgapur, West Bengal

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To cite this article: Chatterjee, S., & Das, A. (2025). Micro-level population forecasting and built-up area modelling: Durgapur, West Bengal. *Population Geography*, 47(2), 17–36.

Abstract

The implementation of micro-level planning depends on the availability and use of local resources, such as land ceilings, distribution, surplus, and a region's carrying capacity. Therefore, spatio-temporal modelling of land use, urban growth, and expansion is crucial to support decentralised planning. The aim is to model urban growth by projecting future populations for 2021, 2031, and 2041 at a micro-level and predicting built-up expansion through 2032. For this, six trend extrapolation methods were compared: Simple Linear, Simple Exponential, Simple Geometric, Constant Share, Shift Share, and Share of Growth. Built-up areas were forecasted using Artificial Neural Networks within a GIS environment. The trend extrapolation methods yielded satisfactory results, with the Simple Linear and Constant Share methods displaying lower percentage errors. The Durgapur Municipal Corporation projected the highest populations for 2021 (644,441), 2031 (701,662), and 2041 (744,881). Spatial modelling indicates a total increase in built-up area of 39.75 sq. km between 2017 and 2032, with the largest rise in the Faridpur-Durgapur block (25 sq. km), followed by Andal and Pandaveswar. Trend extrapolation methods are a practical approach for small-area total population forecasting. The built-up area model forecasts significant growth from 2017 to 2032, with Durgapur and Andal emerging as population hubs. This research addresses gaps in small-area forecasting studies by examining methodological approaches in data-scarce environments and exploring the urban dynamics of an emerging centre in a developing country. The study aims to raise policymakers' awareness of the rapid expansion of unplanned settlements surrounding the Durgapur region.

***Keywords*:** Microlevel population forecasting, trend extrapolation, built-up prediction modelling, artificial neural network

Introduction

The pivot of any planning and policymaking is the development of the people. National and state-level planning, also known as sectoral, macro-level, or regional planning, focuses on broader goals, e.g., the allocation and utilisation of resources at the state and district levels. Sectoral

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Article:
Received: 16.11.24 Reviewed: 06.06.25 Accepted: 01.07.25

planning is set at the top level and flows down to a specific administrative level, e.g., state or district level. (Mishra et al., 2000, p. 43). Whereas micro-level or decentralised planning commences at the grassroots level. It focuses on the people, the most important factor for the development (Mishra et al., 2000, p. 43) and strengthens the weak aspects of macro-level planning by linking with sectoral goals. Local-level resource utilisation, emphasising local problems and people's participation, not only enhances infrastructure but also reduces the cost of implementing the plan by minimising the scope for corruption at different levels. Besides, the ease of implementation of the plans is another factor (Jana, 1999). In India, agriculture is a significant economic activity, and the majority of the population lives in rural areas. Centralised planning does not appear effective in such a structure. (Majumdar, 2003). Microlevel studies are also necessary for cases involving changes to block- or district-level administrative boundaries over time. In that scenario, it is best to select more micro-level administrative units, such as census tracts, towns, and villages. Implementation of micro-level planning depends on resources and their utilisation, i.e., land ceiling, land distribution, surplus, and local resource potential. Hence, modelling land-use distribution, urban growth, and expansion in the spatio-temporal domain is necessary to support decentralised planning. This study combines the geographical and statistical components of population expansion, and the reference framework it provides will be used for spatial, micro-level, decentralised planning.

Durgapur city, one of India's largest industrial hubs, began to evolve between 1955 and 1960, with the establishment of numerous public- and private-sector enterprises. Hence, the city is an Industrial city based on its functional characteristics. The most dominant factor of population growth or formation of settlement patches at urban centres and their peripheral areas can be attributed to the development of industries and mines over the years (Chatterjee & Sarkar, 2018). Being part of the Damodar Valley and the Chota Nagpur Plateau, it possesses enormous mineral resources, especially coal. The region possesses excellent economic prospects, even though the country's first shale gas reserve was recently discovered by the Oil and Natural Gas Corporation of India (ONGC) in the region (Offshore energy, 2011). Since the emergence of the urban centres, the region has witnessed a rapid growth of industries, mines, settlements and other built-up areas; consequently, that rapid development has brought a considerable amount of environmental degradation associated with the same (Chatterjee & Sarkar, 2018). Therefore, it is necessary to assess the region's sustainability through future predictions and simulations. From a methodological perspective, this study also strengthens the applicability of the simple trend extrapolation method and ANN for micro-level population forecasting and built-up area modelling.

Literature Review

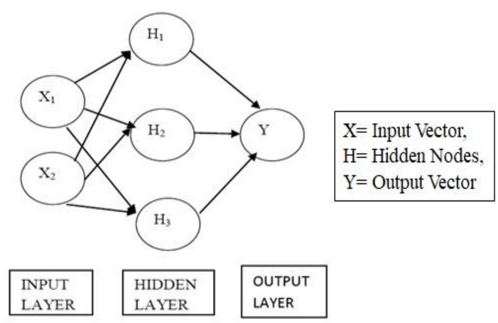
Population projection is the numerical output of a process, subjective or objective, based on assumptions about the future population (Isserman & Fisher, 1984; Keyfitz, 1972). A forecast is a type of projection that produces an almost accurate prediction, according to the analyst. Unlike projections, forecasts are judgmental in nature (Murdock, 2019; Smith et al., 2013, p. 3). Small-scale area projection is becoming increasingly important because it enables detailed planning, such as deciding where to build new schools, hospitals, and roads, whether to increase power plant output, and how to assess the environmental impact of population growth. Small-scale forecasting is often avoided due to a lack of data, the tedious process of collecting, sorting, tabulating, analysing, and presenting data. For example, even in a village-level study, a small-scale area may encompass many villages, significantly increasing the workload. Additionally, population size presents another challenge. However, when block- or village-level boundaries change frequently, micro-level forecasting becomes essential to address these issues effectively.

