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Urban Growth Modeling Using Logistic Regression and Geo-informatics: A Case of Jaipur, India

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Abstract

The study comprises of the logistic regression based urban growth modeling of Jaipur, Rajasthan, India to demarcate the places having higher probabilities of growth in future and also to understand the dependency of urban growth on different driving parameters. Various physical and socio-economic parameters prepared using remotely sensed spatial data were taken into consideration which showed varying level of contribution in the growth process. The built-up data for two different time periods (2008 and 2017) and other geospatial datasets were taken to perform the logistic regression modeling and to obtain the future urban growth probability map as well as to rank the participation of driving forces. The Receiver Operating Characteristics (ROC) curve was plotted to ensure the accuracy of the model. Also, a graph of overall accuracy versus cut value is proposed to determine the change in the behavior of the logistic regression model with varying probability threshold. The optimum cut of value for logistic regression model for the considered parameters was examined. Despite its inability to deal with the temporal dynamics, logistic regression is an empirical formula based robust method for modeling the unplanned urban growth, especially for developing countries like India where the growth is desultory.

Introduction

Urban growth can be elucidated as the densification or expansion of an urban area. Urban growth is responsible for the incautious use of land resources and energy, and large-scale intrusion onto agricultural land. With increased influence of human behavior on urban ecosystems, the urban change have been heeded in the last decade. Indian cities form a complex fabric of human habitation depicting unique cultural and socio-economic heritage. The flourishing urban culture of the country is continuously undergoing a process of change, with new elements being added and old structures getting degenerated, thus making the urban area an unpredictable system. Urban growth in the Indian context is dramatically unplanned, driven by a diverse range of demographic, economic, cultural and political factors. These determining factors of urban growth are of huge attention to urban planners, policymakers and environmentalists. An advanced knowledge of the future growth patterns can contribute to improvisation in the policy making process. As of now, most of the urban plans have failed in this haphazardly populated country (Adhvaryu, 2011; Kanga et al., 2017; Tomar et al., 2017). The probable reasons for failing urban planning practices are the lack of spatio-temporal transformation knowledge, urban growth dynamics and deficiency of decisions aiding tools (Geertman and Stillwell, 2004; Masser and Campbell, 1991; Roy et al., 2017).

Many researchers have proven the effectiveness of models in unfolding and approximating urban growth and have subsequently stated the urban growth modeling to be the essential part for improved policy making (Clarke and Gaydos, 1998; Vaz et al., 2012; Sadhu et al., 2017). Previous studies (Dubovyk, et al., 2011; Arsanjani, 2013; Aljoufie et al., 2013; Singh, 2016) enlightened the necessity and significance of analyzing the spatio-temporal urban growth. Urban growth modeling has evolved in the recent past due to escalated computing abilities, upgraded resolution of satellite imagery and exigency for sustainable growth. Previous studies (Han, 2009; Li et al., 2017; Singh and Kanga, 2017) modeled the urban growth pattern of different urban centers across the world using various models including Cellular Automata (CA), Markov Chain (MC), logistic regression and hybrid models such as CA-MC, CA-logistic regression and logistic regression-MC-CA (Aburas et al., 2016; Al-sharif and Pradhan, 2013; Batty, 2007) Among all introduced models, CA-based models have gained huge attention in the recent past as it works on logically pre-defined transition rules.

Among all introduced models, CA-based models have gained huge attention in the recent past as it works on logically pre-defined transition rules and is able to capture the temporal growth dynamics. The complex growth pattern and the nature of CA models to work on microscopic level limits the CA model from modeling the urban growth of Indian cities. Understanding and modeling the complex urban growth of cities in India is quite challenging, a robust approach for such scenario is required which is fulfilled by the logistic regression models. Previous studies (Tayyebi et al., 2013; Wu, 2002; Singh et al., 2017) advised that modeling the growth of complex urban structures such as that of India cities is best suited using a CA-Logistic Regression hybrid model. The logistic regression based models determine the coefficients of the participating dependent variables by performing the maximum likelihood estimation (MLE). The estimated coefficients depict the dependency of urban growth on respective independent variables.

The present study is an approach to model the urban growth and demarcate the places having higher growth probabilities for Jaipur, Rajasthan, India using the logistic regression model and to understand the urban growth clinging to different demographic and econometric factors. Despite its inability to deal with the temporal dynamics, logistic regression is an empirical formula based vigorous method for modeling the urban growth, especially for developing countries like India where the growth is unpremeditated. Logistic regression models are empirical formula based models where the presence or absence of growth depends on a number of independent variables. The coefficients are determined by performing the maximum likelihood estimation (MLE) which depict the dependency of urban growth on respective independent variables.

