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Finding robust model for Urban Growth Prediction based on Land Use Land Cover Classification: A comparative study of CA Markov based Models LCM and MOLUSCE

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ABSTRACT

Background: Scientific information of future LULC is fundamental to make proper land use planning to fulfill the rising human demands and their wellbeing without causing lasting damage to environment.
Objectives: This paper is an attempt to identify the robust model among CA MARKOV based model Land Change Modeler (LCM (IDRISI) and MOLUSCE Model (QGIS Plugin) to predict urban growth for 2020 using LULC dynamics during 2000-2010 of Jaipur city, India, and Austin in America.
Methodology: The predicted maps were compared with observed map and accuracy was checked through mathematical equation as well as Kappa Index Statistic Assessment Tool of MOLUSCE Plugin.
Results: The results obtained through CA Markov method are robust and more accurate compared to MOLUSCE model. Therefore, it is highly recommended for government and non-government officials to study LULC dynamics and urban growth predictions in order to build urban resilience.
Conclusion: The study also highlights the importance of integrating road network data in improving prediction accuracy. These findings contribute to the development of sustainable urban planning strategies in rapidly growing cities.

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1. INTRODUCTION

Urban growth is one of the biggest environmental issues worldwide and an important development issue in developing countries like India. It has serious environmental, social, and economic implications in terms of food, clothing, housing, transport, pollution, sanitation, power, telecommunications, and health care. Continuous monitoring of land uses and land cover (LULC) changes for the past, present and predicting future changes are of utmost necessity for scientists, agriculturalists, urban planners, environmentalists, and policy makers to take timely actions to manage populace and related issues (Maurya et al. 2022). This work has been accomplished by studies around the world to plan proper land use policies and sustainable management (Guidigan et al. 2019). LULC prediction enable to build resilience in an urban area for upcoming catastrophes and climate shocks too.

The present study is an attempt to urban growth prediction using CA Markov and MOLUSCE models based on LULC integrated road network for Jaipur, India and Austin, USA. Urban growth prediction helps

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in urban planning, resource allocation, management, and conservation, and building resilience.
The objectives of present study are
(1) to find robust method of urban growth prediction amongst MOLUSCE and CA Markov
(2) to find differences in results of urban growth prediction using CA Markov and Molusce models
(3) to check the influence of Road network in predicting urban growth
For the above objectives, Jaipur City from India and Austin from USA are selected.

1.1. Literature Review

Urban growth prediction has been the subject of research for several reasons (Achmad et al. 2018; Al-Darwish et al. 2018; Clarke & Gaydos, 1998; Ebrahimipour & Farshchin, 2021; Guidigan et al. 2019; Jafari et al. 2016; Jayasinghe et al. 2019; Liu et al. 2019; Mc Cutchan et al. 2020; Mosammam et al. 2017; Samat, 2009). Studies across the world tried to achieve greater insight in extracting data, monitoring, and predicting LULC or urban growth with the help of available and advancing technology. The integration of RS and GIS proved useful in extracting accurate data and to process it for LULCC and its analysis. The prediction of LULC is achieved by different models available either as integrated software's or plugins. Mosammam et al. (2017) used a spatial approach through Idrisi Selva to quantify urban sprawl in Qom, Iran. Clarke & Gaydos, (1998) employed a combination of satellite data and a Loose-Coupling automation model based on Scale-independent classical cellular automation to predict urban expansion in San Francisco, Washington, and Baltimore. Semantic-based Urban Growth Prediction was done by Mc Cutchan et al. (2020). Another study came from Maurya et al. (2016) to investigate and predict urban growth in urban Jaipur. They used Toposheets from the India Geological Survey combined with Landsat MSS, TM, and ETM + data to prepare LULC maps while 2021 map was predicted through multilayer perceptron data. The SLEUTH is another model used to predict urban expansion and is employed by Liu et al. (2019) for East China. Jat et al. (2017) used the SLEUTH Model to anticipate the urban expansion of Ajmer city using Land Cover Deltatron (LCD) with Urban Growth Model (UGM).
CA Markov model is also employed to predict urban growth for Seberang Perai area in Penang State, Malaysia (Samat, 2009), Gilan, Iran (Jafari et al. 2016), Banda Aceh, Indonesia (Achmad et al. 2018), IBB city of Yemen (Al-Darwish et al. 2018), in Bojnourd, North Khoasan (Ebrahimipour & Farshchin, 2021). While CA Markov Model to predict urban growth was employed by (Aithal et al. 2013) for Greater Bangalore, India, in Vijayawada, Andhra Pradesh, (Kusuma & Pradesh, 2017), in fast urbanizing cities of India including Mumbai, Delhi, Chennai, Pune, and Coimbatore (Bharath et al. 2018), in Pune, Maharashtra (Yadav et al. 2019). The projection of urban growth for Chennai, Tamil Nadu, India was carried out using a neural network coupled agents-based Cellular Automata model (Aarthi & Gnanappazham, 2018). Guidigan et al. (2019) studied the LULC dynamics and its impacts in Benin Republic using MOLUSCE model and validate the results by comparing the observed and predicted LULC maps.
In a study by Mondal et al. (2016), urban development was studied and predicted for Guwahati, India and used Kno, K Location statistics and K Location strata statistics for validation of predicted maps. Most of the previous studies focused only on LULC prediction but failed to present area statistics under each class and validation and accuracy assessment was not done properly.
Furthermore, no such study except (Jayasinghe et al. 2019) has conducted a comparison to identify the most robust technique to make urban growth prediction and such studies in India are very limited.
A study conducted by Mountrakis & Triantakonstantis, (2012) reviewed available urban growth projection models. It found that Spatial Autocorrelation and Heterogeneity models are mainly used with several underlying modelling methods like CA, ANN, Fractal Modeling, Decision Trees Regression, and Agent-Based Modeling. Of all these models, Cellular Automata was discovered to be the most extensively used method as it was employed by 83 percent of the academics, followed by Logistics Regression (23 %), ANN (12%), Fractal Modeling (10%), Agent-Based Modeling (9%), and Decision Trees (2%). Jayasinghe et al. (2019) did a comparative evaluation of urban growth models (FUTURES, SELUTH, and MOLUSCE). The study concluded that MOLUSCE is easy to implement with limited data and have acceptable accuracy, FUTURES is a robust, customizable, and flexible to incorporate policy scenarios while SLEUTH is extensively used. Study further revealed that it is not

fair to compare which model perform better than the other considering the variations of implementation, techniques, and procedures.