The choice of forecasting methods depends on factors such as population size, growth pattern, time horizon, resources, and data availability. Some techniques focus solely on the total population, while others include elements of population change, such as age-, sex-, and race-specific births, deaths, and migration. For projecting the total population, simple extrapolation methods such as linear, exponential, shift-share, and share-of-growth often suffice, especially for short- to medium-term periods. More advanced methods, like cohort-component models, require extensive data, including details on births, deaths, migration, and demographic structure. Structural models require data on both explanatory and dependent variables, whereas urban systems models rely on specifics such as vacant land, zoning laws, employment, transportation, and related factors. Basic trend extrapolation and ratio methods only need total population figures from two points in time (the latter for the constant-share method). Nonetheless, at national, state, and multi-regional levels, the cohort component method is generally regarded as the "gold standard." However, the data required for this model across many small areas can be substantial and often unavailable. Typically, the more complex, accurate, or comprehensive an approach is, the less precise it may be compared to simpler methods. Although advanced techniques can provide more detailed insights, they often lead to larger errors. From a research perspective, forecast accuracy is crucial and is a key factor in selecting a forecasting method. However, it is not the only consideration; utility, timeframe, costs, and ease of implementation also influence its suitability. Accuracy can be evaluated through bias (average percentage difference) and precision (algebraic error). MALPE (Mean Algebraic Percentage Error) assesses bias by balancing positive and negative values, while MAPE (Mean Absolute Percentage Error) is the most widely used for evaluating population forecast accuracy. Overall, MAPE is generally preferred for population forecasting and accuracy assessment over other error metrics.

Given the current context of population growth, planners and city administrators must understand future scenarios using suitable forecasting and predictive methods. A model is a simplified representation or abstraction of reality. In contrast, simulation can be defined as the imitation of a real-world process or phenomenon (Banks et al., 2001). Simulations help us forecast the behaviour of systems over time, enabling us to anticipate the future occurrence of these phenomena. The application of ANN is evident in various fields of earth science, such as examining land-use patterns across border regions, modelling the spatial distributions of rainfall, land surface temperature, and urban growth, and predicting LULC. Cellular automaton combined with Markov chain modelling is another emerging technique in LULC modelling within the GIS environment (Yirsaw et al., 2017). The Artificial Neural Network (ANN) has become a proficient tool for analysing changing land-use patterns in an area. ANNs, or neural networks, are a specialised branch of Artificial Intelligence that offers advantages over traditional statistical modelling (Gardner & Dorling, 1998; Lu et al., 2012). ANNS resemble the structure of interconnected neurons in the human brain, where nodes (neurons) in the input layers connect to nodes in the hidden layers, ultimately forming an output node (Figure 1a). ANNs have proven to be essential tools for pattern recognition and function approximation (Luk et al., 2001). Several types of modelling tools are available, but justifying their use can be difficult. Therefore, validation and calibration are vital to any analysis.

Figure 1a

The Basic Structure of an Artificial Neural Network (ANN)



This study aims to examine changes in built-up and non-built-up areas of three blocks in Paschim Bardhaman District: Faridpur, Andal, and Pandaveshwar, in relation to the area's population dynamics. Population growth and the expansion of built-up areas are strongly linked in many regions worldwide. The area's population was estimated using a comparative analysis of six trend extrapolation methods, selecting the most accurate one. A forecast for future land use and land cover (LULC) in 2032 was produced by applying the Cellular Automata-artificial neural network (ANN) technique within a GIS environment. Landsat images from 1987, 2002, and 2017 were sourced from the USGS website at 15-year intervals. These images were classified into two main categories: built-up and non-built-up, for each respective year. A projection for 2032 has also been developed.

The Artificial Neural Network (ANN) has become an effective method for analysing the changing land-use patterns of an area. ANNs, or neural networks, are a specialised branch of Artificial Intelligence that provide advantages over traditional statistical modelling (Gardner & Dorling, 1998; Lu et al., 2012). ANNS resemble the structure of interconnected neurons in the human brain, where nodes (neurons) in the input layers connect to nodes in the hidden layers, ultimately forming an output node (Figure 1a). ANNs have proven helpful for pattern recognition and function approximation (Luk et al., 2001). Several modelling tools are available, but their justification can be challenging. Therefore, validation and calibration are vital for any analysis.

