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Original Article

Significance of Measuring the Accuracy of Cellular Automata Markov Chain for Land Use Projections in District Gurgaon in Haryana, India

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Abstract - *The significance of measuring the accuracy of Cellular Automata Markov Chain (CA MC) for land use projections lies in urban planning, environmental management, and sustainable development. The reliability of the CA MC model in predicting Land Use (LU) changes requires the accuracy and robustness of the model that uses data from a study area to compare the land cover (LC) changes over a period. The model with appropriate transition rules compares the significant LC changes for LU prediction. The reliability metrics assess the prediction model using the Kappa coefficient, overall accuracy, user accuracy, and producer accuracy to measure the predicted changes for chance agreement. The study reassigns the non-diagonal elements of the state transition matrix, derived from the confusion matrix, by interpreting them as TRUE rather than considering FALSE and discarding them to provide improved measured overall accuracy. These reassigned changes provide realistic insights into district Gurgaon's predicted changed map in Haryana, India, which can help policymakers, urban planners, and stakeholders make informed decisions about land management, infrastructure development, and resource allocation. An overall model accuracy of 81.33% for predicted LC data supports policymakers in developing plans and policies to assess LU patterns and trends for sustainable practices aligned with environmental conservation and economic needs***.

Keywords - *Cellular Automata, Markov Chain, Kappa coefficient, Spectral signature, Urbanization.*

1. Introduction

Land use (LU) projections are the basis of long-term planning and sustainable land management that balances economic growth, social equity, and environmental conservation for future generations. LU diversifications highlight the landscape changes impacted by Land Cover (LC) change dynamics. Predicting LC change patterns at a thirty-year interval by the Cellular Automata (CA) Markov Chain (MC) model can support long-term sustainable urban development plans and decision-making processes. The LC prediction model is a combination of spatially explicit rules of CA and the probabilistic transitions of MC in a temporal framework [1]. The land transformation data for the last thirty years substantiate the LC classification analysis to estimate future change scenarios to promote urban growth while emphasizing community engagement as an alternative conservation measure [2]. LC dynamics developed by these models factor land areas clustered into agriculture, forest, urban, and water bodies as the impactful classifications [3].

LC prediction with the CA MC model works stochastically by determining one state if the previous state of the system is known. Thus, the spatiotemporal data in LC prediction determines the state(t) based on the system's temporal state(t-1). At its core, a Transition Probability Matrix (TPM), derived from the confusion matrix, aims to forecast LC changes with observed data. The TPM elements are the probability of LC pixels either remaining in the same class or transforming to another class designated in the cluster dynamics [4]. The accuracy of LC classification is necessary for sustainable land management as it directly influences the effectiveness of conservation efforts, resource management, and policy development. Ensuring high accuracy in LC data helps to maintain ecological balance, support economic activities, and mitigate the impacts of climate change. From the literature survey, various LULC models predict LC changes, highlighting the ability to capture spatial and temporal dynamics of land use changes. The accuracy of these models varied, depending on the input data, model-specific configurations, and interpretation of the TPM elements derived from the land transformation confusion matrix. This study has the novelty of predicting LC patterns of a large growing region emerging after thirty years, considering additional elements of the TMP as TRUE. The literature reviews found no realistic interpretations of confusion matrix elements as TRUE that transformed from one state to another, other than the diagonal elements. The novelty of this study lies in interpreting the non-diagonal elements of TMP elements of the model for accuracy measurement and considering a few of these elements TRUE, which were usually discarded as FALSE. These elements form valid land change scenarios. Projecting such changes in the spatial distribution will fulfill the needs of policymakers regarding major land classifications like agricultural land, forest coverage, urban expansion, and availability of water bodies. The study aims to cluster and reclassify land areas in a hybrid ML model and assess the model's accuracy, validated against published data from government reports.

2. Background

Several studies have demonstrated the efficacy of the CA-Markov model in various geographical contexts, highlighting its robustness in simulating land use changes over time. Research has shown that the model can effectively capture urban sprawl, deforestation, and agricultural expansion, making it a valuable tool in land management. The accuracy of these projections varied based on specific characteristics, the quality of input data, and the model performance. In the context of Gurgaon, a rapidly urbanizing district, existing literature emphasizes the need for accurate land use projections to manage urban growth and mitigate environmental impacts. By measuring the accuracy of the CA-Markov model in this region, the projections can align with land use trends to enhance the model's reliability for future planning and policymaking.