Study Area

In the present study, the capital city of Rajasthan, Jaipur which is also known as the 'Pink City' is taken as a study area. Located in Eastern Rajasthan the latitude and longitude extent of Jaipur ranges between 26°47' to 27°02' North and 75°36' to 75°55' East. The average elevation from mean sea level is 431m with annual precipitation 603mm. Summers are as hot as 47 ^{0}C and temperature in winters drops below 0 ^{0}C. The city is surrounded by forests and hilly terrain in the Northeastern corridor. The total population of the Jaipur city is 3.046 million and the district population density is 470 people/km^2.

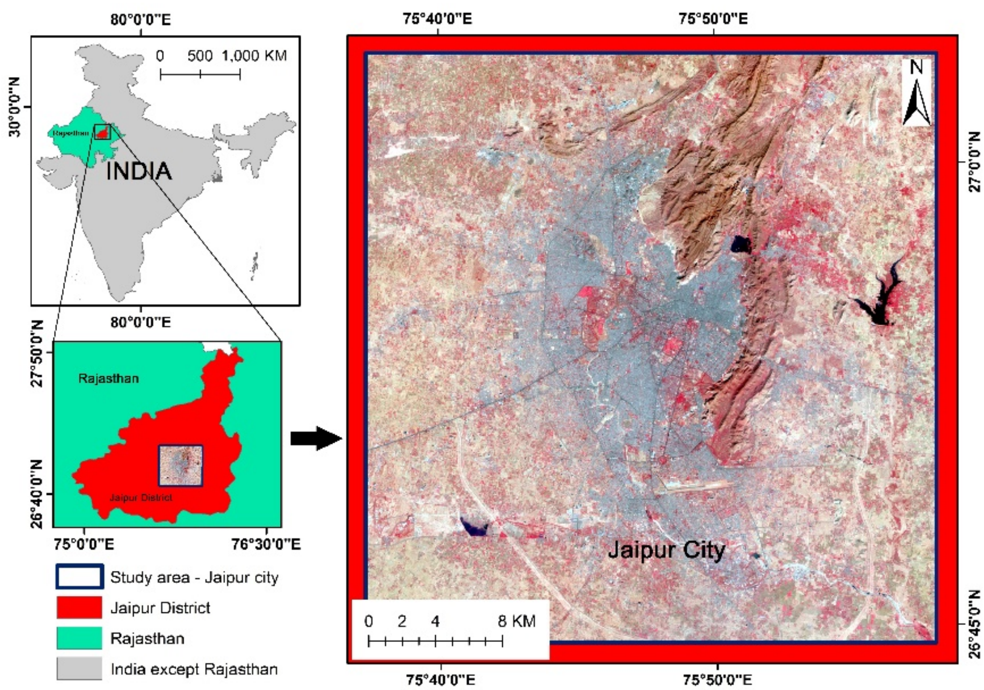

Figure 1: Jaipur, India was taken as the study area.

Materials and Methods

Data Use: For modeling the urban growth using the logistic regression model, a set of variables were prepared using the different spatial data and fitted in the model to estimate the coefficients using MLE. The determined coefficients were used to validate the model by simulating the growth between the year 2008 and 2017 using the 2008 data. Later, the built-up growth probability map for future was produced using the year 2017. A brief methodology has been shown in figure 2.

Table 1: Details of data used in the study

Data Type	Details	Date of acquisition
LANDSAT 5 TM	Path: 147; Row: 41	2008/11/14
LANDSAT 8 OLI	Path: 147; Row: 41	2017/11/23
SRTM-1 DEM	N26E75 N27E75	2000/02/11 2000/02/11
Transport network	Roadways (NH & major)	
Placemarks	Medical facilities, educational centers, Industries and hotels	