Materials and Methods

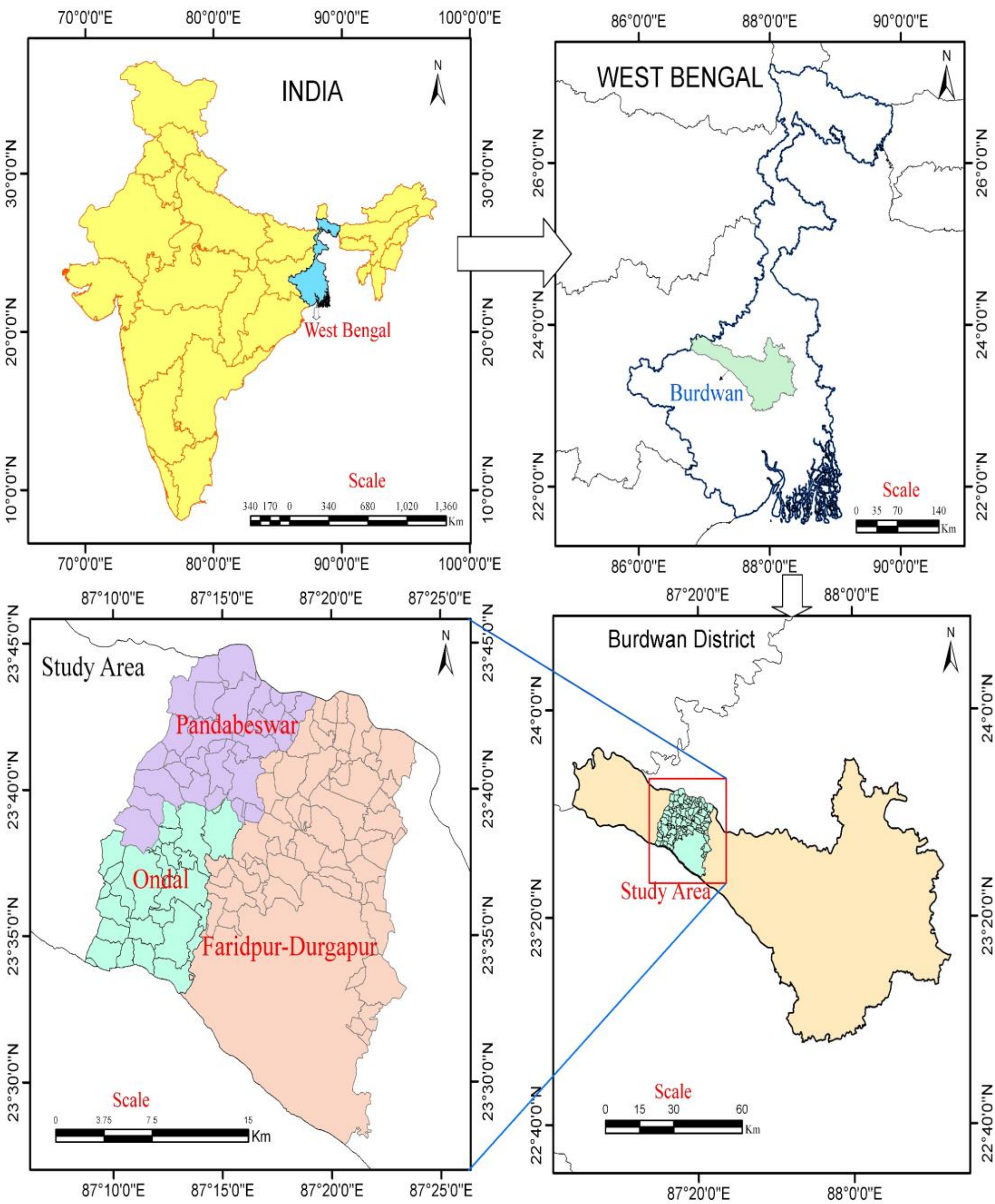
Study Area

Three Community Development (CD) blocks in Burdwan district, namely Faridpur-Durgapur, including Durgapur Municipal Corporation (DMC), Andal, and Pandabeswar, have been selected for the study. Forecasting has been conducted at the micro-level, i.e., villages, towns, municipal corporations, and municipalities, with a total of 114 Micro Administrative Units (MAUs) in these three blocks, covering approximately 495.5734 sq km. These MAUS have been designated as the study area (Figure 1). Industrial development has been the primary driver of population growth in the region; therefore, all the MAUs are either within or adjacent to the Durgapur Industrial belt. The region serves as a transition zone between the Chhotanagpur Plateau and the Ajay-Damodar-Darakeswar Plain.

Therefore, both the alluvial plain and the dissected denudational plateau, known as the Rarh region, are visible in the study area, interwoven with hillocks, mounds, and low-lying valleys. The overall slope of the study area is gentle, descending from west to east, with the highest elevation of 163 m above mean sea level (MSL) at the Sonpurbajari coal mine area and the lowest of 32 m MSL at Damodar.

Figure 1b

Location and Extent Map of the Study Area



Source: Reproduced from general administrative maps & police station maps

Figure 1c

The Flow Chart of the Methodology Followed by the Present Study

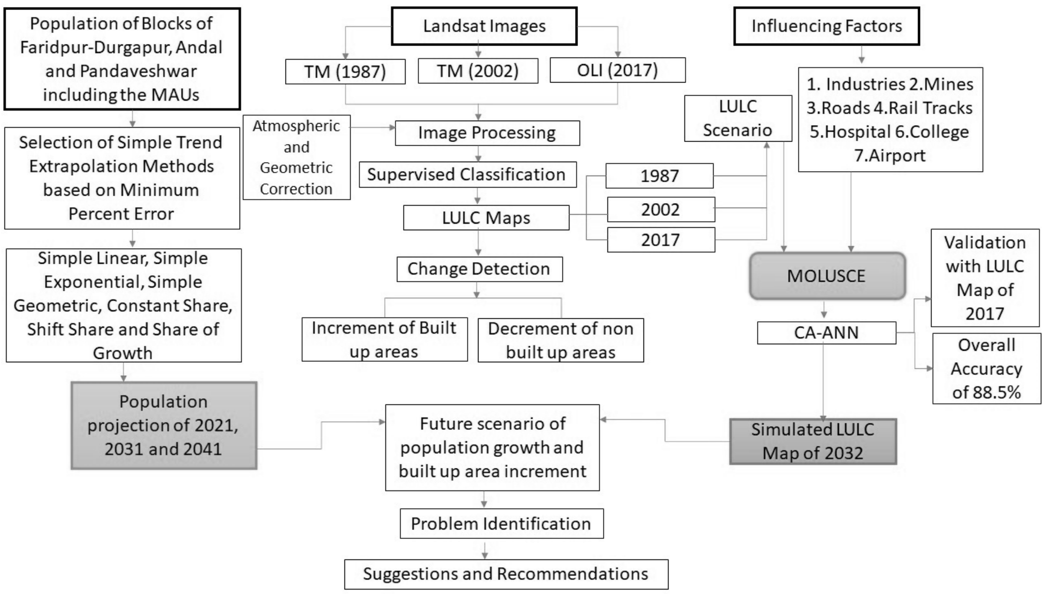


Table 1

Decided Parameters for Population Forecast

Base year	Launch year	Target years	Base period (#Years)	Projection horizons (#Years)	Projection interval (#Years)
1961	2011	2021, 2031, 2041	50	10, 20, 30	10

Source: Determined by the author

Forecasting Future Population

Since the population forecast depends on the trend of population growth (Smith et al., 2013), such as linear, exponential, geometric, or growth similar to that of the larger parent area (for the ratio method), each forecasting technique is based on its own assumptions and equation (Table 2). Unlike national trends, growth in smaller areas is not consistent over time. Therefore, in the current study, total population forecasting for the years 2021, 2031, and 2041 has been carried out using six simple trend extrapolation techniques: simple linear, simple exponential, simple geometric, constant share, shift-share, and share of growth, across all administrative units. For the methods of constant share, shift-share, and share of growth, the projected populations for the Burdwan district in 2021, 2031, and 2041 were derived from the population projection study based on the "United Nations Medium variant projection up to 2051" (Rudra, 2017). We calculated the accuracy of each technique as a percentage error, and the technique with the lowest percentage error was selected as the forecast. The parameters used for these estimates are listed in Table 1.

