*Article*

# Urban Expansion Simulation Based on Various Driving Factors Using a Logistic Regression Model: Delhi as a Case Study

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**Abstract:** During the last three decades, Delhi has witnessed extensive and rapid urban expansion in all directions, especially in the East South East zone. The total built-up area has risen dramatically, from 195.3 sq. km to 435.1 sq. km, during 1989–2020, which has led to habitat fragmentation, deforestation, and difficulties in running urban utility services effectively in the new extensions. This research aimed to simulate urban expansion in Delhi based on various driving factors using a logistic regression model. The recent urban expansion of Delhi was mapped using LANDSAT images of 1989, 2000, 2010, and 2020. The urban expansion was analyzed using concentric rings to show the urban expansion intensity in each direction. Nine driving factors were analyzed to detect the influence of each factor on the urban expansion process. The results revealed that the proximity to urban areas, proximity to main roads, and proximity to medical facilities were the most significant factors in Delhi during 1989–2020, where they had the highest regression coefficients: −0.884, −0.475, and −0.377, respectively. In addition, the predicted pattern of urban expansion was chaotic, scattered, and dense on the peripheries. This pattern of urban expansion might lead to further losses of natural resources. The relative operating characteristic method was utilized to assess the accuracy of the simulation, and the resulting value of 0.96 proved the validity of the simulation. The results of this research will aid local authorities in recognizing the patterns of future expansion, thus facilitating the implementation of effective policies to achieve sustainable urban development in Delhi.

**Keywords:** urban expansion; simulation; driving factors; land use/cover change; urban expansion intensity; logistic regression; Delhi; India

## 1. Introduction

Urban expansion models are a useful tool for understanding the dynamics of the urban environment [1]. Many researchers and scholars have applied various techniques to predict and simulate urban expansion [2–6]. Simulating future urban expansion helps in the effective management of land use/cover in cities [5,7]. In this regard, several models have been developed to simulate future urban expansion in many cities. For instance, Karimi et al. have used the support vector machine (SVM) technique to predict urban expansion in Guilford County, NC, USA [2]. Omar et al. have used a hybrid model of Markov chain and logistic regression to simulate future urban expansion in Aswan city, Egypt [8]. Tayyebi et al. have utilized a logistic regression model to simulate urban expansion in the Shiraz Metropolitan Area of Iran [5]. Hossein et al. have employed artificial neural networks (ANNs) to simulate urban expansion in Mumbai, MH, India [9].

Recognizing the driving factors of urban expansion is crucial for local authorities and urban researchers [10]. Therefore, a number of studies have focused on examining and analyzing the driving factors behind urban expansion in many cities [11–13]. A literature review has shown that the driving forces of urban expansion vary from city to city [4,14,15] in both the Global South and the Global North. In the Global South, for instance, Salem et al. found that the population density and the proximity to main roads are the most significant factors affecting urban expansion in Cairo, Egypt [16]. Appiah et al. claimed that the increased demands for new housing and good accessibility to new extensions are the most important factors in Bosomtwe, Ghana [17]. Batsuuri et al. argued that urban planning policy is the main factor behind urban expansion in Ulaanbaatar city, Mongolia [18]. Ju et al. found that the distance to the downtown area is the most influential factor in Beijing, China [19]. Rahman et al. indicated that population growth and migration from small cities and rural areas to the city are the main causes of urban expansion in Delhi, India [20]. Moreover, in the Global North, Gielen et al. indicated that urban density and proximity to the city center are the most important influential factors for urban expansion in Valencia, Spain [21]. Lien and Anton found that the distance to roads and flood risk are the most significant factors in Brussels, Belgium [22]. Tavares et al. stated that municipal master plans and land regulation are the key driving factors behind urban expansion in the central region of Portugal [23]. Table 1 provides a summary of the main driving factors of urban expansion described in previous studies.

**Table 1.** A summary of the main driving factors of urban expansion in previous studies.

| Author | Location | Region | City, Country | Main Driving Factors |
|---|---|---|---|---|
| Salem et al. | | Africa | Cairo, Egypt | Population Density and Proximity to Roads |
| Appiah et al. | | Africa | Bosomtwe, Ghana | Demands for New Housing and Accessibility |
| Batsuuri et al. | Global South | Asia | Ulaanbaatar, Mongolia | Urban Planning Policy |
| Ju et al. | | Asia | Beijing, China | Distance to the Downtown Area |
| Rahman et al. | | Asia | Delhi, India | Population Growth and Migration from Small Cities and Rural Areas |
| Gielen et al. | | Europe | Valencia, Spain | Urban Density and Proximity to the City Center |
| Lien and Anton | Global North | Europe | Brussels, Belgium | Distance to Roads and Flood Risk |
| Tavares et al. | | Europe | Coimbra, Portugal | Municipal Master Plans and Land Regulation |

Many methods have been employed to investigate the driving factors that cause urban expansion in cities. Li et al. have used the partial least squares (PLS) method to analyze the influence of driving factors on urban expansion in Wuhan city, China [24]. Kindu et al. have used a combination of descriptive statistics, GIS-based processing, and regression analyses to investigate the driving factors of urban land use change in Ethiopia, Africa. Shu et al. have used logistic regression analysis to investigate the factors that cause urban expansion in Taicang City, China [3,4].

Alsharif and Pradhan argue that the logistic regression model (LRM) is an appropriate method for analyzing the driving forces of urban expansion in developing countries, where urban expansion is strongly affected by socio-economic factors [25]. In the LRM, the effect of each driving factor on urban expansion can be easily measured [4,26]. Meanwhile, in some other models, such as ANN models, the contribution of each factor in the urban

expansion process cannot be explicitly identified; hence, less important variables may be included in the model [12]. In addition, the result of the analysis of the LRM can be used for the spatial simulation of urban expansion [27,28]. Therefore, this study has utilized the LRM to examine the driving factors causing urban expansion in Delhi and simulate the future urban expansion based on the outputs of the model.

Delhi is the capital of India and the second-largest metropolitan city after Mumbai (Census 2011). During recent decades, Delhi has witnessed exponential growth. The built-up area of Delhi has expanded steadily from 195.30 km$^2$ in 1989 to 435.12 km$^2$ in 2020 [29,30]. This urban growth has led to environmental degradation, particularly in the last few years [31–33]. Many studies have discussed the land use/cover change in Delhi and its impacts [34–36]. However, so far, little attention has been paid to analyzing the pattern of urban expansion in Delhi and the driving forces that influence this expansion [37]. Therefore, this research seeks to analyze the driving factors that influence urban expansion in Delhi and predict the pattern of urban expansion. The novelty of the work lies in analyzing the pattern of urban expansion in Delhi during the last three decades and its intensity, trends, and driving factors; we then simulate the future urban expansion based on the results of these analyses using a logistic regression model.