2.1. Spectral Signature Mixing

Hyperspectral remote sensing images capture information about objects' reflectances information about the reflectance of objects on the Earth's surfaces. Spectral Signature unmixing examines the spectral profile of a pixel to identify its spectral components as end members with the highest proportion and assigns the pixel to one among the available distinct land cover classes. Endmembers are pure spectral signatures of the different LC classifications. The redefined pixels enhance classification accuracy. Understanding the elements in spectral mixing and deploying appropriate classifications are essential to improve the reliability of classification results. The assumption in spectral unmixing is that the spectrum of a mixed pixel is a linear combination of constituent end members weighted by their respective abundances.

3. Materials and Methods

The framework of this study provides a basis for classifying LC patterns to balance socio-economic dynamic equilibrium in urban development processes emphasized by human activities, human decisions, and human behaviors that influence LC changes [5]. The study explores the spatial dynamics of LC changes in urban growth, expansion of built-up areas, agricultural land consumption, deforestation, land fragmentation, and water bodies [6].

3.1. Study Area

In Haryana, Gurgaon experienced fast economic growth triggered by increased industry opportunities. It witnessed fast urbanization accelerated by economic growth, transforming an agriculture-based district town into a modern city, drawing huge investments during the last few decades. It is selected as the study area, as shown in Figure 1, with diagonal corners ((28.68814 N, 76.43381 E), (28.08512 N, 77.38744 E)) and spread across a vast area of ~1285 square KM that witnessed rapid spatial growth during the last three decades.

3.2. Data Collection

The essence of the study is to simulate a futuristic thirty-year LC change using satellite images in the CA-MC Model. A search in EarthExplorer of USGS [7] for Landsat images, with search parameters (1) dates between March-April-May in 1993 and 2023, (2) cloud cover less than 5%, and (3) set study area = Gurgaon district contour resulted in 29 satellite footprints, substantiated by Worldwide Reference System (WRS) Path = 146, 147 and Row = 40, 41, shown in Table 1.

Table 1. Landsat Image Footprints covering district Gurgaon contour

Footprint	146_40	146_41	147_40	Total
Count	10	10	9	29

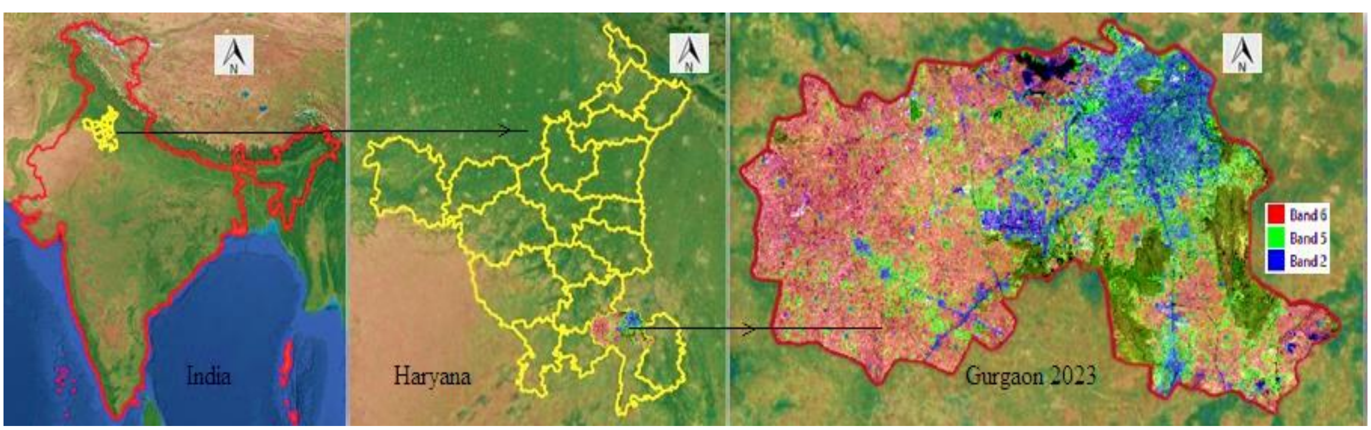


Fig. 1 Map of India > Haryana > Gurgaon (in false color 6-3-2)