2. METHODOLOGY

2.1. Data Used

2000 and 2010 Landsat 5 TM and 2020 Landsat 8 OLI data were acquired from United States Geological Survey (USGS) having spatial resolution of 30 m for both Jaipur and Austin. These data have geographical coordinate system (GCS) based on the World Geodetic System (WGS 84). The other essential data namely Road Network was acquired from Open Street Maps, while Digital Elevation Model (DEM) from Earth Data Portal of NASA. From these data sets other raw data (road distance, slope, urban distance) are prepared. Table 1 and Fig. 1 showed the raw and final data used in this study.

Table 1. Raw data used in this study.

S. No.	Data Type	Source	Acquiring Date (yyyy.mm.dd.)		Path & Raw		Resolution
			Jaipur, India	Austin, USA	Jaipur, India	Austin, USA	
	Satellite data						
1.	Landsat 05 TM	USGS	2000.04.14	2000.04.31	147 / 41	027/039	30 m
2.	Landsat 05 TM	USGS	2010.04.10	2010.05.03	147 / 41	027/039	30 m
3.	Landsat 08 OLI	USGS	2020.04.21	2020.04.12	147 / 41	027/039	30 m
	Essential data						
4.	Road Network Map	OSM Data	-		-		-
5.	DEM	Aster Dem	-		-		90 m

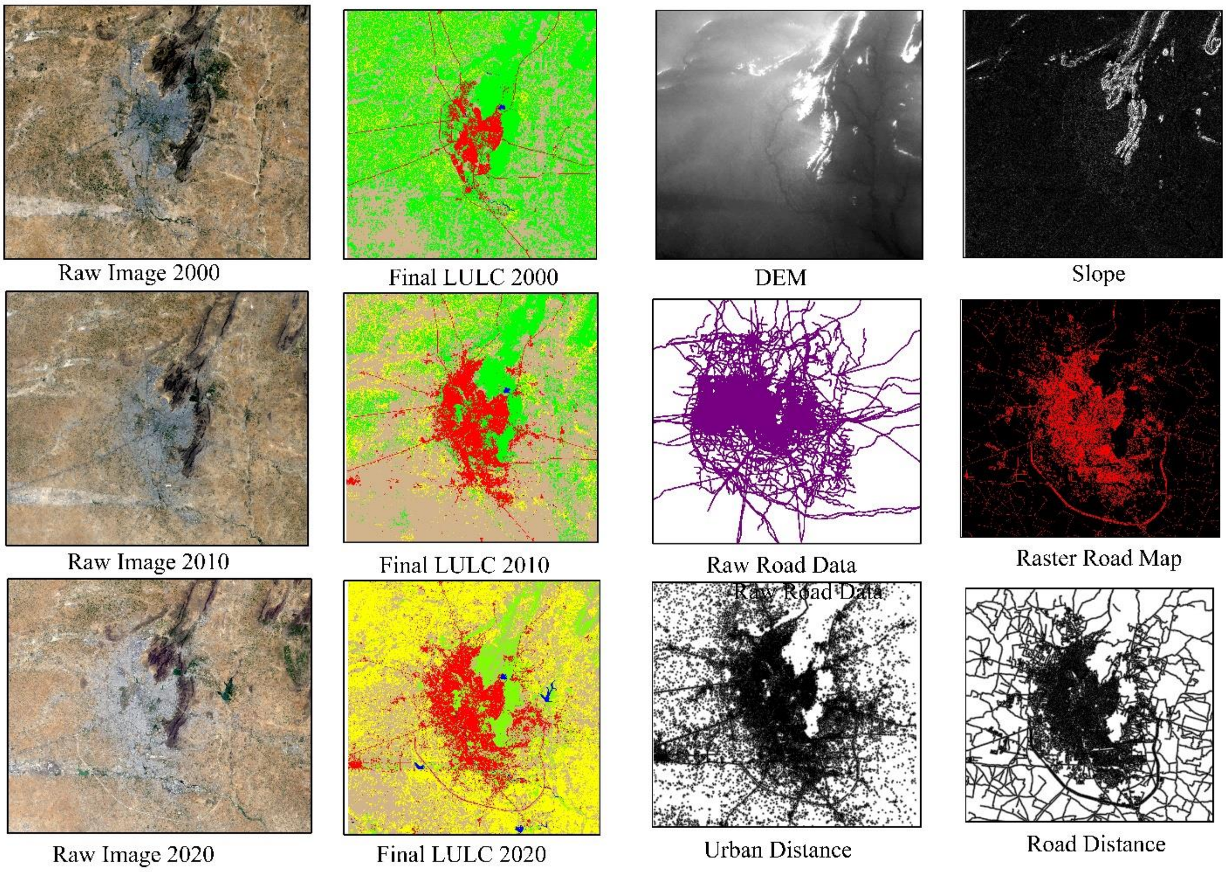

Fig 1. Data visualization used in Analysis

Table 2a. LULC data accuracy through; a)Accuracy assessment and , b) Kappa statics (Jaipur, India)