The structure of this research includes four sections. The first section covers the introduction and the literature review. The second section presents the study area, the data used in the research, and the methodology. The third section includes the findings of the research and a discussion of the results. The fourth and last section provides the conclusions of the research.

## 2. Materials and Methods

### 2.1. Study Area

The study area is the National Capital Territory (NCT) of Delhi (hereinafter referred to as Delhi), the capital city of India and one of its megacities. Delhi occupies an area of approx. 1500 km$^2$ and is located at 28.33° to 29.0° N latitude and 76.83° to 77.33° E longitude. The total population of Delhi exceeds 11 million inhabitants, and the annual growth rate was recorded as 3.9 percent during 1991–2001, which is twice the national average [38]. The rapid urban expansion in Delhi has led to the loss of large areas of arable land, which has had a negative impact on urban sustainability [39,40]. Therefore, the issue of urban expansion is considered one of the most urgent issues in Delhi. Figure 1 shows the study area and its location within India.

### 2.2. Dataset

The combination of remote sensing (RS) data and geographical information systems (GIS) has been used to investigate LULC change [41,42]. For this research, we collected data from different sources. First, Landsat images for 1989, 2000, 2010, and 2020 were acquired free of charge from the USGS Earth Explorer website and utilized in detecting the spatio-temporal changes in Delhi. Second, shapefiles of roads, water bodies, and railways were derived from the OpenStreetMap database. In addition to 4 shapefiles of tourist places, restricted areas, industrial areas, and higher education institutes were derived from Google Earth. Table 2 provides detailed information about the data sources.

**Table 2.** Data sources.

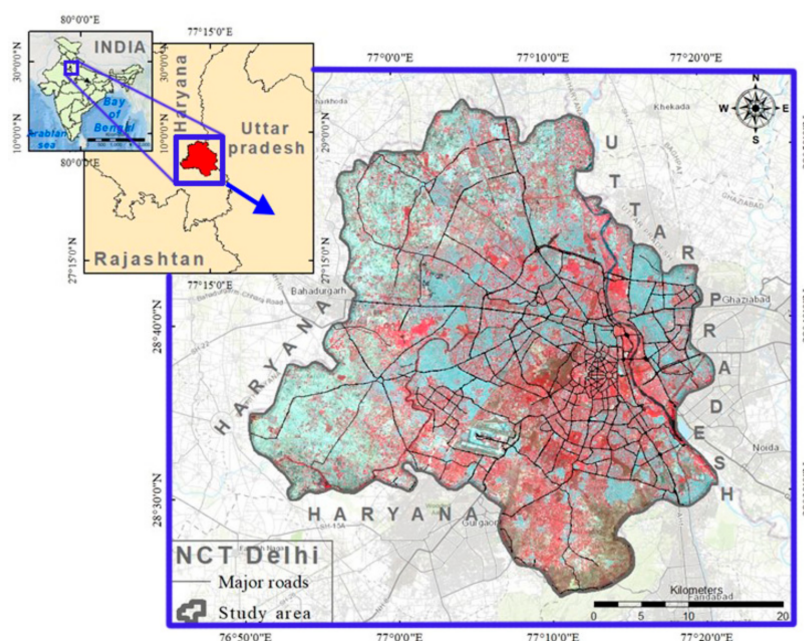| Data | Source | Date of Acquisition |
|---|---|---|
| Landsat-5 | | 1989/12/12, 1989/12/05 |
| Landsat-7 | USGS Earth Explorer | 2000/04/06, 2000/03/14 |
| Landsat-5 | website (30 m Res.) | 2010/12/22, 2010/11/29 |
| Landsat-8 | | 2020/05/07, 2020/05/16 |
| Shapefiles of Roads, Water Bodies, Railways, etc. | OpenStreetMap and Google Earth Pro | 2020/06/09 |

**Figure 1.** Location map of the study area (the NCT of Delhi) with reference to India. The map is composed of false-color composite bands.

*2.3. Methodology*

This research utilized a quantitative method to analyze the collected data. Remote sensing and GIS techniques were used during the pre-processing stage. The detection of land use/cover change was conducted using the maximum likelihood supervised classification (MLSC) method. One hundred and fifty samples were selected in each Landsat image to apply MLSC using the Terrset software. Four land use/cover (LUC) types were detected during the classification process, which were:

(1)    Built-up;
(2)    Vegetation;
(3)    Water bodies;
(4)    Others.

To assess the classification accuracy, 200 random points were selected and compared to the corresponding location in Google Earth. For each of the observation years (1989, 2000, 2010, and 2020), the overall accuracy was calculated, which ranged from 85 percent to 91 percent, while the kappa coefficient ranged from 0.80 to 0.90, which indicates a high degree of accuracy [43,44].

In addition, the built-up features, which included industrial complexes, suburban areas, informal settlements, etc., were extracted in order to examine the urban expansion and later to calibrate the model. The urban expansion intensity ($I_{ue}$) was calculated to analyze the intensity of urbanization for each of the spatial units in Delhi NCT. The urban expansion intensity was computed according to the following formula:

$$I_{ue} \; = \; \frac{\Delta U_i \times 100}{TLA \times \Delta t} \tag{1}$$

where $I_{ue}$ is urban expansion intensity, $\Delta U_i$ is urban expansion during 1989–2020, $TLA$ is the total area of the metropolitan city of Delhi, and $\Delta t$ is 31 years (the period 1989–2020).

In order to identify the spatial lateral variation in the urban expansion rate during 1989–2020, the study area was split into eight regions at an interval of 45 degrees, taking into account the centroid of the study area [45]. Then, every region was split into concentric rings of a 2 km radius from the city's center. These rings helped to visualize the growth of the city at different distances from the city's center.

Twelve independent factors were derived based on previous literature and discussion with experts to be included in the model [4,14,15,37,40,46,47]. Then, two factors (economic activities and urban master plans) were excluded from the study due to a lack of data for the study area. In addition, the slope factor was eliminated from the model because of the low value of $R^2$ statistics with this factor. Finally, the total number of independent factors (variables) decreased from twelve to nine factors. These driving factors were proximity to water bodies, proximity to the urban area, proximity to tourist places (most popular tourist sites), proximity to the restricted area (airport zone), proximity to railways, proximity to medical facilities (hospitals), proximity to major roads, proximity to industrial zones, and proximity to higher education institutes. The influence of these nine factors was examined using a logistic regression model (LRM).

To carry out the LRM, a map of urban expansion during the period 1989–2020 was utilized as a dependent variable, which are dichotomous in nature [19,28]. The previous map had two potential land use/cover types: urban expansion where y = 1 if urban expansion exists, and y = 0 if not built-up and urban expansion does not exist [4,8]. The nine driving factors were utilized as independent variables, which are continuous in nature. The Distance command in the Terrset software was used to estimate the influence of the proximity to each factor on the urban expansion process. Each factor was assigned a value ranging from 0 to 1, indicating the weight of the factor's effect on urban expansion. Table 3 shows the dependent and independent variables in the LRM.