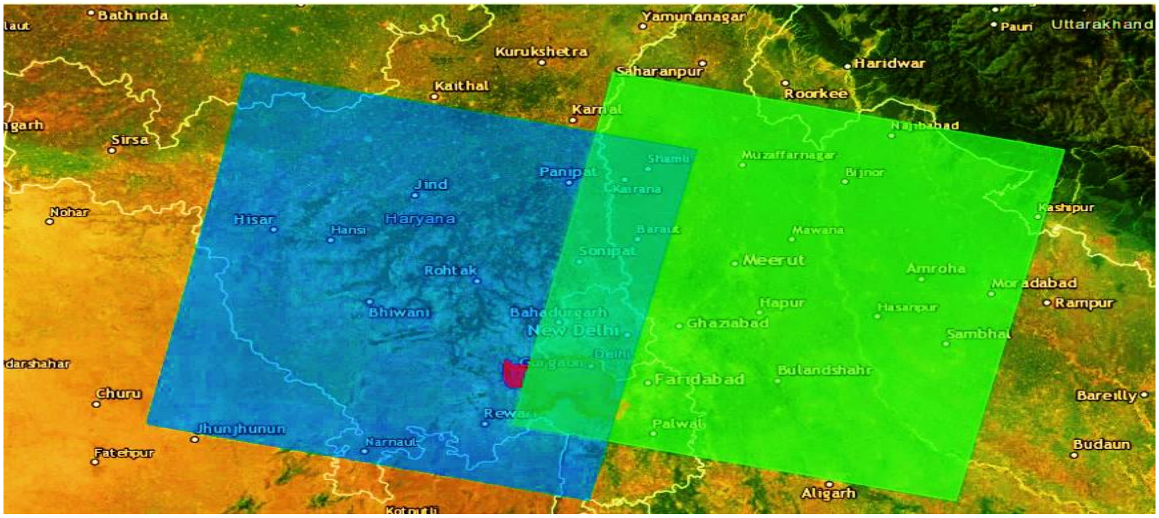


Fig. 2 Landsat Satellite Footprints covering district Gurgaon (EarthExplorer-USGS [7]

Table 2. Landsat scene

Landsat Scene Identifier	Acquired	WRS Path	WRS Row	CC *
LC8146041 2023097 LGN00	2023-04-07	146	41	0.3
LC8147040 2023104 LGN00	2023-04-14	147	40	0.5
LT05_L1TP_1460419930506_20200914 02_T1	1993-05-06	146	40	0
LT05_L1TP_147040 19930513_20200914_02_T1	1993-05-13	147	40	0

** Cloud Cover*

An additional filter with cloud cover from 0% to 0.5% reduced the total count to 8, comprising of (1)146_41 and 147_40 in 1993 from Landsat 5, (2) 146_40 and 147_40 in 2023 from Landsat 8. No single Landsat footprint covers the district of Gurgaon. However, two overlapping footprints can cover the study area marked by a red boundary in Figure 2. The required Landsat images in Table 2 have a minimal time gap between the two acquired instances. These multispectral GIS images (30 m resolution) were corrected with the Dark Object Subtraction (DOS) procedure [8] for atmospheric corrections. It mitigated the atmospheric scattering and haze by subtracting the minimum pixel value (dark pixel) from each pixel within every band [9]. The pre-processing included geo-referencing and mosaicking GIS images to train in R-G-B and NIR spectral bands for LC classification [10].

3.3. LC Classification

Unsupervised classification K-means performed on the Regions of Interest (ROI) for k=30 had an outcome with four reclassified classes: (1) Agriculture, (2) Forests, (3) Urban, and (4) Water bodies. The agricultural land included crop areas, land waiting for sowing, and temporary barren areas. Forests were classified for grown trees, approximately higher than 5 m, with a canopy of more than 10% of trees reaching these dimensions [11]. Urban areas included residential, industrial sheds, factory sheds, etc. Water bodies cover rivers, lakes, canals, and reservoirs. The study included LC changes between 1993 and 2023 to train and validate the model, followed by a prediction after 30 years in 2053.

3.4. LC Prediction

The CA model formulated by C(t, t+1) = R(C(t), n) has C = discrete cellular states, n = number of cellular classifications, t and t + 1 = two consecutive independent time instants, and R = transformation rule of cellular states changes [12]. The Markov Chain applied to a stochastic system predicts LC changes based on the Bayes conditional probability equation given by C(t + 1) = P_{ij} * C(t) where C(t), and C(t + 1) are the two independent system for time = t and (t + 1) states, P_{ij} = state transition matrix calculated by,

$P_{ij} = \begin{bmatrix} P_{11} & \cdots & P_{1n} \\ \vdots & \ddots & \vdots \\ P_{n1} & \cdots & P_{nn} \end{bmatrix}, where\ \sum_{j=i}^{n}(P_{ij}) = 1$; i and j are LU types. Each element in the transition matrix P_{ij} has a value between 0 and 1, indicating the state change transition frequencies [13]. Transitions of cell states are determined by examining the spatial relationships with adjoining cells and applying a series of distinct time intervals to update the composition and arrangement of all cells simultaneously [14].