Accuracy of Forecasts

There is an inverse relationship between population size and forecasting error. Specifically, the smaller the population or jurisdiction, the greater the error (Tayman et al., 1998; Wilson et al., 2022). For example, an error of 1000 people might be 1% at the state level, 20% at the district level, and over 80% at the block level. Another reason for higher error in small areas is that the growth rate tends to change more rapidly and dramatically than in larger areas. The most significant errors usually occur in areas experiencing rapid growth or decline (Smith et al., 2002). In this study, error percentages were calculated for individual units, and MAPE was computed for each method.

Built-up Area Modelling

After performing the necessary pre-processing steps, such as stacking, clipping, radiometric correction, and atmospheric correction on the Landsat data (path 139, rows 44) collected in 1987 (TM), 2002 (TM), and 2017 (OLI) from the United States Geological Survey Earth Explorer website, LULC images depicting built-up areas were generated. Non-built-up areas were extracted from Landsat images from 1987, 2002, and 2017 using the supervised maximum likelihood classification (MLC) method (Figure 2).

For stacking, all the bands except the thermal band have been used. MLC in GIS refers to a classification method in which pixels are assigned to a class based on their maximum probability of belonging to that class (Ahmad & Quegan, 2012).

Table 2

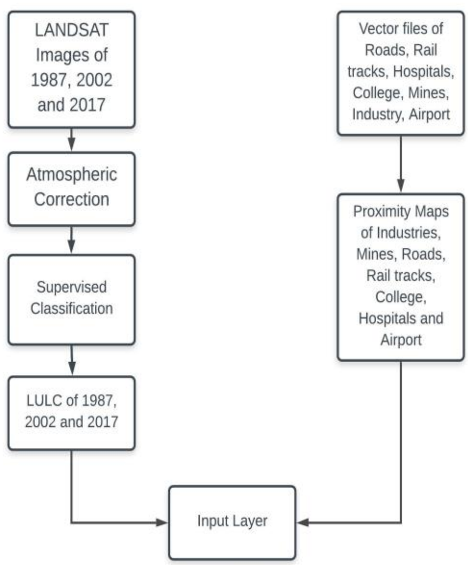
Showing Different Forecasting Methods Applied, Their Assumptions and Equations

<table>
<tr><th>Method</th><th>Assumptions</th><th>Equation</th><th>Components of the equation</th></tr>
<tr><td>Simple Linear (SL)</td><td>The population will change by the same number of persons in the future as it did in the past (Smith et al., 2013)</td><td>$Pt = P_1 + (z)(AANC)$
$AANC = {(P_1 - Pb)}/{y}$</td><td rowspan="3">Pt = Population in the target year,
z = # of years in the projection horizon
P_1=Population in the launch year;
P_b=Population in the base year; and
y= # of years in the base period.
ln= Natural logarithm
e^{rz} =Exponential of rz
$AANC$ Average annual absolute change</td></tr>
<tr><td>Simple Geometric (SG)</td><td>The population will increase (decrease) at the same annual percentage rate during the projection horizon as during the base period.</td><td>$P_t = P_l(1 + r)^z$
$r = (P_1 - Pb)^{1/y} - 1$</td></tr>
<tr><td>Simple Exponential (SE)</td><td>Growth rates are based on continuous compounding</td><td>$P_t = P_{l^{e^{rz}}}$
$r = {[ln(P_1 - Pb)]}/{y}$</td></tr>
</table>

Constant Share (CS)	The smaller area's share of the larger area's population is held constant at the level observed in the launch year.	$P_{it} = (P_{il}/P_{jl})P_{jt}$	i = Smaller area j = Larger Area l = Launch year t = Target Year b = Base Year z = Projection horizon y = Base period
Shift-Share (SS)	Each smaller area's percentage of the larger area's total annual growth will change by the same yearly amount as over the base period	$P_{it} = P_{jt}[\frac{P_{il}}{P_{jl}} + \left(\frac{z}{y}\right)\left(\frac{P_{il}}{P_{jl}} - \frac{P_{ib}}{P_{jb}}\right)]$	
Share of Growth (SOG)	The smaller area's share of population growth will remain the same over the projection horizon as during the base period.	$P_{it} = P_{il} + \left[\frac{P_{il} - P_{ib}}{P_{jl} - P_{jb}}\right](P_{jt} - P_{jl})$	

Figure 2

Preparation of the Input Layer for the Model



Source: Author (for Figs. 2 to 5)

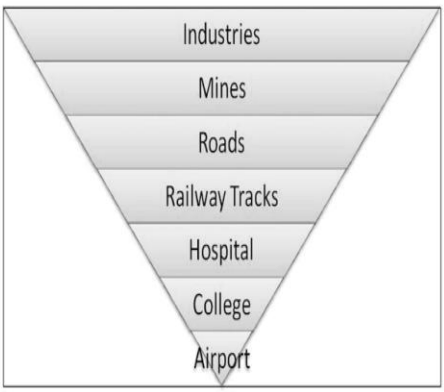
In this study, two principal classes-built up and non-built up were obtained with user accuracy, producer accuracy, overall accuracy and Kappa Coefficient values of 94.67, 93.29,94.16 and 0.91; 96.27, 89.35,94.56 and 0.89; 92.72, 91.59,91.84 and 0.88 for the years of 1987, 2002 and 2017, respectively. Built-up areas include roads, rail tracks, residential complexes, schools, colleges, hospitals, and the like, while non-built-up areas include forests, rivers, and barren lands. Based on these outcomes, a LULC prediction for 2032 has been made using the CA-ANN method in QGIS 2.18 after proper training, calibration, and validation (Figure 5).

Advances in science and technology have enabled us to use various techniques for simulating ideal situations, such as Artificial Neural Networks (ANNs), Markov Chain Analysis, and Logistic Regression; thus, the careful selection of an appropriate method is a fulcrum for gaining insight into future scenarios.