**Table 3.** The dependent and independent variables in the LRM.

| Factors | Name |
| --- | --- |
| Dependent (Y) | 0: No Urban Expansion; 1: Urban Expansion |
| Independent (X1) | Proximity to Water Bodies |
| Independent (X2) | Proximity to Urban Areas |
| Independent (X3) | Proximity to Tourist Places |
| Independent (X4) | Proximity to the Restricted Area |
| Independent (X5) | Proximity to Railways |
| Independent (X6) | Proximity to Medical Facilities |
| Independent (X7) | Proximity to Main Roads |
| Independent (X8) | Proximity to Industrial Areas |
| Independent (X9) | Proximity to Higher Education Institutes |

The probability of future urban expansion follows the logistic regression curve and can be computed using Equation (2):

$$P = (Y = 1|X) = \frac{\exp \sum_{k=0}^{k} b_k x_{ik}}{1 + \exp \sum_{k=0}^{k} b_k x_{ik}} \tag{2}$$

where P is the probability of urban expansion; X is the independent factors, $x_{(0 \sim k)}$, which might cause expansion; and b is the estimated parameters, $b_{0 \sim k}$, which are the coefficients of driving factors. Figure 2 shows the methodological flow chart of the study.
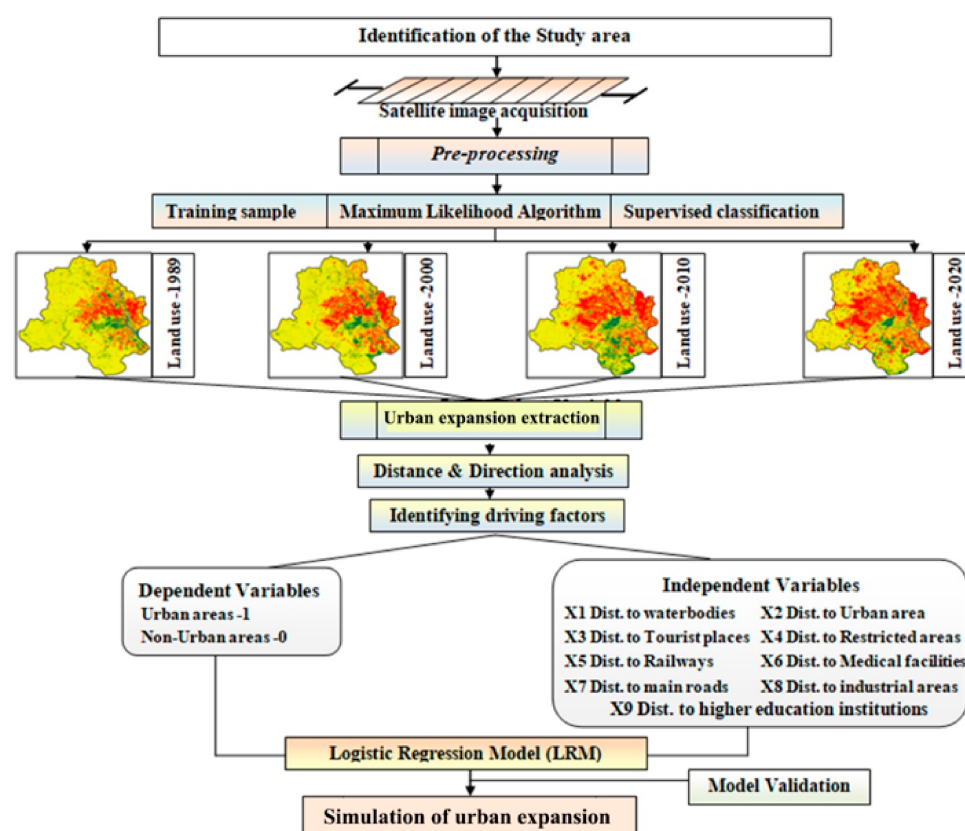
**Figure 2.** Methodological flow chart of the study.

## 3. Results and Discussion

### 3.1. Land Use/Cover Dynamics

The land use/cover (LUC) maps were derived from multi-temporal satellite images and then analyzed to detect urban expansion in Delhi from 1989 to 2020. Table 4 shows the characteristics and description of LULC feature classes.

**Table 4.** Characteristics and description of LULC feature classes.

| Feature Class | Description |
|---|---|
| Built-Up | All Man-Made Structures Such as Residential Zones, Commercial Areas, etc. |
| Vegetation | Agricultural Lands, Arable Land, Cropland, Parks, etc. |
| Water Bodies | All Water Bodies Such as Rivers, Lakes, Ponds, etc. |
| Others | Fallow Land and Degraded Areas, Vacant Spaces, etc. |

The results revealed that the built-up area had risen dramatically from 195.30 sq. km to 435.12 sq. km during 1989–2020. The periodic observation shows that the built-up area was 195.30 sq. km in 1989, increased to 268.11 sq. km (17.73%) in 2000 and then to 351.21 sq. km in 2010, and finally increased to 435.12 sq. km in 2020, as shown in Table 5.

The vegetation area has slightly decreased from 130.56 sq. km in 1989 to 127.03 sq. km in 2000, then to 120.92 sq. km in 2010, and finally to 111.39 sq. km in 2020. Moreover, the water bodies have slightly decreased from 14.34 sq. km in 1989 to 13.84 sq. km in 2000, then to 13.59 sq. km in 2010, then increased slightly in 2020 to 14.11 sq. km. The LUC category of "others" decreased from 1171.90 sq. km in 1989 to 1103.12 sq. km in 2000, then to 1026.37 sq. km in 2010, and finally to 951.48 sq. km in 2020. Figures 3 and 4 show the LUC changes between 1989 and 2020.