a) Accuracy Total			
Classes	2000 Producer/User	2010 Producer/User	2020 Producer/User
Vegetation	85.71/90	95/95	93.33 /93.33%
Agriculture	100/95	94.44/85	88.89%/100%
Barren	100/100	90.48/95	93.75%/93.75%
Built-up	100/90	100/100	93.75%/93.75%
Water	100/100	100/93.75	100%/ 93.75%
Overall	93.88%	93.75	93.75%
b) Kappa statics			
Vegetation	0.8727	0.9368	0.8462
Agriculture	0.9380	0.8154	1.0000
Barren	0.9364	0.9360	0.9219
Built-up	1.0000	1.0000	0.9219
Water	0.8775	0.9259	0.9231
Overall Accuracy	0.9236	0.9221	0.9219

Table 2b. LULC data accuracy through; a)Accuracy assessment and , b) Kappa statics (Austin, USA)

c) Accuracy Total			
Classes	2000 Producer/User	2010 Producer/User	2020 Producer/User
Vegetation	90.48%/95%	78.26%/90%	100 /90.28%
Agriculture	94.74%/90%	85.71%/90%	100%/100%
Barren	86.36%/95%	100%/100%	100%/100%
Built-up	95%/95%	94.44%/89.47%	84.21%/100%
Water	100%/95%	100%/94.74%	100%/ 100%
Overall	93.40%	91.43%	94.17%
d) Kappa statics			
Vegetation	0.9376	0.8720	0.789
Agriculture	0.8782	0.8750	1
Barren	0.9369	1	1
Built-up	0.9384	0.8730	1
Water	0.9391	0.9365	1
Overall Accuracy	0.9192	0.8953	0.8992

2.2. Data Processing

Data processing consisted of classification of Landsat data products in ArcMap 10.7 and Erdas Imagine 15. LULC classes considered in the process include water bodies, vegetation, urban, barren land and agriculture. The essential data was processed in ArcMap which was first converted into 8-bit unsigned thematic format through Erdas Imagine. After classifying data into Land use land cover classes, data was processed in MOLUSCE and LCM for predicating 2020 LULC maps. The predicted map of 2020 each with LCM and MOLUSCE was validated with observed LULC map of 2020 and finally the results obtained were compared in two ways. Firstly, the results were validated through mathematical equation involving area computation from predicted and observed 2020 LULC map and secondly through kappa index statistics validation function of MOLUSCE model. The methodology flow chart of the study is given in figure 2.

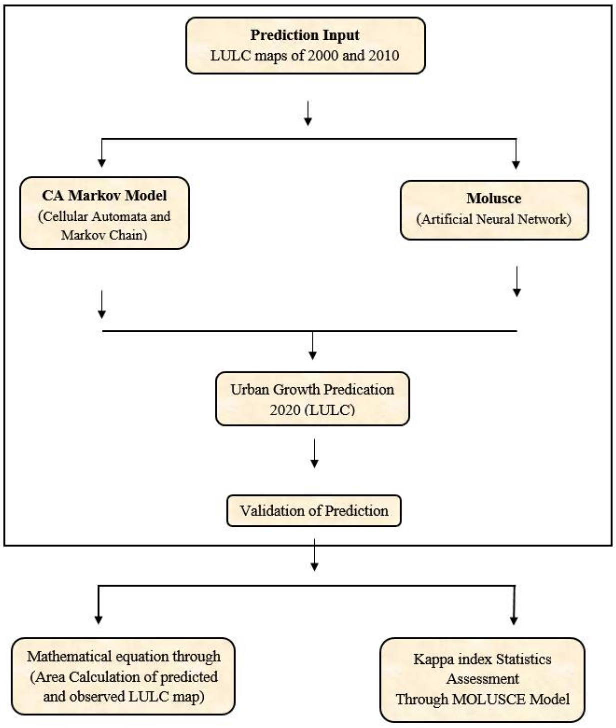

Figure 2. Methodology flow chart

2.3. Prediction and Validation Method of LULC

In this study, LULC prediction for 2020 was carried out using 2000 and 2010 validated supervised classified LULC images. For which Cellular Automata Markov chain and a cellular automaton multi-layer perceptron artificial neural network (MLPANN) dependent MOLUSCE (Modules for Land Use Change Evaluation) and LCM models based on great significance of LULC transitions were used. LCM model is an integrated software of Idrisi Selva while MOLUSCE model is a plugin for QGIS. Both these models are constructed to analyze and forecast present to future LULC and are based on spatial data analysis with different techniques. Both models (LCM, and MOLUSCE) support Cellular Automata, The Land Change Modeler (LCM) module in TerrSet (formerly marketed as IDRISIS) represents a comprehensive decision-support platform for detecting, modeling, and projecting land cover transitions and MOLUSCE demonstrate that this QGIS-based plugin integrates cellular automata mechanisms with transition probability matrices derived from paired historical LULC maps and spatially continuous explanatory variables such as distance to roads, water bodies, and urban settlements. Regarding the outputs, LCM produced thematic data in unsigned 8-bit format while MOLUSCE produced CCI file which is a single layer or grey scale imagery and is to be converted into unsigned 8-bit format. The following are the steps involved in predicting LULC change:

1. Variable selection: to improve the model's accuracy, distances to important roads were utilized as a variable.
2. Change detection: transition matrices and change maps were created in this step, which were then employed in the modelling process.
3. Transition potential estimated for 2000-2010 through the MLP-ANN and Markov approaches generates separate probability matrices that supports the prediction model.
4. Prediction of land use and land cover: MOLUSCE's LCM and MLP-ANN simulation tabs were used to forecast 2020 LULC.