The availability and proximity of amenities, such as railway stations, schools, colleges, industrial complexes, and hospitals, greatly influence the settlement pattern of an area. The main factors that have determined the study area's existing land-use pattern are industries, mines, roads, rail tracks, hospitals, colleges, and airports (Figure 3a).

Figure 3a

Arrangement of Factors According to Their Weight of Influence Upon the Existing Land Use Pattern of the Study Area



The input layers comprise LULC maps for 1987 and 2002 in stage 1 (Figure 4) and 2002 and 2017 in stage 2 (Figure 5), along with proximity maps of influencing factors, including industry, mines, roads, rail, hospitals, colleges, and airports. All proximity maps are in raster format (Figure 3b). To obtain the proximity maps, vector files of the influencing factors were converted to raster format, and the proximity maps were generated in QGIS. These proximities, or factor maps, are normalised to values between 0 and 1. This enables us to examine the effects of the proximity factors on the LULC scenario of the study area, where the built-up area is a function of all the above-mentioned proximity factors. In the Input Layer, all factors are arranged in the model according to their influence on the built-up area. The LULC simulation has been carried out to generate maps for 2017 and 2032 using the MOLUSCE plugin in QGIS 2.18.

The final simulated images for 2017 and 2032 were produced using ANN analysis with the Cellular Automata-Artificial Neural Network (CA-ANN) model. The ANN Multilayer Perceptron was run for 1000 iterations, incorporating 10 hidden layers and five validation cycles. Using LULC images from 1987 and 2002, along with relevant influencing factors, a simulated LULC map for 2017 was generated and validated against the actual 2017 LULC map, achieving an overall Kappa score of 88.5%. This included a Kappa (overall) of 0.80713, Kappa (histogram) of 0.99680, and Kappa (location) of 0.80972. Similarly, the LULC for 2032 was simulated using input layers from 2002 and 2017, along with the influencing factors layers.