**Table 5.** Land use/cover dynamics from 1989 to 2020.

| LUC Change Category | Area of 1989 | | Area of 2000 | | Area of 2010 | | Area of 2020 | | Change (%) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | sq. km | % | sq. km | (%) | sq. km | (%) | sq. km | (%) | 89/00 | 00/10 | 10/20 |
| Built-Up | 195.30 | 12.92 | 268.11 | 17.73 | 351.21 | 23.23 | 435.12 | 28.78 | 72.81 | 4.82 | 5.55 |
| Veg. | 130.56 | 8.63 | 127.03 | 8.40 | 120.92 | 8.00 | 111.39 | 7.37 | −3.53 | −0.23 | −0.63 |
| Water | 14.34 | 0.95 | 13.84 | 0.92 | 13.59 | 0.90 | 14.11 | 0.93 | −0.50 | −0.03 | −0.03 |
| Others | 1171.90 | 77.50 | 1103.12 | 72.95 | 1026.37 | 67.88 | 951.48 | 62.92 | −68.78 | −4.55 | −4.95 |

Source: Authors.
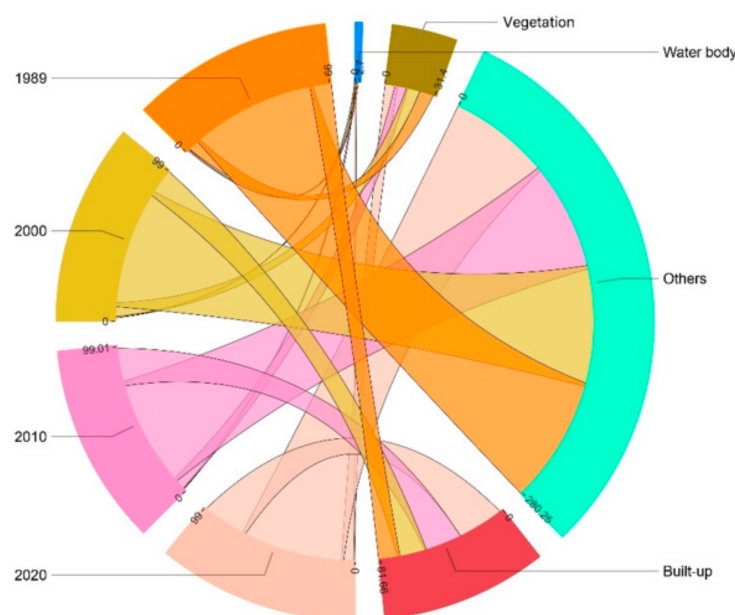


**Figure 3.** The chord graph for the percentage of LUC changes between 1989 and 2020.

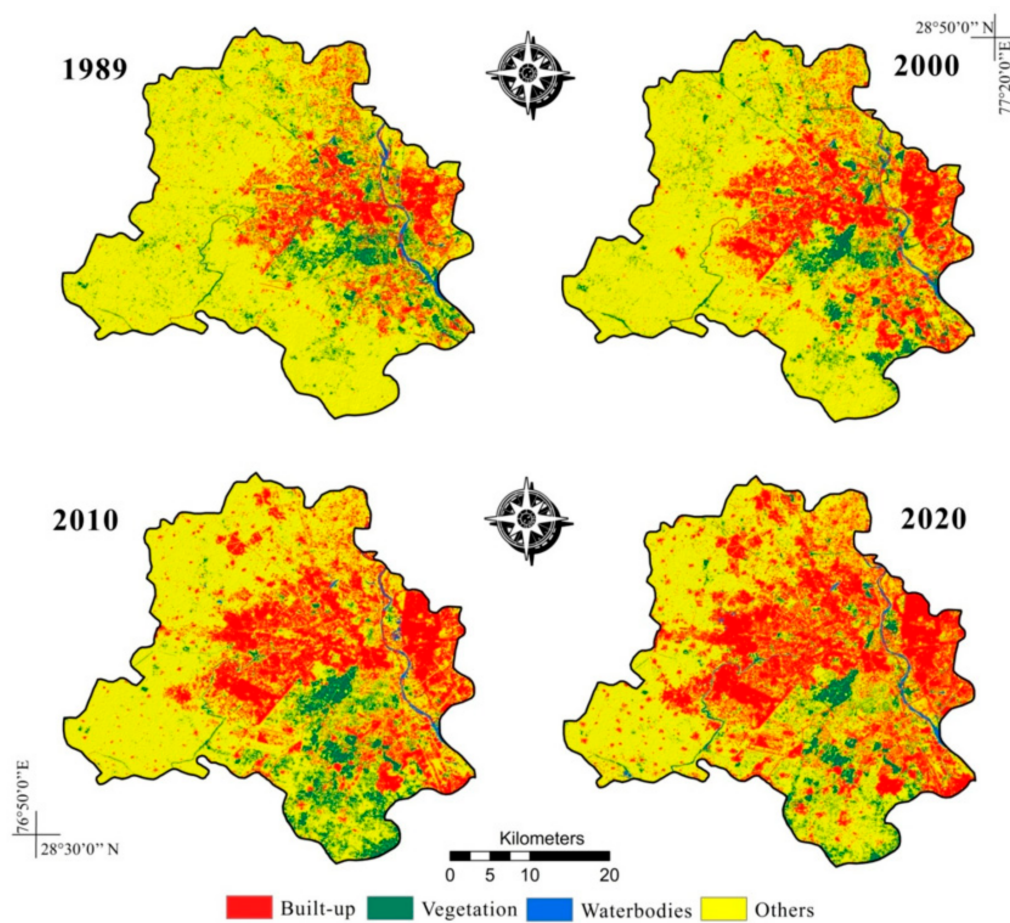*3.2. The Trend of Urban Expansion in Delhi from 1989 to 2020*

To visualize the distance and direction of urban expansion in Delhi from 1989 to 2020, the built-up features were extracted from the LULC maps and represented separately. Multiple ring buffers were used to show the change in the built-up area at different distances. These rings represented the variation in the built-up area from the center of Delhi to the periphery of the city in order to represent the trend of urban expansion, as shown in Figure 5.

The analysis showed that the buffer zones within 22 km of the center of Delhi continued to expand at a high rate. However, the outlying zones between 8 and 14 km from the city center were considered the densest zones of urban expansion. In addition, there was an inverse relationship between urban expansion and the distance from the center of Delhi within the range of 2 km to 12 km, as shown in Table 6.

**Table 6.** The trend of urban expansion according to the distance from the center of Delhi.

| Distance from the Center of Delhi (km) | % Built-Up Area | | | |
|---|---|---|---|---|
| | 1989 | 2000 | 2010 | 2020 |
| <2 | 1.43 | 2.20 | 2.35 | 1.85 |
| 4 | 4.62 | 5.44 | 4.58 | 4.26 |
| 6 | 6.98 | 8.46 | 8.12 | 8.11 |
| 8 | 12.23 | 10.57 | 11.52 | 10.44 |
| 10 | 10.88 | 10.69 | 9.16 | 9.67 |
| 12 | 9.46 | 9.75 | 11.78 | 11.20 |
| 14 | 9.01 | 8.26 | 9.17 | 7.75 |
| 16 | 6.27 | 6.85 | 8.24 | 8.60 |
| 18 | 9.86 | 8.44 | 8.98 | 9.51 |
| 20 | 10.94 | 8.51 | 7.75 | 7.45 |
| 22 | 8.50 | 7.25 | 6.58 | 6.46 |
| 24 | 4.36 | 4.92 | 4.10 | 4.51 |
| 26 | 4.11 | 3.94 | 3.17 | 3.68 |
| 28 | 0.94 | 2.40 | 1.97 | 2.84 |
| 30 | 0.86 | 1.04 | 1.07 | 1.79 |
| 32 | 0.95 | 1.26 | 1.43 | 1.70 |
| 34 | 0.02 | 0.01 | 0.02 | 0.16 |
| 36 | 0.00 | 0.02 | 0.02 | 0.02 |

Source: Authors.