The results from change detection, variable selection and transitional potential through LCM mentioned above were published earlier in the form of a journal paper entitled "Land use/land cover dynamics study and prediction in Jaipur city using LCM model integrated with road network" authored by (Maurya et al. 2022). While transitional potential through MLP-ANN and LULC prediction for Jaipur (India) and Austin (USA) cities is carried out in present study.

2.4. Study Area

This study focused upon Jaipur City, Rajasthan India and Austin, USA to assess the performance of LCM and MOLUSCE urban growth prediction models. Jaipur city has seen an unprecedented population growth on account of it being an oldest, seventh largest, tourist destination, world heritage site and one of earliest planned city of India. With a mere count of 294,021 inhabitants in 1950 the population now estimated to have risen to 4,007,505 in 2021 (Maurya et al. 2022). Austin established on December 27, 1839, is the 11 most population city in USA, fourth most populous city in Taxas and the second most populous state capital city. As of 2021, Austin had an estimated population of 964,177, ("City and Town Population Totals: 2020-2021". United States Census Bureau. Retrieved September 7, 2022.) up from 961,855 at the 2020 census ("Austin's Population Continues Another Decade of Growth According to U.S. Census Bureau | AustinTexas.gov". *www.austintexas.gov*. Retrieved October 10, 2022.).

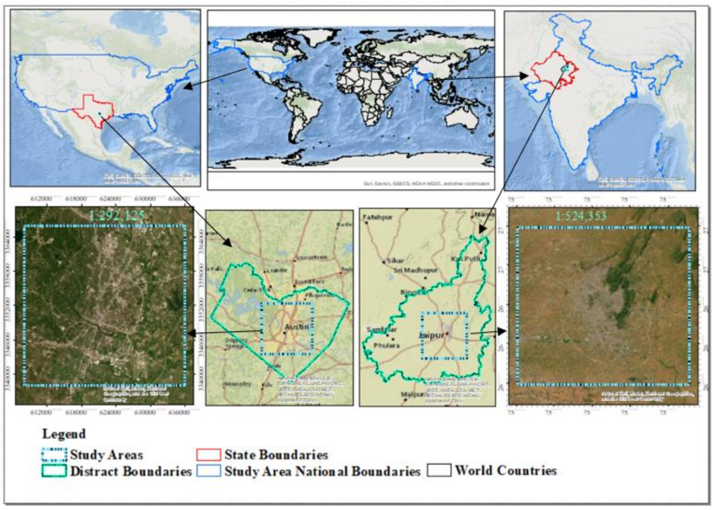

Fig 3. Study area location map

3. RESULTS

3.1. Identification of LULC and its dynamics between 2000 to 2020

The land use land cover maps were prepared and classified into 5 classes, viz Vegetation, Agricultural, Barren, Built-up, and Water Body. The Jaipur city experienced drastic changes in LULC classes particularly in agriculture, barren and built-up during 2000–2020 (table 3). The changes in LULC have negative impacts on climate and environment through carbon sinks, intensity of runoff, loss of biodiversity, people, and their livelihood (Gidey et al. 2017; Hurni et al. 2005; Nourqolipour et al. 2014; Sang et al. 2011). The analysis of land use conversion matrix showed that vegetation, agriculture, built-up and water bodies are all decreased at the expense of built-up or urban area. In 2000, the built-up area accounted for 110.68 km^2 (4.75% of total) which has increased to 225.47 km^2 (9.68% of total) in 2010 and 301.82 km^2 (12.9% of total) in 2020 (Maurya et al., 2022) at Jaipur. The estimated area under each class is given in table 2. Similarly, the built-up increased from 98.31 km^2 (12.55% of total) to 135.39 km^2 (17.28%) in 2010 and 210.42 (26.86%) in 2020. These results depicting that both cities are growing exponentially. Other classes have decreased vegetation, agriculture, barren, built-up, and water.

Table 3a. Matrix summary of LULC 2000, 2010 and 2020

Classes	Year 2000 Area in Km²	Year 2010 Area in Km²	Actual 2020 Km²
Vegetation	1252.36 (53.79%)	485.37 (20.85%)	306.22 (13.15%)
Agricultural	213.39 (9.16%)	284.25 (12.21%)	915.72 (39.33%)
Barren	749.53 (32.19 %)	1331.91 (57.20%)	791.05 (33.97%)
Built-up	110.68 (4.75%)	225.47 (9.68%)	301.82 (12.96%)
Water	2.37 (0.10%)	1.33 (0.06%)	13.52 (0.58)
Total	2328.33	2328.33	2328.33

Table 3b. Matrix summary of LULC 2000, 2010 and 2020, Austin

Classes	Year 2000 Area in Km²	Year 2010 Area in Km²	Actual 2020 Km²
Vegetation	606.88 (77.47%)	504.49 (64.40%)	469.47 (59.93%)
Agricultural	14.22 (1.82%)	87.15 (11.13%)	6.38 (0.82%)
Barren	49.33 (6.30%)	39.53 (5.05%)	82.90 (10.58%)
Built-up	98.31 (12.55%)	135.39 (17.28%)	210.42 (26.86%)
Water	14.65 (1.87%)	16.83 (2.15%)	14.22 (1.82%)
Total	783.41	783.41	783.41