Figure 3b

Proximity Maps of the Influencing Factors

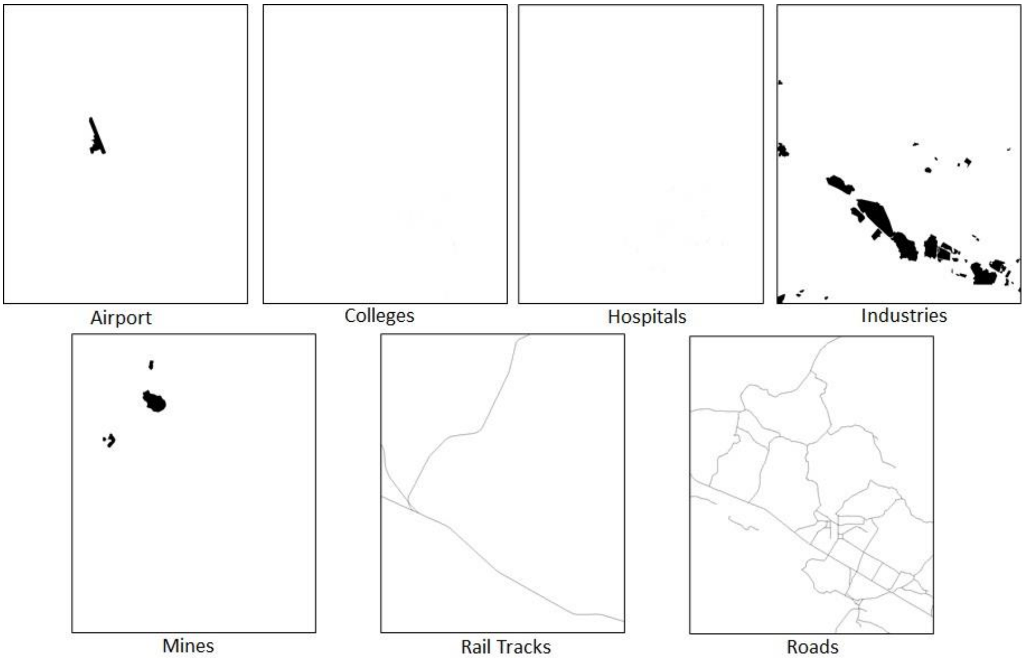


Figure 4

Derivation of the Output Layer From the Model: Stage 1

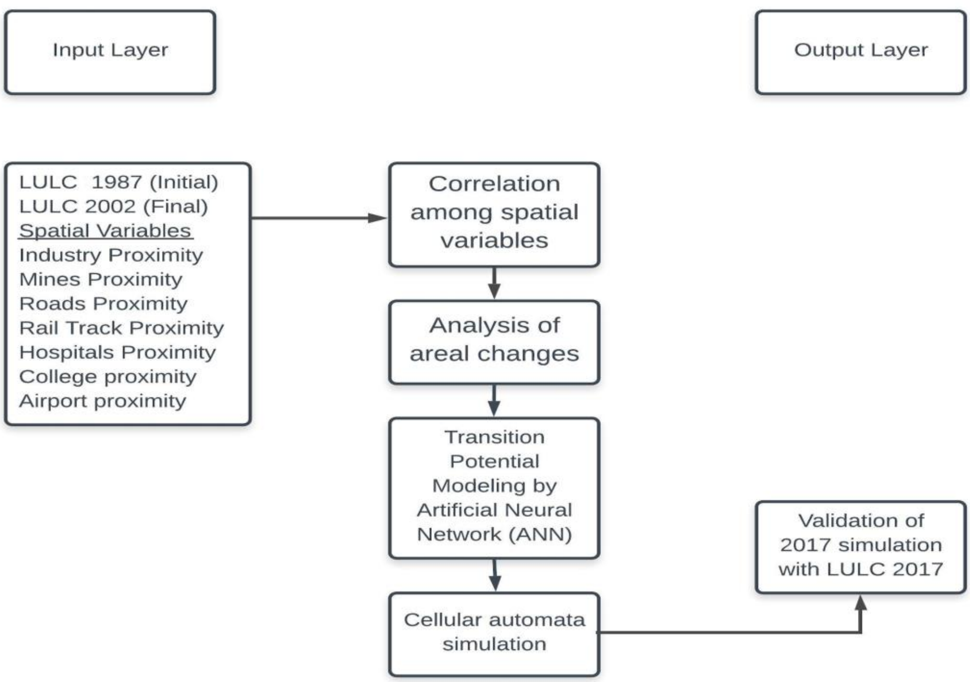


Figure 5

Derivation of the Output Layer From the Model: Stage 2

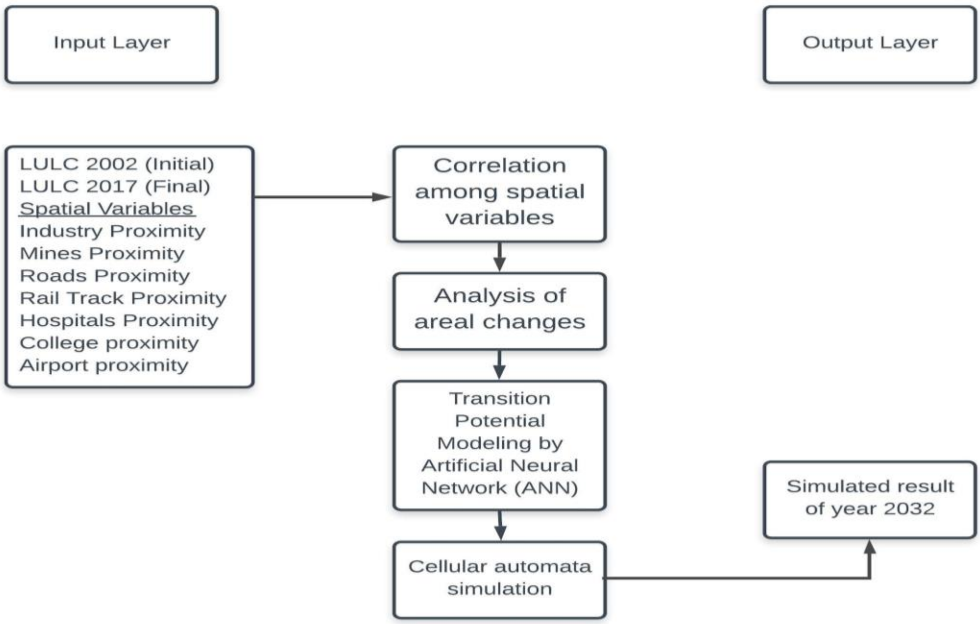


Table 3

Landuse and Landcover Classification Values in Sq. Km.

Pearson's Correlation Matrix (1987-2002)							
	Industry	Airport	College	Rail Track	Mines	Hospital	Roads
Industry	_	0.0979	0.795347	-0.05043	-0.50293	0.81825	0.48342
Airport	_	_	-0.2137	0.350677	0.697173	-0.1520	0.3479
College	_	_		-0.221312	-0.82224	0.98300	0.34436
Rail Track	_	_		_	0.30653	-0.16523	0.3368
Mines	_	_	_	_	_	-0.7801	-0.00703
Hospital	_	_	_	_	_		0.37443
Roads							

Table 4

Pearson's Correlation Matrix of the Factors Affecting the LULC: 2002–2017

Pearson's Correlation Matrix (2002-2017)							
	Industry	Airport	College	Rail Track	Mine	Hospital	Road
Industry	_	0.0979758	0.795347	-0.0504	-0.50293	0.818256	0.48342
Airport	_	_	-0.213705	0.3506	0.6971733	-0.15205	0.34799
College	_	_	_	-0.2213	-0.82229	0.983004	0.34436
Rail Track	_	_	_	_	0.306533	-0.165235	0.33687
Mine	_	_	_	_	_	-0.78019	-0.0070
Hospital	_	_	_	_	_	_	0.37443
Road	_	_	_	_	_	_	_

Source: Tables 4 to 7, 9, 10 and 11 computed in this Study from LANDSAT Images

Using LULC images from 1987 and 2002, along with relevant influencing factors, a simulated LULC map for 2017 was generated and validated against the actual 2017 LULC map, achieving an overall Kappa score of 88.5%. This included a Kappa (overall) of 0.80713, Kappa (histogram) of 0.99680, and Kappa (location) of 0.80972. Similarly, the LULC for 2032 was simulated using input layers from 2002 and 2017, along with the influencing factors layers. Calibration, training, and validation are essential steps for achieving accurate results throughout the ANN process. Layers between the input and output layers are known as hidden layers, which enhance analysis by enabling forward and backward propagation. These mechanisms assign weights and produce meaningful outputs. It is important to note that the activation function within the CA-ANN structure involves repeated forward and backward propagations, loading numerical probability values into the hidden-layer neurons. This process generates a validated, self-learning outcome that encapsulates the system's overall functionality.

Discussion and Results

It is to be borne in mind that the analysis in this modelling is done in a two-stage process. First, we perform training and validation using a reference image from a year (Figure 6). For this, we use the classified images from 1987 and 2002 as inputs to the model, along with rasters of the influencing factors, to obtain a simulation LULC map for 2017. After validating it against our original LULC map for the same year, a simulation of the LULC scenario was conducted in 2032.

One essential part of our analysis involves calculating the correlation between factors or variables that influence built-up magnification in this study area (using the Pearson Correlation method). It presents a matrix showing the level of correlation among the variables (Table 3). It has been observed that the built-up area has been steadily increasing over the years. It grew from 25.78 sq.km in 1987 to 72.05 sq.km in 2002 (Table 4) and eventually to 98.91 sq.km in 2017 (Table 5). The model forecasts that the built-up area will increase to 138.72 sq.km in 2032 (Table 6).

The transition matrix shows the percentage change in the two classes, built-up and non-built-up, over 15 years (1987-2002). It was found that 62% of the built-up area remained built-up in the subsequent year, 2002, and almost 12% of the non-built-up area was transformed into built-up area (Table 6).