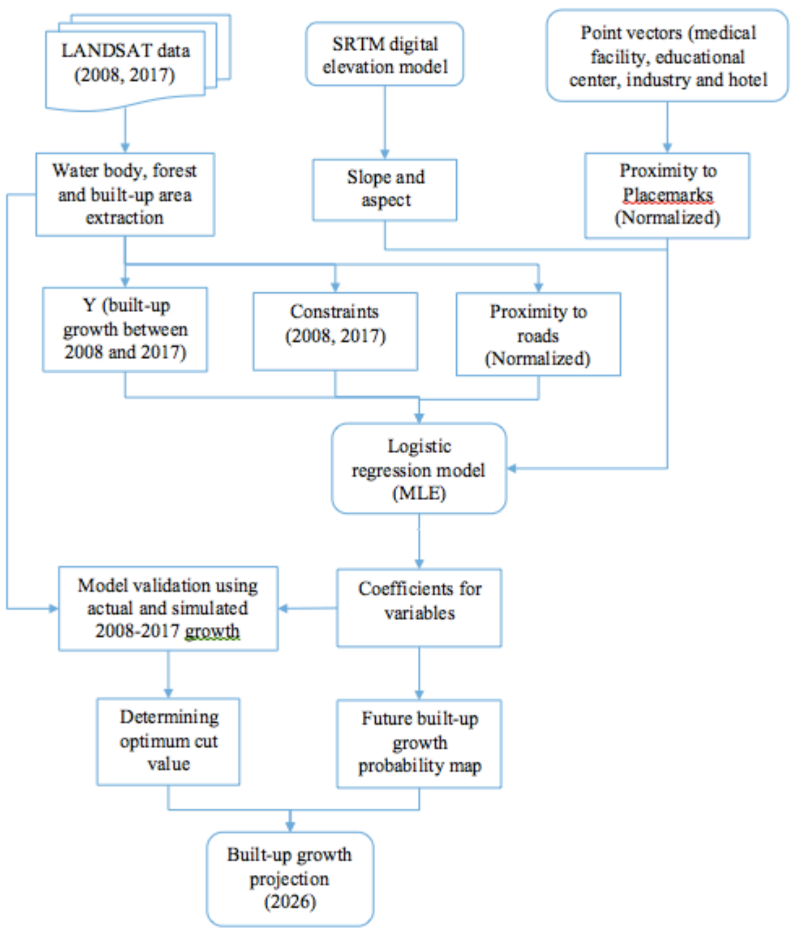

Figure 2: Methodology flow chart adopted in the study

Logistic regression model algorithm

The logistic regression model is used for estimating the state of dichotomy of *Y* being 1 or 0 representing success and failure respectively. Here, Y is the dependent variable that is a function of a set of independent variables that can be dichotomous, continuous or categorical in nature and the success and failure are defined as the presence and absence of urban growth.

$$g(Y) = \beta_0 + \sum_{i=1}^{n} \beta_i X_i \quad (1)$$

In formula (1), $g()$ is a linear combination linking the dependent variable *Y* and the set of independent variables X_i. β_0 is the constant and β_i is the coefficient associated with the independent variable X_i to be estimated by using the maximum likelihood estimation (MLE) in the logistic regression model. The value of *i* ranges from 1 to *n,* where *n* represents the total number of independent variables considered.

$$P(Y = 1|X_1, X_2 \dots X_n) = \frac{exp\left(\beta_0 + \sum_{i=1}^{n}(\beta_i X_i)\right)}{1 + exp\left(\beta_0 + \sum_{i=1}^{n}(\beta_i X_i)\right)} \quad (2)$$

Formula (2) as mentioned in [33] shows the probability of dependent variable *Y* being 1 linked with different independent variables X_n, *i.e.,* the probability of occurrence of the urban growth. The details of variables for the logistic regression model has been shown in Table 2.

Table 2: List of variables in the logistic regression model

Variable Name	**Description**	**Data type**
Dependent		
Y	1 and 0 showing presence and absence of built-up growth	Dichotomous
Independent		
X1	Constraints (Built-up, water body, forest areas) - 2008, 2017	Dichotomous
X2	Distance to Built-up (2008, 2017)	Continuous
X3	Distance to road network	Continuous
X4	Distance to medical facility	Continuous
X5	Distance to educational center	Continuous
X6	Distance to industries	Continuous
X7	Distance to hotel	Continuous
X8	Slope	Continuous
X9	Aspect	Continuous
X10	Northing coordinates	Continuous
X11	Easting coordinates	Continuous

Variables preparation

For modeling the urban growth pattern, spatial data of two different time periods were used to prepare independent variable data sets. The built-up growth between 2008 and 2017 was prepared to be used as a test sample for performing the regression to evaluate the coefficients for different parameters. The water bodies and built-up features for the year 2008 and 2017 were prepared using the LANDSAT 5 TM and LANDSAT 8 OLI data. The SRTM DEM (digital elevation model) was used to evaluate the slope and aspect of the study area. The roadways vector layer was used to compute the proximities to major roads and the point data for medical facilities, educational centers, industries, and hotels were used to obtain the respective proximities.

Built-up growth from 2008-17 (*Y* for regression)

The built-up growth was computed by spatially calculating the difference between the 2008 and 2017 built-up land. The resulting growth *Y* acted as a test sample in the logistic regression model fit to estimate the coefficients of independent variables. The prepared dichotomous layered contained values 1 and 0 showing the presence and absence of built-up growth respectively.