Prediction and its Validation

MOLUSCE and LCM methods were used to predict LULC patterns in 2020 based on 2000 and 2010 LULC maps. To validate the results of prediction, the predicted and observed LULC maps of 2020 were compared through transition potential modelling and two different methods namely a mathematical equation and another was kappa index statistic (Kamusoko et al. 2009; Guidigan et al., 2019) were used. The first method uses mathematical equation (100-SQRT((Difference)^2), here are difference between observed and predicted LULC map of 2020 was used. According to this equation, LULC classes namely vegetation, agriculture, barren, water and has 74.97%, 34.48%, 49.77%, 88.61% and accuracy respectively when predicted through LCM model whereas 66.36%, 25.36%, %, 32.14%, 8.38% and as per MOLUSCE model, The prediction accuracy of built-up (urban) area was 88.92% as per LCM and 83.71% based on MOLUSCE at pre-defined level of 90.00% accuracy and 1.0 kappa coefficient of 2000 LULC while at 100% accuracy and 1.0 kappa of 2010 LULC data at Jaipur (Table 4). The low accuracy of some classes such as vegetation and agriculture land were due to the mixing of their pixel because these two classes reflected light in the same spectrum on a satellite image and were consequently identified as a single feature at several locations During the monsoon, vegetation area increases while bare land decreases, and this pattern is reversed during the winter season. Similarly, area under water also tends to increase due to excessive monsoonal rain. The newly constructed ring road was reflected as barren land on satellite images (Mourya et al. 2022). On the other hand, Austin has a good score in overall accuracy than the Jaipur which is 68.97% by LCM and 66.36% by MOLUSCE; whereas the classes (vegetation, agriculture, barren, water and built-up) results are 98.18%, 25.21%, 43.01%, 85.67% gained LCM and 94.65%, 23.96%, 41.69%, 83.69% gained MOLUSCE; the built-up (urban) accuracy was 92.79% obtained LCM and 87.85 % MOLUSCE model. The Austin city results are good enough, but we could get better results with recent high-quality datasets such as Sentinel 2 with 10 meters remote sensing satellite data cause the city's building as small which mostly covered by vegetation which resulted a bit low accuracy with 30 meters data. High resolution data could distinguish the vegetation and built-up area, but it also has temporal limitation (data available only after 2016). The other method of validating simulation accuracy used here was kappa index statistic, which is a validation function of MOLUSCE. Kappa statistics, Error Budget validation, and Error Map validation are the three forms of validation available in MOLUSCE. While kappa overall (Kovr), kappa histogram (Khisto), and kappa location (Kloc) are the three components of kappa statistics (Asia Air Survey and Next GIS 2017), whose equations are given below.

1. Kappa overall:
$$K = \frac{P\ (A) - P\ (E)}{1 - P(E)}$$
2. Kappa location
$$K_{loc} = \frac{P\ (A) - P\ (E)}{P\ max - P(E)}$$
3. Kappa histogram
$$K_h = \frac{P\ max - P(E)}{1 - P(E)}$$

Where $P(A) = \sum_{i=1}^{C} p_{ii}$, $P(E) = \sum_{i=1}^{C} p_{iT}p_{Ti}$, $Pmax = \sum_{i=1}^{C} \min\ (p_{iT,}p_{Ti})$ and pij is the i,j-th cell of contingency table, piT is the sum of all cells in i-th row, pTj is the sum of all cells in j-th column, c is count of raster categories.

According to LCM the accuracy in terms of Kovr was 0.330, Khisto was 0.587 and Kloc was 0.563 whereas according to MOLUSCE model these values were 0.206, 0.461, and 0.448 respectively at Jaipur. LCM obtained 0.429 Kovr, 0.842 Khisto, and 0.510 Kloc and MOLUSCE gained 0.390 Kovr, 0.718 Khisto, and 0.544 Kloc. Here, Jaipur has low Kappa accuracy cause Agriculture overestimated in actual 2020 LULC. We have not focused on agriculture class overestimation due our focus is for built-up or urban expansion and simulation for future). additionally pervious mentioned anthropogenic causes ring road southern corridor which can't be simulated by any model, water bodies area has been increasing which as well is also an anthropogenic cause due to it. The water area increased due to building concrete structures for Amanisha River, Kanota Dam water area and increasing level due to urban and industrial waste.

Table 4. Predicted Data Accuracy Assessment using Mathematical Equation in %

Class Name	CA Markov		Molusce	
	Jaipur	Austin	Jaipur	Austin
Vegetation	74.97	98.18	66.36	94.65
Agriculture	34.48	25.21	25.36	23.96
Barren	49.77	43.01	32.14	41.69
Built-up	88.92	92.79	83.71	87.85
Water	10.61	85.67	8.38	83.69