Table 5

Change of Built-up and Non-Built-Up Area Between 1987 And 2002

LULC	1987 (In Sq Km)	2002 (In Sq. Km)	Δ (Change of Area in Sq. Km)	1987 (% of the Area)	2002 (% of the Area)	Δ%
Built-up	25.78	72.05	46.27	5.1854	14.4913	9.3058
Non-Built-up	471.39	425.13	-46.27	94.8145	85.5086	-9.3058

Table 6

Change in Built-up and Non-Built-up Areas Between 2002 and 2017.

LULC	2002 (In Sq. Km)	2017 (In Sq. Km)	Δ (Change of Area in Sq. Km)	2002 (% of the Area)	2017 (% of the Area)	Δ%
Built-up	72.05	98.91	26.86	14.49130	19.89449	5.403193
Non-Built-up	425.13	398.26	-26.86	85.50869	80.10550	-5.403193

Table 7

Change of Built-up and Non-Built-up Area Between 2017 and the Simulated Year 2032.

LULC	2017 (In Sq. Km)	2032 (In Sq. Km)	Δ (Change Of Area In Sq. Km)	2017 (% Of The Area)	2032 (% Of The Area)	Δ%
Built-up	98.91	138.72	39.81	19.8944	27.9026	8.0081
Non-Built-up	398.26	358.45	-39.81	80.10550	72.0973	-8.0081

Similarly, the transition matrix in Table 8 shows that 0.6400, or 64%, of the built-up area remained built-up in 2017, whereas 0.1241, or 12%, of the non-built-up area was transformed into built-up in 2017 (Table 7).

Finally, it is found that the 0.99 or 99% built-up area of 2017 is expected to remain built up in 2032, and the 0.0999 or almost 10% non-built-up area is likely to be transformed into built-up in 2032 (Table 8).

The simulation of the LULC map for the year 2032 has been prepared with an overall accuracy of 88.5%, i.e., the percentage of correctly classified pixels relative to the referenced (actual) pixels is 88.5% (Table 9).

Table 10 depicts the increment of built-up areas at the cost of the decrement of the non-built-up regions over the years. The built-up area is predicted to reach 138.72 sq km in 2032, almost 40 sq km more than in 2017.

Table 8

Transition Matrix Between Built-up and Non-Built-up: 1987–2002

Transition Matrix (1987-2002)		
LULC	Built-up	Non Built-up
Built-up	0.626532	0.373468
Non-Built-up	0.118573	0.881427

Table 9

Transition Matrix Between Built-up and Non-Built-up: 2002–2017

Transition Matrix (2002-2017)		
LULC	Built-up	Non-built-up
Built-up	0.640021	0.359979
Non-built-up	0.124195	0.875805

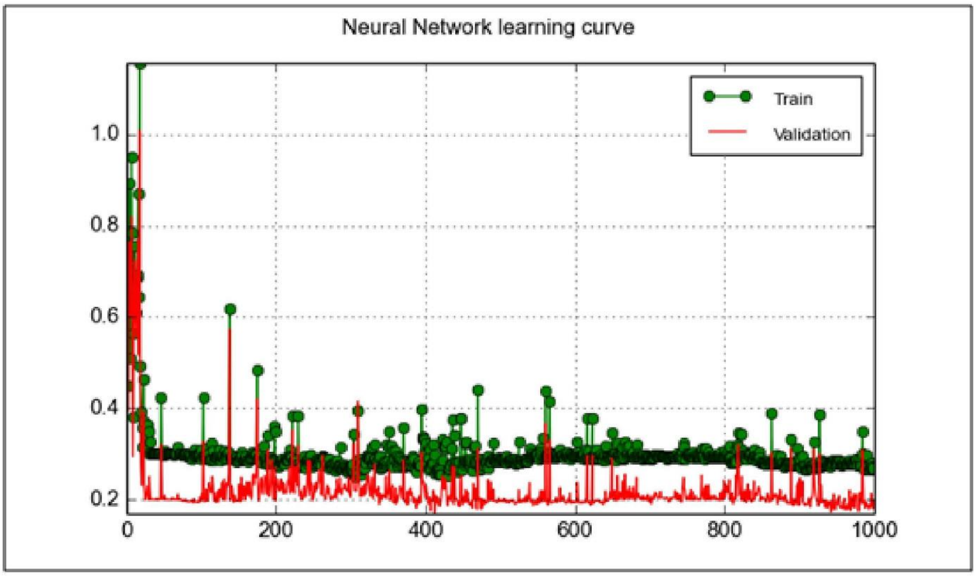
Table 10

Transition Matrix Between Built-up and Non-Built-up: 2017–2032

Transition Matrix (2017-2032)		
LULC	Built-up	Non-built-up
Built-up	0.999982	0.000018
Non-built-up	0.099974	0.900026

Figure 6

Artificial Neural Network Learning Curve Images



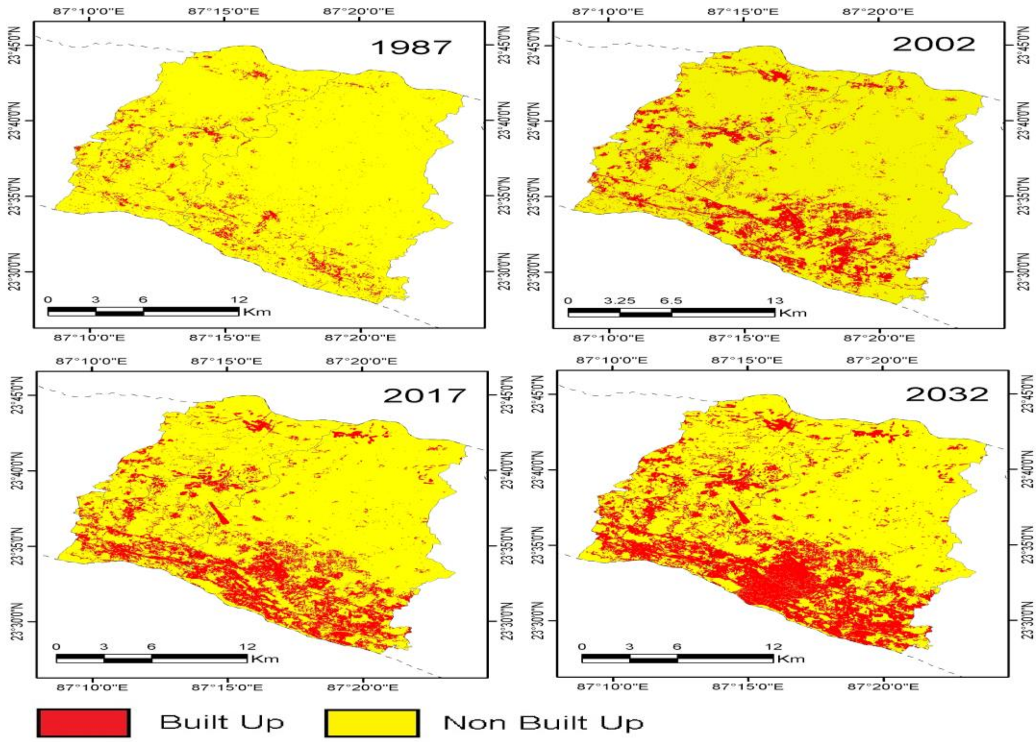
Source: Computed in this study from LANDSAT