Constraints (built-up, water bodies, protected areas)

The constraints consist of the built-up patch, water body and forest areas which remain constant with due course of time except for the built-up land which increased from 2008 to 2017. The prepared layer was dichotomous in nature and therefore held the value 1 and 0 showing the presence and absence of a constraint feature. This binary thematic layer has been used to train the model that no built-up growth can take place in an already urbanized area or protected land. The built-up layer for the year 2008 was used for regression and 2017 for future probability prediction.

Distance to built-up area

The distance to built-up area shows the proximity to the already built-up area of a point on the map. The prepared raster layer was normalized and continuous in nature such that pixels closest to the built-up patch held highest value *i.e.* 1 and the pixel at a maximum distance from the built-up patch in the raster layer held the value 0. The built-up patch of the year 2008 was replaced by the built-up patch of 2017 from regression to future growth probability prediction.

Distance to major roads

The proximity to all the features were and normalized in such a way that the pixel nearest to the feature holds a value 1 and the farthest one holds 0. The distance to the roads were prepared using the line road vector layer whereas medical facility, educational centers, industries and hotels were generated in terms of vector points in the GIS environment. Same layers was used during the model calibration and future prediction. The distance to different facilities were considered in to get a glimpse of their ranking in the growth process.

Slope and aspect

The slope of an area represents the inclination values in degrees, here ranging from 0 degrees to 55 degrees, whereas aspect shows the direction of slope in 9 different classes *viz.,* North, Northeast, East, Southeast, South, Southwest, West, Northwest and Flat. Both the layers were prepared using the SRTM 30m data downloaded from USGS portal (https://earthexplorer.usgs.gov.in).

Northing and Easting coordinates

The prepared northing and easting coordinates were continuous in nature normalized between 0 and 1. The values in the easting coordinates layer were minimum *i.e.* 0 at the western edge of the study area increasing continuously towards east and maximum *i.e.* 1 at the eastern edge. Similarly, the cells at the southern edge of the northing coordinates layer held the minimum value *i.e.* 0, continuously increasing towards north direction reaching highest value *i.e.* 1 at the north edge. The necessity of considering the northing and easting coordinates is to assist the model in determining the orientation of growth.

Result and Discussion

The logistic regression model was used to fit the variables in a linear equation form and to derive the coefficients of independents driving the growth process. The actual and simulated growth between 2008 and 2017 was compared to find the goodness-of-fit of the model.

Variables

The variables for future built-up growth prediction were fitted in the logistic regression model. The data type of variables were dichotomous and continuous in nature, as per the requirement. All the continuous variables were normalized between 0 and 1 except for the slope, where the cells contained actual slope values in degrees. Figure 3 shows the variables used in the present study.

The independent variables along with the sample *Y* was used for the logistic regression model fit. The independent variables involved in the logistic regression model along with their statistics are illustrated in Table 3. The highest coefficient value was estimated for the distance to built-up area and the lowest was assigned to the aspect of the area calculated using the digital elevation model.