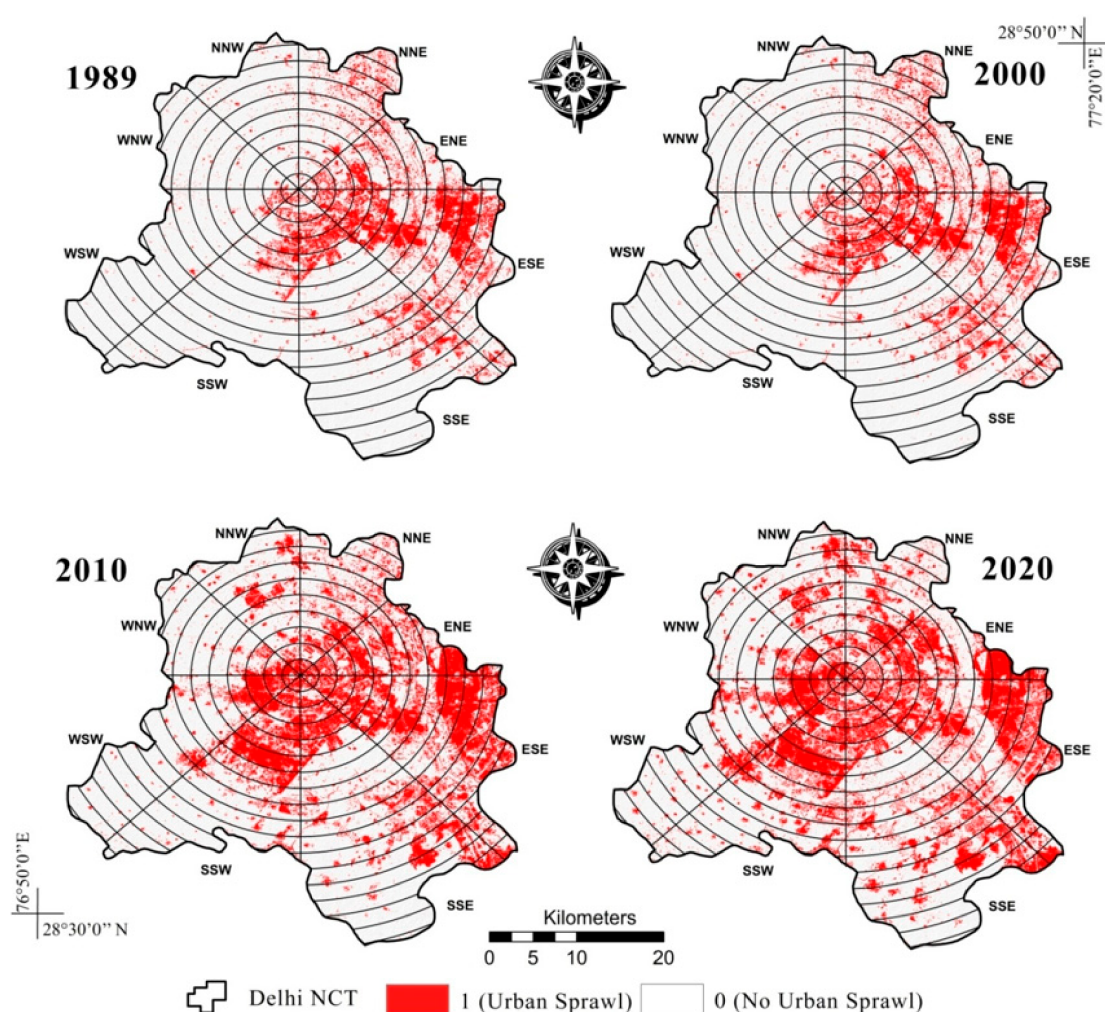**Figure 4.** Land use/cover dynamics from 1989 to 2020.

**Figure 5.** The trend of urban expansion in Delhi from 1989 to 2020.

During the period from 1989 to 2020, most of the urban expansion was observed in the East South East (ESE) direction, followed by South South West (SSW) and West South West (WSW). The high rate of urban expansion in such zones is most probably due to the good urban infrastructure, such as roads, medical facilities, educational centers, etc. Table 7 shows the urban expansion intensity in each direction.

**Table 7.** Urban expansion intensity in each direction.

| Direction | 2020 | 2010 | 2000 | 1989 | Urban Expansion Intensity (%) |
|---|---|---|---|---|---|
| North North West | 16.40 | 14.05 | 4.75 | 3.91 | 0.0267 |
| North North East | 21.76 | 17.56 | 12.41 | 9.77 | 0.0256 |
| East North East | 56.57 | 52.68 | 38.07 | 27.34 | 0.0623 |
| East South East | 160.99 | 140.48 | 136.74 | 97.65 | 0.1351 |
| South South East | 65.27 | 52.68 | 48.26 | 37.11 | 0.0601 |
| South South West | 56.57 | 42.15 | 17.96 | 11.72 | 0.0957 |
| West South West | 39.16 | 21.07 | 7.24 | 5.86 | 0.0710 |
| West North West | 18.40 | 10.54 | 2.68 | 1.95 | 0.0351 |

Source: Computed by the authors.

It is worth mentioning that the urban complexes situated adjacent to the study area (NCT area of Delhi), such as Ghaziabad, Noida, and Gurugram, which are part of the broader NCR region, are also affected by massive urban expansion.

The nature of urban expansion in Delhi is noticeably different from that of developed countries; in Delhi, the pattern of urban expansion is chaotic and dense, particularly in the peripheral villages. This pattern has resulted in habitat fragmentation, deforestation, and difficulties in running urban utility services effectively in the new extensions. In addition, the rapid urban expansion has led the surrounding villages on the peripheries to become incorporated into the urban boundary of Delhi. Currently, these villages are known as urban villages and are characterized by informal housing, high population density, and a lack of proper infrastructure. Furthermore, the urban expansion was mostly clustered in Delhi's eastern and central regions, close to the Yamuna River.

### 3.3. Lack of Spatial Planning in Delhi

Spatial planning is crucial for managing urban expansion, especially in developing countries [48,49]. Watson argued that urban planning in Indian megacities gave little attention to the spatial planning approach [50]. Due to poor spatial planning, various forms of chaotic expansion have occurred in Delhi during the last decades [40,51,52]. Nallathiga et al. and Sharma stated that poor spatial planning in Delhi has led to unplanned and haphazard urban expansion, particularly in the peripheries [29,52]. Therefore, the factor of spatial planning is considered one of the main factors that influence urban expansion in Delhi. Jain et al. argued that managing the urban expansion in Delhi is still possible if the government shifted from land use based master planning towards strategic spatial planning [53].