The increases in total built-up area from 1987 to 2002 and from 2002 to 2017 are 46.27 sq. km and 26.86 sq. km, respectively. These are mainly concentrated in the Durgapur and Andal urban centres in the southern and southeastern parts of the study area. A slight expansion of the built-up area in the northern part is observed, driven by mine expansion (Figure 7). Consequently, a consistent upward trend in built-up areas has been recorded over the years and is likely to continue, driven by high population growth. The model forecasts that the built-up area will reach 138.72 sq. km by 2032 (Table 6). On a block-wise basis, the most significant increase in built-up area was observed in Faridpur Durgapur Block, rising from approximately 65 sq. km in 2017 to around 90 sq. km in 2032 (Figure 8).

In addition to the common trend of positive population growth, some MAUs experienced negative population growth, e.g., Bhaburia, Chak-Laudoha, and Kamardanga in the Faridpur Durgapur block, and Hansdiha in the Pandabeshwar CD block.

Figure 7

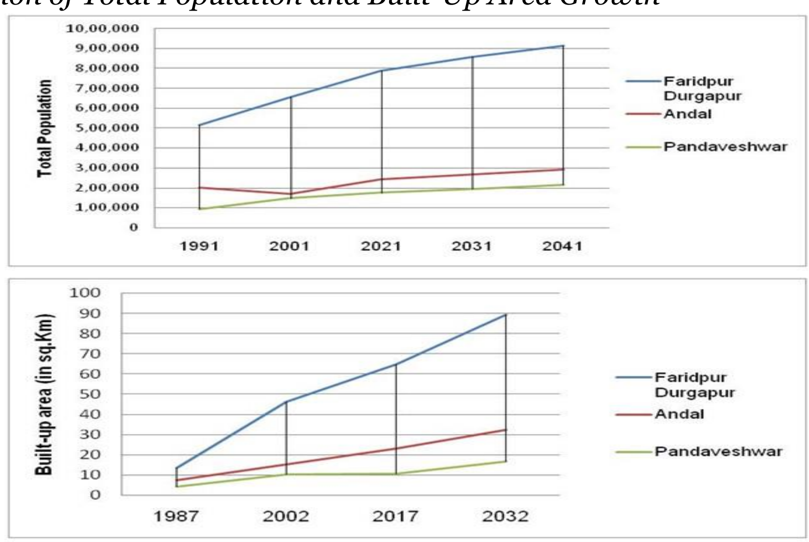
Land Use Land Cover Scenario of the Study Area From 1987–2017 and Simulated Land Use and Cover Scenario for 2032



Source: Generated from LANDSAT Images

Figure 8

Association of Total Population and Built-Up Area Growth



Source: Prepared from District Census Handbooks of Burdwan district and Landsat images

Among them, the highest negative growth observed for Hansdiha of Pandabeshwar (Table 11) is because the settlement area of Hansdiha village has completely transformed into the Sonpurbazari open-cast coal mine area (Mourya & Chakraborty, 2012)

Table 11

Validation Result Showing Parameters of Kappa Statistics

Percentage of accuracy	88.5285
Kappa (Overall)	0.80713
Kappa (Histogram)	0.99680
Kappa (Location)	0.36534

Out of the 112 forecasted administrative units, 77 units have produced sufficient accuracy. Hansdiha, Bhaburia, and Chaklaudoha showed a negative change; Kamardanga showed no change; and the remaining units failed to meet the required accuracy, i.e., an upper threshold of 20 % error. Among all six methods, constant share has been selected for 25 units, simple linear for 23 units, shift share for 12 units, share of growth for eight units, simple exponential for six units and simple geometric for four units with MAPEs of 8.625226, 6.383572, 5.916224, 4.948268, 9.409007 and 2.883625, respectively. The highest forecasted population for DMC was 644,441, 701,662, and 744,881 for 2021, 2031, and 2041, respectively.

Urban growth forecasting is a vital tool for regional planning, providing essential information to manage expansion, encourage sustainable development, and ensure the efficient allocation of resources. The present study demonstrates that increments in built-up areas are closely linked to population growth over time. Population forecasts based on simple trend extrapolation methods and built-up area modelling using CA-ANN are expected to provide valuable insights into the behavioural patterns of growth and development of the MAUs at small-scale units, aiding urban planners, administrators, and decision-makers to consider people and land within the framework of sustainable and inclusive planning. Despite some limitations, simple trend extrapolation methods remain useful for population forecasting, particularly at smaller scales in a developing country like India. Notably, growth in built-up areas and population is mainly observed in the south and southeastern parts of the study area, often at the expense of non-built-up land. The results highlight and predict further increases in built-up regions, which could impact sustainable growth by significantly affecting local resources and the environment. Further research and studies focusing on micro-level planning and assessment are recommended, particularly in the context of sustainable development and comprehensive inclusive growth within urban planning.

Acknowledgement

UGC-NET JRF fellowships from the University Grants Commission of India and the Department of Geography at Jadavpur University support this study. The authors would also like to thank Dr Kaberi Samanta and Dr Basudeb Bhatta of the CAD Centre at Jadavpur University for their cooperation.

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