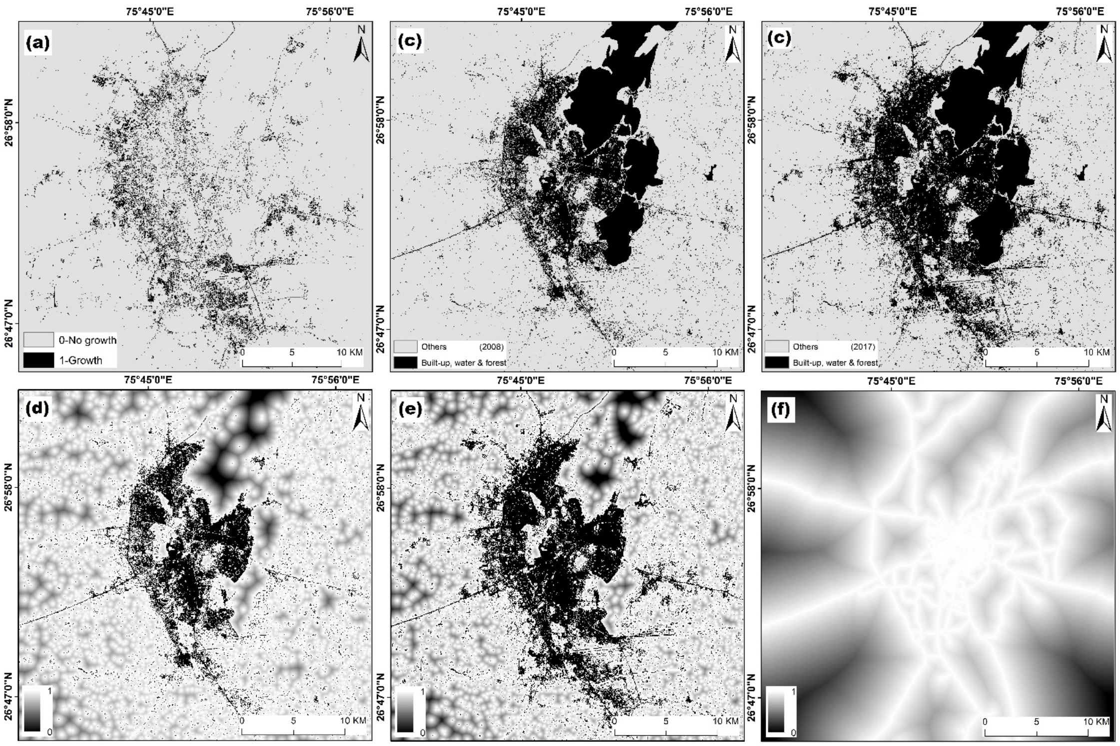

Figure 3: Map showing (a) Built-up growth (2008-2017), (b) constraints in 2008, (c) constraints in 2017, and distance to (d) built-up 2008, (e) built-up 2017, (f) roads,

Table 3: Statistics of variables as obtained from logistic regression model

Variable name	Coefficient	Standard error	Sig.(P>chi-square)
Intercept	-30.360	0.147	0.00
X1	-0.912	0.32	0.00
X2	21.654	0.156	0.00
X3	2.176	0.044	0.00
X4	4.649	0.049	0.00
X5	1.879	0.045	0.00
X6	0.780	0.033	0.00
X7	1.002	0.042	0.00
X8	-0.022	0.002	0.00
X9	-0.001	0.002	0.68
X10	-0.729	0.017	0.00
X11	-1.960	0.020	0.00

Dependent

The dependent variable *Y i.e.,* built-up growth between the year 2008 and 2017 was computed to be used as the test sample for the logistic regression model. The coefficients were determined using the dichotomous values of *Y* showing presence and absence of urban growth which were then used in the built-up growth probability prediction purpose.