### 3.4. The Logistic Regression Analysis

The urban expansion between 1989 and 2020 was extracted in a map to represent the dependent variable in the logistic regression analysis. This map had two values: y = 1 if urban expansion was present and y = 0 if urban expansion was not present. Figure 6 shows urban expansion in Delhi from 1989 to 2020.
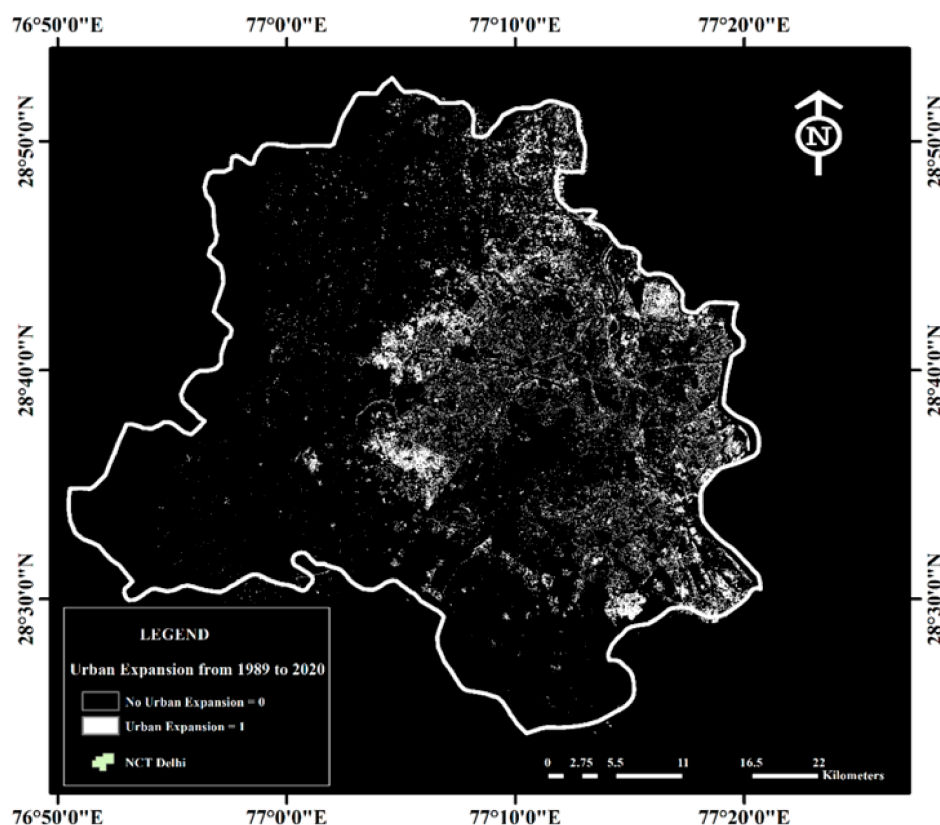


**Figure 6.** Urban expansion in Delhi from 1989 to 2020.

Nine independent factors were examined in the LRM to estimate the influence of each factor on urban expansion. The coefficients of independent factors clarified the nature of the correlation between urban expansion and the driving factors in Delhi during 1989–2020. A higher coefficient value for independent factors refers to a greater probability of urban expansion, while the odds ratio refers to the percentage of success versus the percentage of failure for the independent factor [54,55]. Table 8 shows the values of the nine independent factors.

**Table 8.** The values of the nine independent factors.

|   | Variable | Coefficient | Odds Ratio (OR) |
|---|---|---|---|
| 1 | Proximity to Water Bodies | 0.095 | 0.780 |
| 2 | Proximity to Urban Area | 0.884 | 0.230 |
| 3 | Proximity to Tourist Places | 0.042 | 1.000 |
| 4 | Proximity to Restricted Area | 0.037 | 1.000 |
| 5 | Proximity to Railways | 0.109 | 0.850 |
| 6 | Proximity to Medical Facilities | 0.377 | 0.540 |
| 7 | Proximity to Main Roads | 0.475 | 0.360 |
| 8 | Proximity to Industrial Areas | 0.056 | 1.000 |
| 9 | Proximity to Higher Education Institutes | 0.027 | 1.000 |

Source: Computed by the authors.

The findings of the LRM revealed that the nine independent factors had varying degrees of influence on urban expansion. The odds ratio (OR) for the factor of proximity to water bodies was 0.780, which means that the predicted expansion in an area close to a water body was estimated to be 1.28 times greater than the predicted expansion in an area far from a water body. The OR of urban expansion around existing urban centers was 0.230, which means that the predicted expansion in an area near to an existing urban center was estimated to be 4.35 times greater than the predicted expansion in an area far from an existing urban center.

The OR was 1 for proximity to tourist places, proximity to a restricted area, proximity to industrial areas, and proximity to higher education institutes, which means that there was no impact of these factors on the urban expansion process within the study area. The OR for distance to railways was 0.850, which means that the predicted urban expansion in an area close to a railway was estimated to be 1.18 times greater than the predicted urban expansion in an area further away from a railway. The OR for proximity to medical facilities was 0.850, which means that the predicted expansion in an area close to medical facilities was estimated to be 1.85 times greater than the predicted expansion in an area far from medical facilities.

The OR for proximity to main roads was 0.360, which means that the predicted expansion in an area near to main roads was expected to be 2.77 times greater than the predicted urban expansion in an area far from main roads. Figure 7 shows the raster layers of independent factors (driving factors) in the LRM.

The strong influence of the factor of proximity to main roads on urban expansion in Delhi was similar to its influence in other cities, such as Cairo in Egypt and Atlanta in Georgia [56–58]. This result is also in line with previous results presented by Sharma in 2013, who found that the ribbon growth pattern along roads was the dominant pattern of urban expansion when monitoring the urban dynamics in Delhi from 1998 to 2011 [26].