The observed and predicted 2020 LULC map from LCM and MOLUSCE are shown in Figure 4 and area statistics of each LULC class are given in Table 5. The comparison was done against observed LULC map of 2020. According to observed LULC map of Jaipur, vegetation covers 306.22 km^2 of area, agriculture covers 915.72 km^2, barren land occupies 791.05 km^2, built-up covers 301.82 km^2 and water occupies 13.52 km^2 in 2020. While prediction through MOLUSCE (ANN-MLP) showed that from 2010 to 2020, vegetation declined from 485.36 km^2 to 304.72 km^2 with a total decrease of 180.65 km^2, agriculture declined from 284.25 km² to 57.40 km² with the decrement of 266.85 km². Barren land has inclined from 1331.91 km² to 1614.88 km² with the increment of 1482.97 km² while surface water was decreased from 1.33 km² to 0.32 km². On the other hand, LCM prediction for 2020 showed a decrease in vegetation from 485.28 km^2 to 453.28 km^2 with a total decrease of 32.09 km^2. Land area under agriculture declined from 284.25 km² to 279.13 km² with decrement of -5.12 km². Barren land has also declined from 1331.91 km² to 1259.51 km² accounting to a decrease of 72.40 km² and surface water decreased from 1.33 km² to 1.16 km². As per supervised LULC Map of Austin city classes coverage portion are vegetation 469.47 km^2, agriculture, 6.38 km^2, barren 82.90 km^2, built-up 210.42 km^2, and water 14.22 km^2 in 2020; while the models simulated trough MOLUSCE are 518.03 km^2, 88.20 km^2, 39.24 km^2, 121.73 km^2, and 6.15 km^2 respectively. The LCM model gained 460.94 km^2, 75.28 km^2, 35.65 km^2, 195.27 km^2, and 16.26 km^2. The LCM simulation from 2010 to 2020, vegetation declined from 504.49 to 460.94 with the decrement of 43.55, agriculture declined 87.15 to 75.28 with decrement of 11.87, barren declined from 39.53 to 35.65 with decrement 3.88, and water declined 16.83 to 16.26 with decrement with 0.57. Similarly, the MOLUSCE model simulation shows that vegetation decreased from 504.49 to 498.03 with decrement of 6.46, agriculture decreased from 87.15 to 86.2 with the decrement of 0.95, barren decreased from 39.53 to 39.24 with decrement of 0.29 and water decreased from 16.83 to 16.15 with decrement of 0.68. Both models reflect that the vegetation, agriculture, and water bodies have declined during 2010 to 2020 simulation in both cities.

The urban area has increased from 225.47 km² in 2010 to 351.00 km² in 2020 (MOLUSCE) with increment of 125.53 km² and according to LCM the increase was

109.78 km² accounting to 335.25 km² (Table 2) in Jaipur. However, the built-up area in 2020 as per observed LULC map was 301.82 km^2 with an accuracy of 94.74%, which according to mathematical equation (Accuracy value *100/ Accuracy percentage) would equal to 318.57 km² if its 100% is calculated. Similarly, as per kappa statistics it has an accuracy of 0.87 or 87% meaning that built-up area would be 366.17 km² if its 100% is calculated. This suggests that the 2020 predicted LULC maps had high accuracy in estimated nearly the same urban growth as obtained from observed 2020 LULC map. Similarly, urban area has increased from 135.39 (2010) to 141.73 (2020) by MOLUSCE projection with increment of 6.34 and LCM projection shows that increased to 195.27 in Austin. However, the urban (built-up) area in 2020 as supervised LULC map 210.42 with an accuracy of 100% (as per accuracy report) and kappa accuracy also 1 which represents 100 %. Thus, the LCM obtained 92.79% and MOLUSCE obtained 87.85 %. Both cities and models experiment shows that the LCM outperformed with accuracy for urban predication.

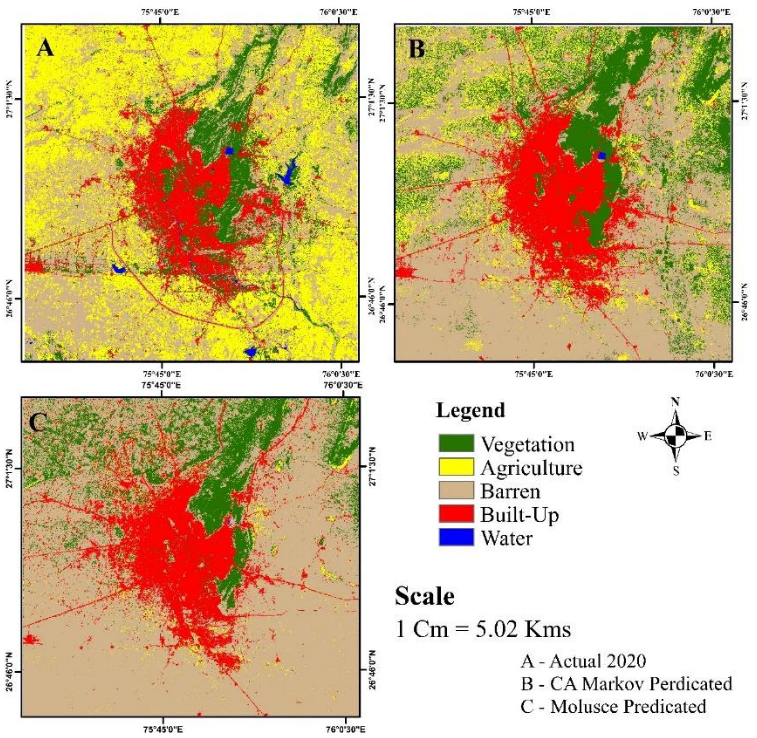

Fig 4. Predicated and Observed 2020 LULC Maps of Jaipur, India.

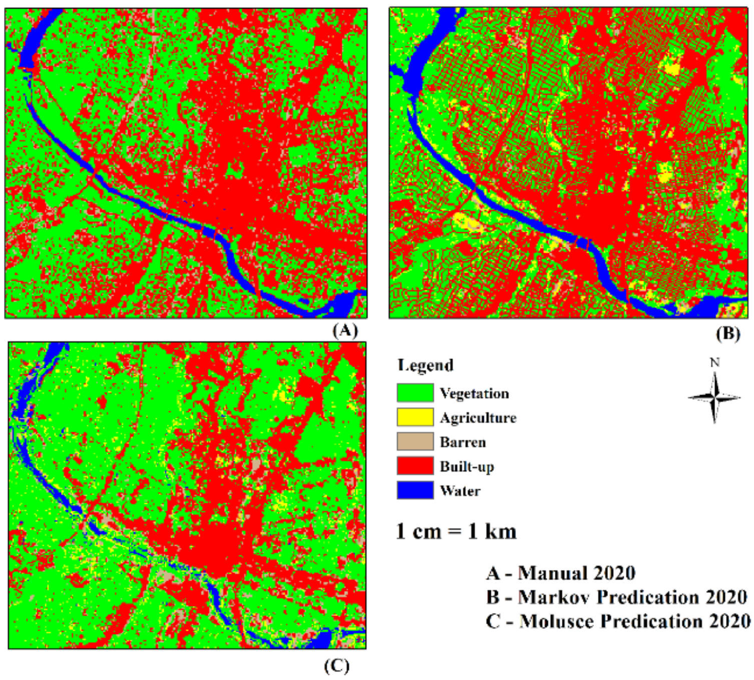

Fig 5. Predicated and Observed 2020 LULC Maps of Austin, USA.