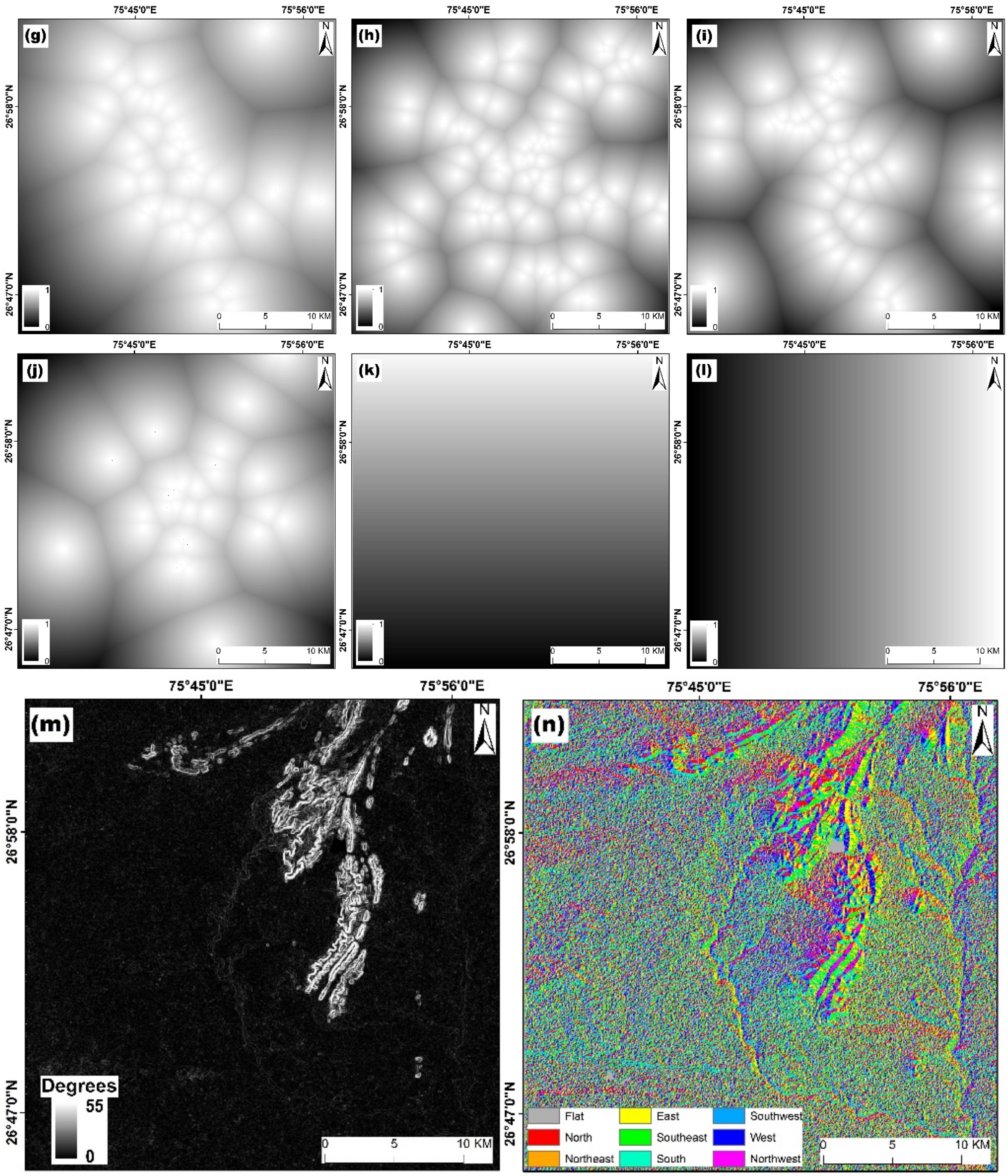

Figure 3: (g) medical facility, (h) educational centers, (i) industries, (j) hotels; (k) northing coordinates and (l) easting coordinates, (m) slope and (n) aspect of the study area.

Independent variables

Among all the independent variables, the ones associated with the built-up area *i.e.* constraints and distance to the built-up area were updated by replacing the 2008 data by 2017 from modeling to prediction. The coefficients of the dependent variable depict their participation level in determining the growth process which has been discussed in the subsection below.

Constraints (built-up, water bodies, protected areas): The constraints were used to restrict the model that from predicting the built-up growth in these areas. The coefficient of the constraints as obtained from the logistic regression model was -0.912. The negative sign here shows that the presence of constraints does not promote the built-up growth.

Distance to built-up area: The distance to built-up variable trains the model to increase the chances of growth in the vicinity of an already urbanized area. The coefficient of this variable as mentioned in Table 3 was 21.654 which shows its favoring nature in the growth process.

Distance to major roads: Distance to roads was considered as people tend to settle closer to the roads. The coefficient of the distance to roads obtained from the logistic regression model was 2.176 which shows a positive impact on the growth process.

Distance to medical facilities, educational centers, industries, and hotels: The proximity to medical facilities, educational centers, industries, and hotels showed a positive role in the growth process with coefficient values 4.649, 1.879, 0.780, and 1.002 as obtained from the logistic regression model. This supports the fact that the people are more likely to settle in areas closer to the basic facilities.

Slope and aspect: The coefficient for the variables slope and aspect were computed as -0.022 and -0.001 which shows a negative relation with growth. This was quite obvious in the case of slope as people tend to settle in plain areas and not on a steep terrain. The very low negative value of the coefficient of aspect shows that it does not affect the urban growth process at all and hence was barred from the prediction purpose.

Northing and Easting coordinates: The northing and easting coordinates reflected the coefficients -0.729 and -1.960 respectively. The negative sign here is due to the design of the variable and hence would have been positive if the cells at the eastern edge of the easting coordinate layer contained lower values and vice versa and the north edge cells in the northing coordinate layer contained lower values. The comparatively higher value of the easting coordinate shows that built-up patch of the study area is favored more in growing towards the east-west direction. Since the city limits are constrained by the forest and elevated areas at the Northeastern corridor, therefore, the growth is favored most in the west direction followed by the north and south directions.

Urban growth pattern modeling using logistic regression

The urban growth contributing factors were fitted in the logistic regression model to check the dependency of growth on each one of them. All the independent variables showed the varying level of contribution towards the growth process of which the distance to built-up areas showed the highest contribution followed by the distance to medical facilities and roads, and the aspect showed the lowest amount of contribution. The aspect variable was exempted from participating in the growth prediction process due to its extremely low coefficient value. The variables X1 and X2 were associated with the already built-up area and hence were updated in the growth prediction step by replacing the built-up patch of the year 2008 by 2017.

Model validation

For model validation purpose, the obtained coefficients were used to compute the growth probability for the year 2017 using the layers involved (excluding aspect) in the logistic regression model. The predicted 2017 probability layer was used to extract the built-up cells for different threshold/cut values of probability. A comparative analysis of the built-up growth between the year 2008 and 2017 for the actual and simulated data was conducted to generate the confusion matrix for different cut values.