On the other hand, many researchers have claimed that the population growth rate is the most influential factor on urban expansion in all Indian metropolitan cities [30,32]. Therefore, we recommend analyzing the role of the population factor in future research.
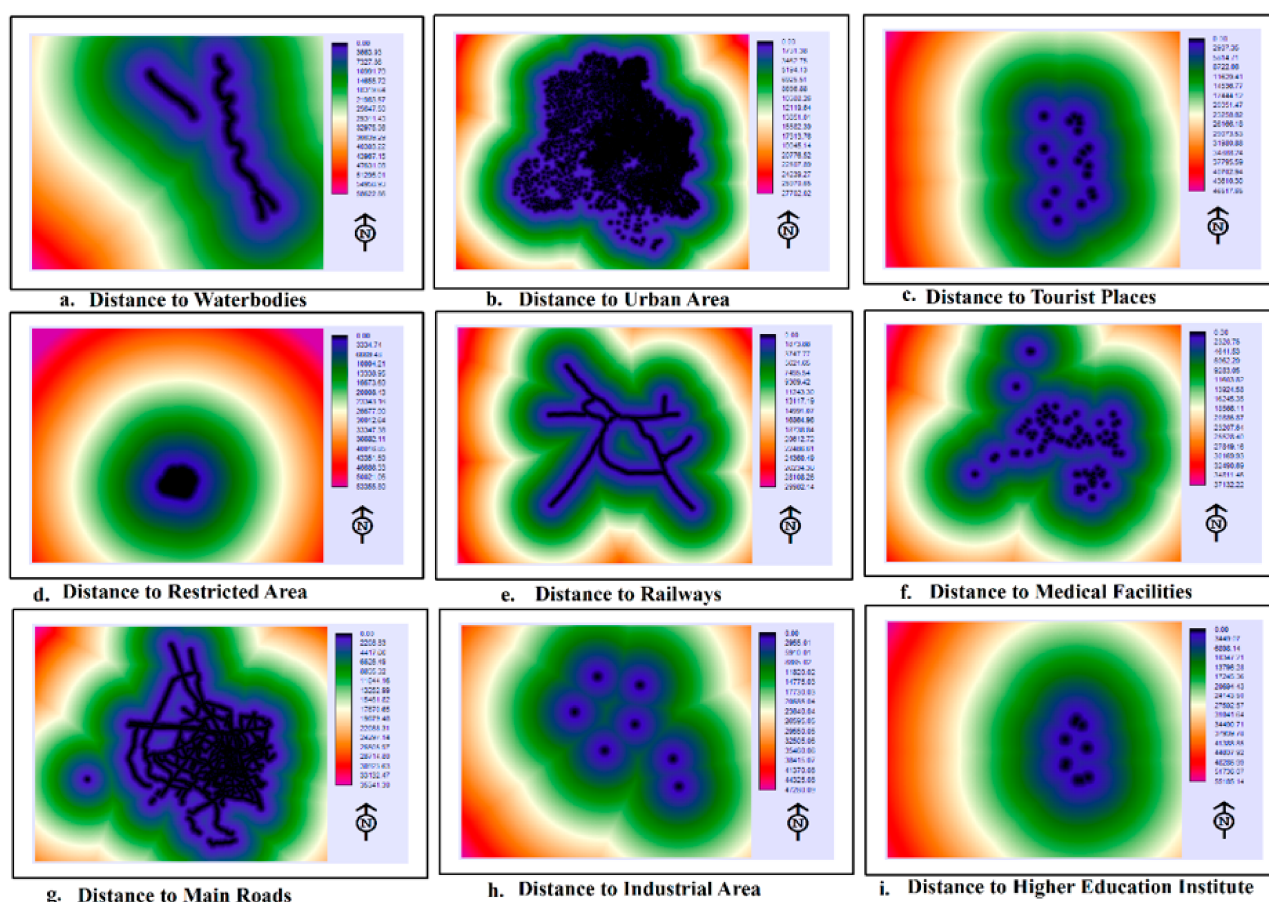
**Figure 7.** Raster layers of independent factors (driving factors) in the LRM.

*3.5. Simulation of Future Urban Expansion*

The simulation of future urban expansion was performed based on the LRM using the following equation:

$$P = (Y = 1|X_1, X_2, \ldots, X_K) = \frac{1}{1 + e - (\alpha + \sum k_i = 1 \beta_i X_i)} \tag{3}$$

where $P = (Y = 1|X_1, X_2, \ldots, X_K)$ is the possibility of urban expansion in a cell, $(X_1, X_2, \ldots, X_k)$, i.e., the likelihood of a cell being urban; $X_i$ is a driving factor of urban expansion, and $\beta_i$ is the coefficient of the driving factor.

The simulation of future urban expansion in Delhi was represented by color classification, as shown in Figure 8. The lighter white color indicates a higher probability of expansion. According to Figure 8, the future urban expansion is predicted to occur close to existing urban areas and parallel to major roads. Most of the cells that are predicted to convert to urban use are currently arable land. In addition, the predicted pattern of urban expansion is chaotic, scattered, and dense on the peripheries. This pattern of urban expansion will cause further deforestation and habitat fragmentation.

The findings of the LRM could be used by local administrative authorities and policymakers in order to adjust the urban expansion on arable land in Delhi. In addition, local administrative authorities should establish strict plans to avoid future informal settlements on the periphery of Delhi. The results of this research will be helpful for local authorities to recognize locations and patterns of future expansion, thus facilitating the implementation of effective policies to achieve sustainable urban development in Delhi.
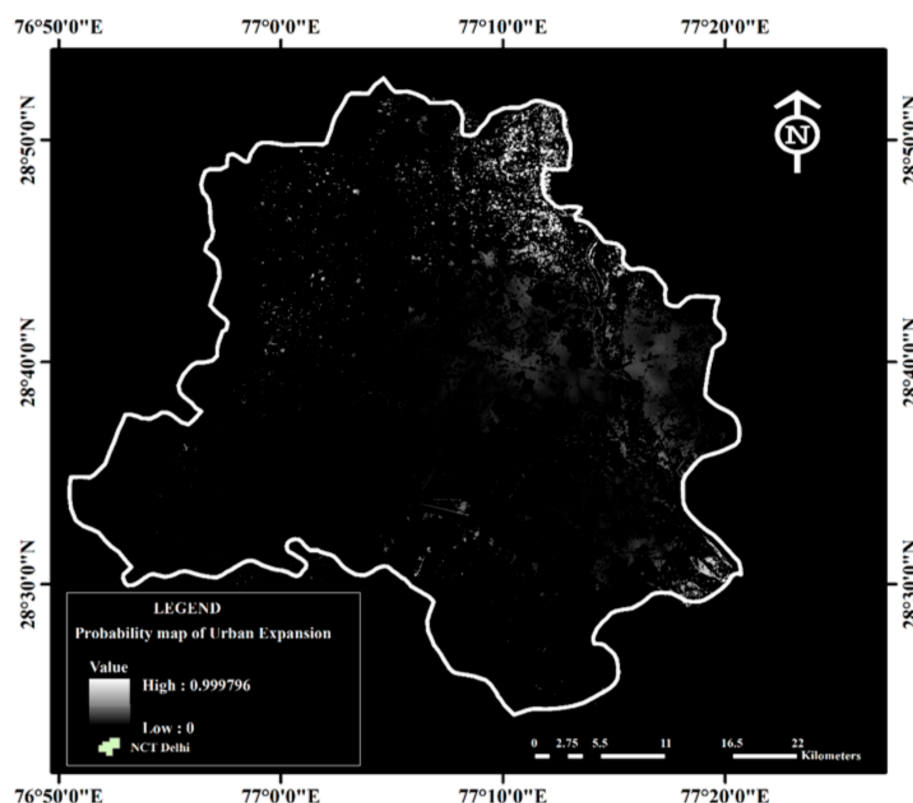
**Figure 8.** Simulation of future urban expansion.