Table 5 (A). Results from the Models, Jaipur India

Class Name	Observed 2020	Molusce Prediction	CA Markov Prediction
Vegetation	306.22	304.72	453.28
Agriculture	915.72	57.40	279.13
Barren	791.05	1614.88	1259.51
Built-Up	301.82	351.00	335.25
Water	13.52	0.32	1.16

Table 5 (B). Results from the Models, Austin, USA.

Class Name	Observed 2020	Molusce Prediction	CA Markov Prediction
Vegetation	469.47	518.03	460.94
Agriculture	6.38	88.20	75.28
Barren	82.90	39.24	35.65
Built-Up	210.42	121.73	195.27
Water	14.22	16.15	16.26

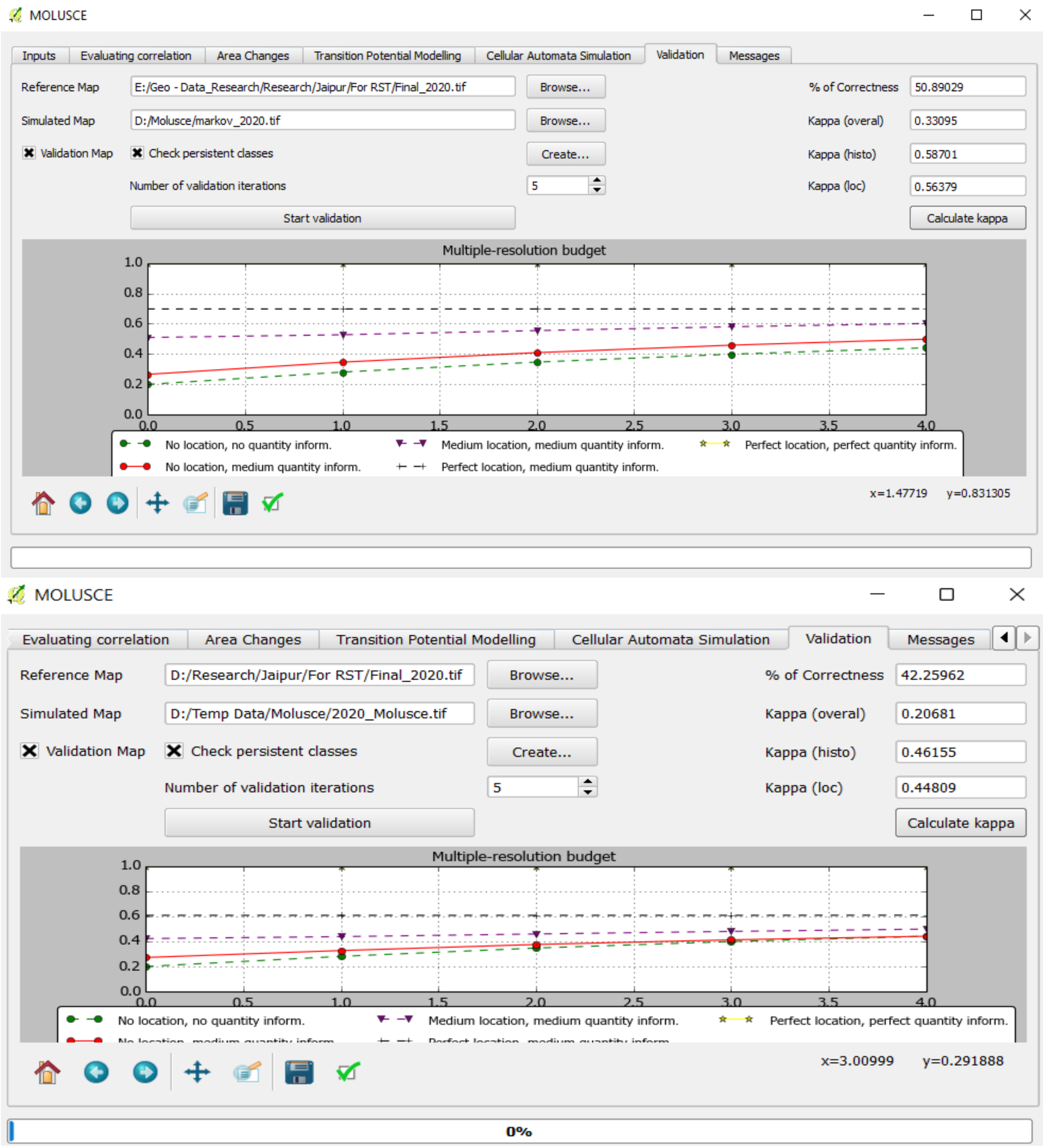

Figure 6 (A). Validation function of Molusce model (Jaipur, India).