Table 4: Confusion matrix for cut value 0.5

		Predicted growth		Percentage correct	Overall accuracy
		0	1		
Actual growth	0	1248571	3411	99.7%	93.2%
	1	87661	4417	4.8%	

Table 5: Confusion matrix for cut value - 0.25

		Predicted growth		Percentage correct	Overall accuracy
		0	1		
Actual growth	0	1174274	77708	93.8%	91.2%
	1	40074	52004	56.5%	

As it can be seen from Table 4 that the percentage of predicted growth accuracy in the confusion matrix for cut value 0.5 is very low, the cut value is the probability threshold above which all the cells are considered as 1 (presence of growth) and below it is 0 (absence of urban growth). The overall accuracy accounts for 93.2% due to high accuracy and a high number of non-growth cells. Such low accuracy percentage of growth occurrence can be due to small cell size which increased the number of non-growth cells comparatively and also due to the complex growth dynamics. The receiver operating characteristic (ROC) curve was plotted between the true positive rate (sensitivity) and the false positive rate (1-specificity) and the area under the curve (AUC) was computed as 0.8933.

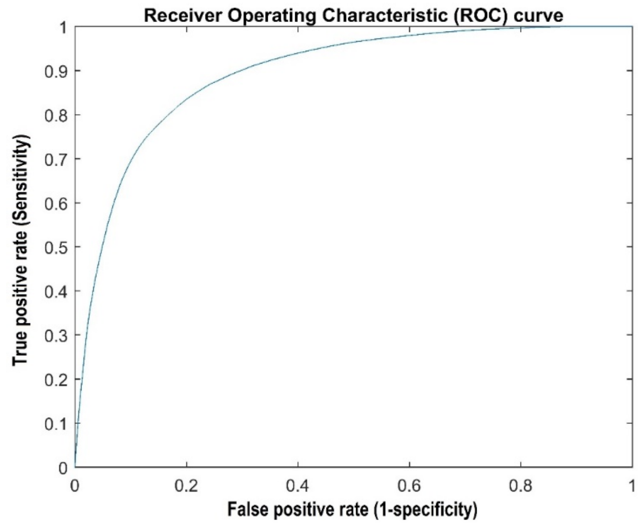

Figure 4: ROC curve for cut value 0.5

The confusion matrix for different probability threshold values showed that a decrease in the threshold increases the built-up growth accuracy with minimal loss in the overall accuracy of the model. Since the accuracy of built-up cells is of much concern, therefore little degradation in the overall accuracy can be ignored. Dropping the cut value to 0.25 (Table 5) lowered the accuracy of predicted non-growth cells from 99.7% to 91.5% but a convincing increase in the accuracy of predicted growth (4.8% to 65.2%) cells was found, accounting to the overall accuracy 89.7%. The accuracy versus cut values graph has been shown in Figure 5.

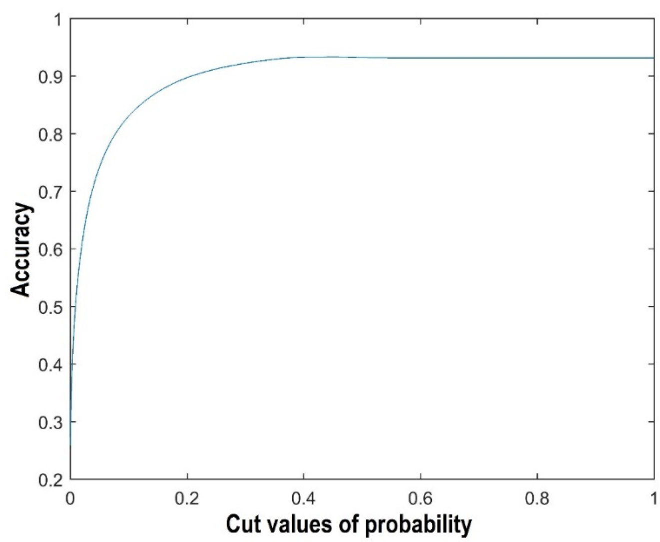

Figure 5: Probability cut values versus accuracy graph

The graph plotted between the accuracy and the probability cut values represents that the accuracy increases gradually with increasing cut value and gets saturated as the cut value reaches 0.38. Hence, the present conditions of the variables used in the study and the coefficients as obtained from the logistic regression model suggest that the optimum threshold of the probability for extracting the built-up growth cells is 0.38 and not 0.5, which is the standard cut value. Taking the lowest possible probability cut value is preferred to ensure higher accuracy of the built-up growth representing cells.

Growth prediction using logistic regression

The probability of the urban growth was computed using (1) and (2) is shown in Figure 6. Two variables *i.e.,* constraints and built-up for the year 2017 along with other independent variables were used to project the growth probability data. It was found that the majority of growth is expected to take place in the western periphery of the built-up extent and in the remote pockets located in the southern outskirts. The probability map was classified in 3 classes as shown in Figure 6.