Our results are similar to the findings of Sarkar and Chouhan 2020, who predicted urban expansion in Siliguri city in India, where they found that the most of the urban expansion is located close to main roads [59]. In addition, the results are compatible with the findings of Nallathiga 2018 and Tripathy 2019, who proved that most of the future expansion in Delhi will take place in the peripheries [1,52].

*3.6. Model Validation*

Model validation was carried out to evaluate the model's effectiveness in estimating future urban expansion. The study utilized the relative operating characteristic (ROC) method, which is extensively adopted to investigate the efficacy of a model. This method depends on comparing the probability map of expansion with the actual expansion map using a set of random points. In this study, the model validation was conducted by comparing the simulation of future urban expansion with the actual urban expansion map of 2020 using random samples of 500 cells in each map. The transition probability matrix was computed by the contingency table displaying the relative frequencies of land change at a certain period. From every contingency table, a single data point (x, y) was created, where x and y were the rate of false positives and the rate of true positives, respectively. The ROC value extended from 0.5 to 1.0, where the value of 1 signified an ideal fit, while the value of 0.5 signified a random fit. The model's ROC score was 0.8646, which means that the expansion probability map was valid. Figure 9 shows the ROC curve of the LRM.
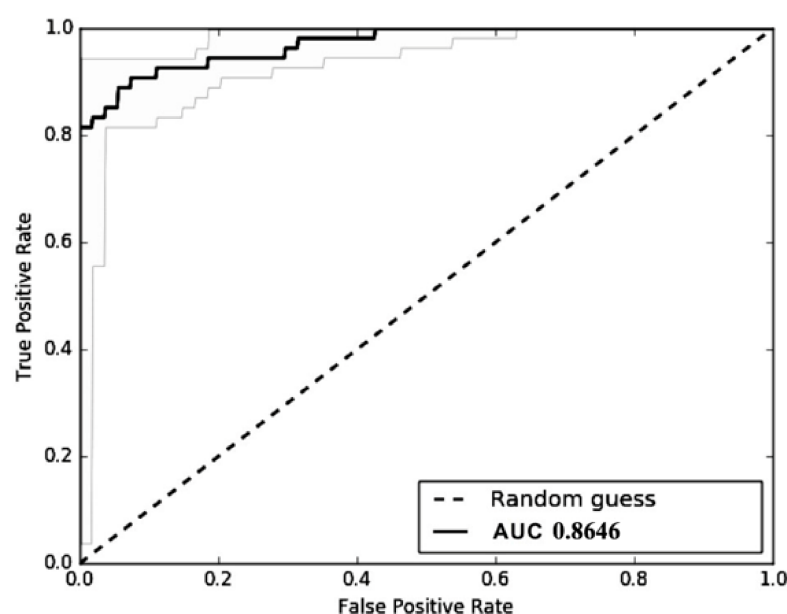
**Figure 9.** ROC curve of the LRM.

*3.7. Limitations and Future Research*

The lack of strategic spatial planning and government control over the urban expansion process in some areas in Delhi has led to a chaotic landscape in such areas [53,60]. However, due to the lack of planning documents in some areas, this factor has not been investigated in this study. Thus, the study strongly recommends studying the effect of spatial planning on urban expansion in Delhi in future studies.

Due to the dynamics of the urbanization process, the urban expansion crosses the boundary of the NCT area towards the neighboring states of Haryana and Uttar Pradesh (India) The other adjoining regions, such as Ghaziabad, Noida, and Gurugram (India), which are part of the broader National Capital Region (NCR), are also affected by massive urban expansion tendencies. Therefore, future studies can be directed towards exploring the urban expansion tendencies in this region.

Despite the ability of the LRM to include several driving factors in the study, some significant factors, such as political factors, cannot be included in the model. Furthermore, the urban expansion probability map provided by the model reveals where urban expansion would occur but does not provide a timeframe. Therefore, some previous studies recommended integrating the Cellular Automata (CAM) Model with the LRM to overcome the inability of the LRM in dealing with temporal dynamics [61,62]. Thus, this study suggests the integration of CAM with the LRM in future research to predict urban expansion. On the other hand, the LRM has a limitation in its ability to capture the non-linear relationships between the dependent and independent factors [63]. Meanwhile, recently, artificial intelligence-based models, i.e., fuzzy ANNs, fuzzy C means clustering (FCM), and the fuzzy deep learning (FDL) model, have proven their accuracy and efficiency in modelling complex nonlinear relationships [9,63,64]. In addition, these models are useful to simulate urban expansion in areas without historical urban land use [65]. Thus, the study recommends using these recent models in simulating urban expansion in future research.

**4. Conclusions**

Despite many previous studies devoted to exploring urban expansion, this study is novel as it provides a comprehensive overview of urban expansion dynamics in Delhi, including its driving factors, spatial patterns, trends, and intensity. The results have revealed that a rapid urban expansion against urban sustainability has occurred in Delhi during 1989–2020. The urban expansion intensity was calculated for each spatial unit in Delhi, and the highest trend was observed on the East South East (ESE) direction,

followed by South South West (SSW). The LRM was used to recognize and improve our understanding of the physical forces that have driven this urban expansion and to detect the most probable locations and patterns of urban expansion in Delhi. The findings of the LRM revealed that proximity to urban centers and proximity to main roads were the most influential factors on urban expansion in Delhi. Additionally, a simulation of future urban expansion in Delhi was performed according to the results of the LRM. The ROC curve was utilized to assess the effectiveness of the model in predicting urban expansion. Most of the cells that were predicted to convert to urban use are currently arable land. In addition, the predicted pattern of urban expansion is chaotic, scattered, and dense on the peripheries. This pattern of urban expansion would cause the loss of large areas of arable land, habitat fragmentation, and problems in operating urban utilities in the new expansions. Finally, the relative operating characteristic (ROC) method was used to assess the accuracy of the simulation. The high score of the ROC curve (0.8646) proved the validity of the model. However, the study recommends using recent artificial intelligence-based models in future research for analyzing and simulating urban expansion in Delhi. Future research can also develop hybrid models, which benefit from the complementary advantages of different models. Such integrations would allow the capture of various drivers and the production of more precise urban expansion simulation models. In addition, future research can be directed towards exploring the urban expansion in the broader scope of the National Capital Region (NCR), which includes the urban centers adjacent to the NCT Delhi. Finally, this research can help local authorities and decision-makers to formulate effective policies to guide urban expansion in Delhi and other megacities, especially in developing countries.

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