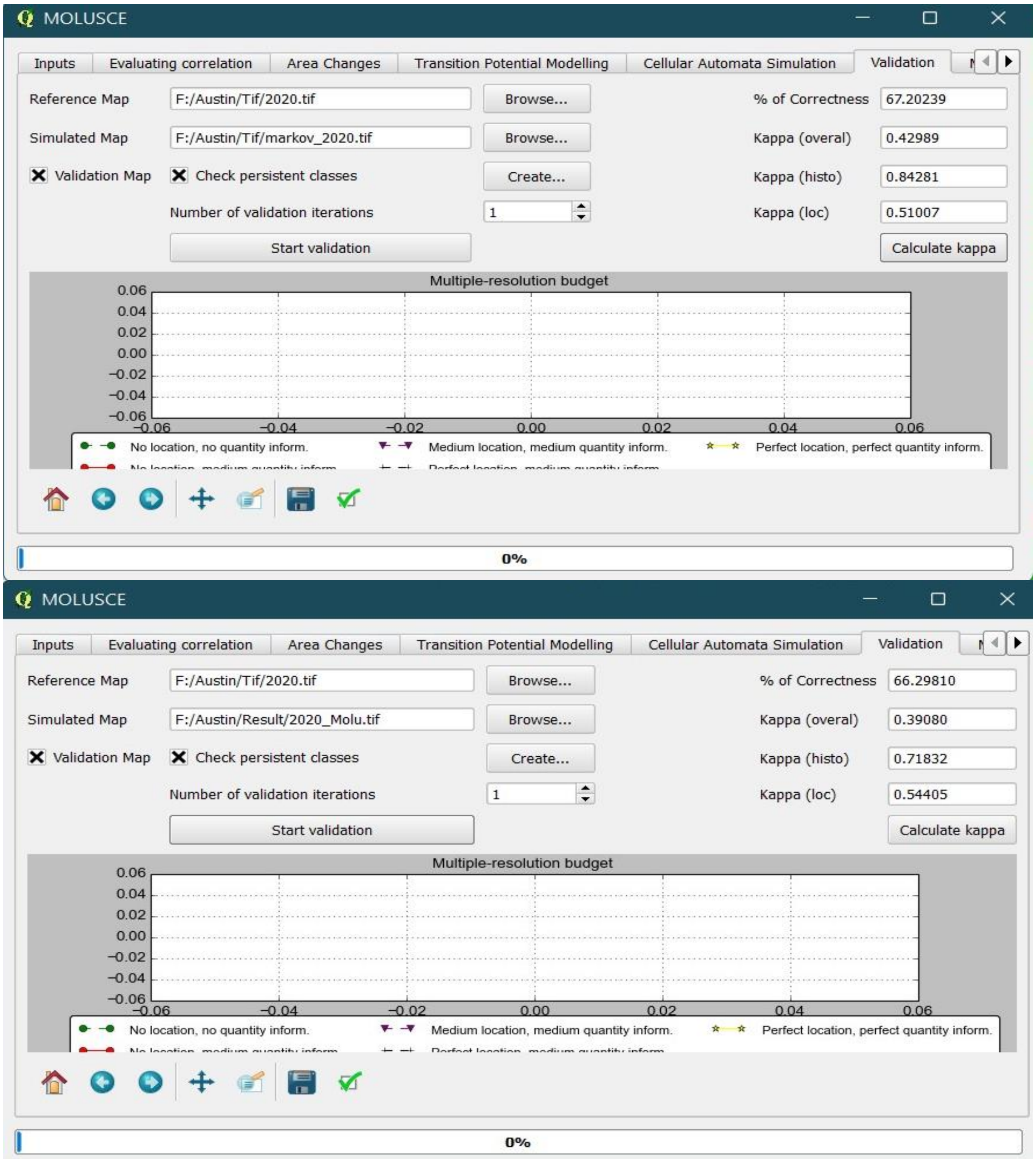

Figure 6 (B). Validation function of Molusce model (Austin, U.S.A).

Because of the fast growth of built-up area, and human activities, there was an overall loss of LULC classes such as agriculture, vegetation, barren ground, and water bodies from 2010 to 2020. These findings point to a concerning future landscape in Jaipur, which will be the outcome of completely damaged natural vegetation. Furthermore, it emphasizes the significance of landscape management and development. MOLUSCE and LCM models were integrated with GIS technology to successfully simulate land use change in Jaipur and Austin Cities utilizing land use maps (2000, 2010, and 2020) and road network data. The findings of the used model are satisfactory, but this study identifies that LCM gives more robust results in comparison to MOLUSCE. In LCM, accuracy of the prediction depends upon the accuracy of input data be it road network, DEM or any other and it works well with these data. Any change in assignment of hierarchies to data will also affects the results of LCM prediction. Unlike LCM, MOLUSCE model do not require additional data such as road network to run the model. However, it has three methods of evaluating correlation which affect, it's prediction results and accuracy. Cramer's coefficient yields better results in comparison to other two methods namely correlation and joint information uncertainty.

4. CONCLUSION

This research work identifies the more robust model among LCM and MOLUSCE to predict urban growth taking the example of Jaipur (India) and Austin (USA) cites. Cellular Automata–Markov Chain (CA–

Markov) within the Land Change Modeler and the multilayer perceptron (MLP) artificial neural network–based MOLUSCE framework were effectively employed to simulate future land use/land cover (LULC) change scenarios in both cities. Additionally, the accuracy of the forecasted LULC map for 2020 was evaluated using a mathematical calculation and the kappa index statistics. This study revealed that LCM model out functions MOLUSCE model used here because it worked on cell conversion and generated prediction based on cell change analysis. The forecasted LULC map depicts the likely spatial and quantitative change in LULC in the future. It showed a decline in vegetation (32.09 km^2)), agriculture (5.12 km^2)), barren land (72.40 km^2) and surface water (0.17 km^2) during 2010-2020. Whereas the built-up area found to have increased to (109.78 km^2) during the same period.

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