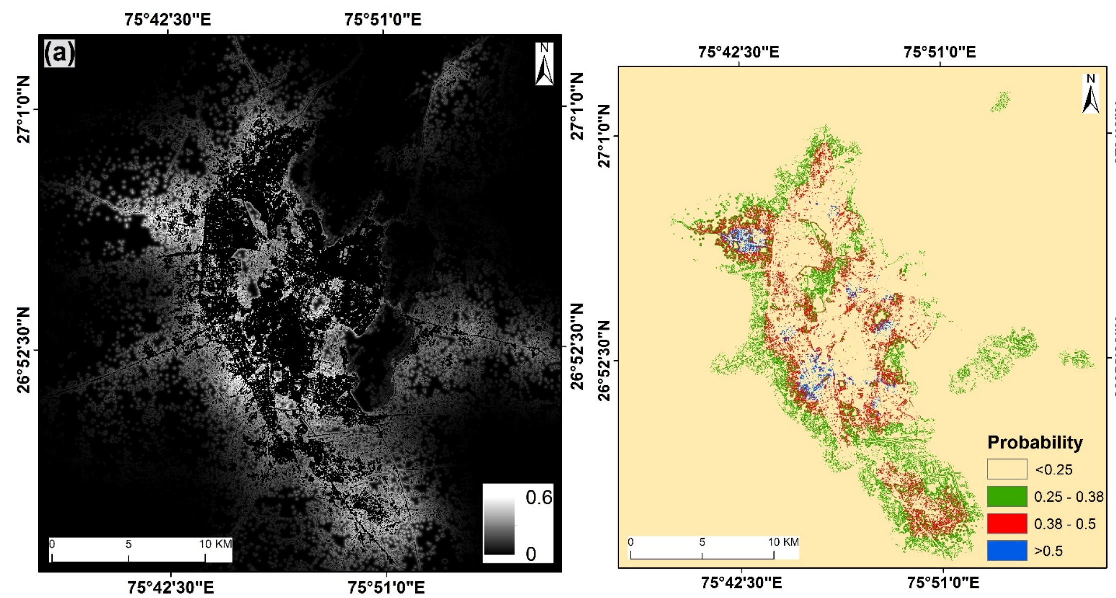

Figure 6: Built-up growth probability map represented in (a) continuous, and (b) designed data type

The built-up growth probability map (Figure 6(a)) for the year 2026 illustrates high chances of urban growth in the northwest corridor and the southern outskirts. The city is also expected to densify in few places inside the built-up patch, also, there are moderate chances of growth of the city in the eastern remote locations along the roads. The categorized probability map (Figure 6(b)) has 3 classes with cut values 0, 0.25 and 0.38. The logic behind such classification can be clarified since the accuracy versus cut value graph (Figure 5) suggests the optimum cut value to be 0.38 and, a hit and trial method suggests that the optimum cut value 0.25, as it gives a high accuracy of built-up growth land without hampering the overall accuracy of the model. Also, the area of built-up land growth as obtained by considering 0.38 as the cut value was found to be 33.86 km^2, whereas, the area obtained using 0.25 as cut value is 83.65 km^2 which is much closer to the actual built-up growth land area between 2008 and 2017 (82.87 km^2). The aforementioned logical standard cut value is 0.5, which contradicts the findings of this study, the probable reason behind this is that the upper extent of the obtained probability map is 0.6, and a cut value 0.5 would have produced convincing results if the probability upper limit would have been 1. Since most of the independent variables were not updated from regression to prediction stage, therefore, it resulted in the decreased upper limit of probability.

Conclusion

The logistic regression model was developed for modeling the urban growth and to obtain the future growth probability map and to deduce the dependency of growth on different physical and socioeconomic variables. The model determined the coefficients for the independent variables using the maximum likelihood estimation (MLE) assigning highest coefficient value to the distance to built-up variable as the built-up growth takes place primarily in the outward direction of the already built-up land. The second highest coefficient value was for the distance to medical facility variable which clarifies that the growth has occurred majorly in places with better accessibility to medical facilities. The third rank was assigned to the distance to roads which shows that the growth was favored in places closer to roads. Model validation was done by computing the confusion matrix and plotting the ROC graph whose area under the curve (AUC) was calculated. The graph of overall accuracy of model versus cut values was plotted and the optimum cut threshold for the logistic regression model was found to be different from the standard cut value. It was also found that a decrease in cut values increases the accuracy of predicted growth cells. Therefore, cut values were dropped for which the agreement of predicted built-up cells were convincing without much degradation in the overall model accuracy. Jaipur city is expected to grow rapidly in the northwestern periphery and the southern part. Since, the growth is restricted by the forest and hills in the north eastern city boundary. The logistic model aided the understanding of multifarious growth process and also gave a glimpse of environmental risk arising from urban growth. The use of statistical models was found to be very effective for the predicting complex urban system within Indian context.

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