Neighborhood and suitability values for LC predictionFor LC prediction, neighborhood and suitability values reflect external influences on state transitions, guided by rules delineating transition potentials [15]. The model produced a transition matrix and a change map using Artificial Neural Network (ANN). It simulated a map to predict LC classification in 2053, with the classification map of 2023 as a reference [16].

3.5. Accuracy Assessment

The overall accuracy assessment is a measure between observed agreement and chance agreement, expressed by K = [P(a) – P(e)] / [1 – P(e)], where P(a) = User Accuracy (UA)/Precision, indicating the probability of a classified image pixel observed, P(e) = probability of a classified image pixel predicted [17]. K is the extent of correct representations of the variables measured against the predictions of the same classifications. The assessment included Producer Accuracy (PA)/Recall and F1-score.

4. Results

4.1. Clustering and Classification

An unsupervised k-means model had k = 30, with distance threshold = 0.005, maximum SD = 0.2, and minimum class size = 100 for clustering. These clusters were reclassified into AGR, FOR, URB, and WAT using ground truth data and Google Maps to generate a reference map. Supervised ML algorithms provided insights into LC changes by mitigating the spectral signature mixing in the images [18]. The models were trained with labeled samples of known land cover types (endmembers) of classified pixels.

4.2. Class Statistics

Class statistics refers to quantitative measures associated with each classification [19], valid for land management, urban planning, and making informed decisions. It provides a comprehensive awareness of the current state and dynamics of LC, applicable in sustainable development and resource management [20], as shown in Table 3. It shows that 67.882% AGR in 1993 changed to 62.213% in 2023, with Δ % by -5.669%. The decrease over the 30 years may be due to the conversion of agricultural land into urban areas or other uses. 19.531% of Forest in 1993 became 16.267% in 2023, indicating a decrease of 3.264%, possibly due to a combination of deforestation, urban expansion, and afforestation changes impacting forested areas. Urban changed (Δ %) by 8.891% from 12.469% in 1993 to 21.360% in 2023. Urban land cover nearly doubled during this period, likely driven by population growth and economic development. Water Bodies 2023 showed a marginal change (Δ %) by 0.042% from 0.118% in 1993 to 0.160%. The change attributed to water management was the creation of new water bodies or natural fluctuations in water areas.

4.3. State Transition Matrix

The State Transition Matrix in LU change analysis is a tabular representation of class transitions [21]. In MC, the State Transition Probability matrix outlines the likelihood of one state moving to another in successive instances. It serves as a tool to study and analyze the dynamics of spatial distribution within a particular geographic arena with demographic dependencies. The rows of a transition matrix are the initial class observations, and the columns represent the final classes after a specific interval. Each cell of the matrix indicates the class transition probability.

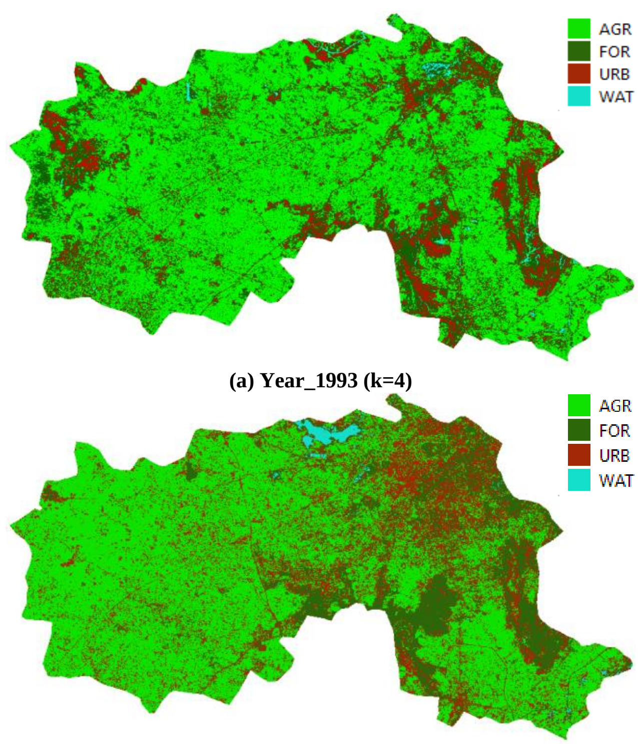
Table 3. Land Usage percent distributions in 1993 and 2023

Class	Year	AGR (%)	FOR (%)	URB (%)	WAT (%)
Initial (I)	1993	67.882	19.531	12.469	0.118
Final (F)	2023	62.213	16.267	21.360	0.160
(F-I) Δ %		-5.669	-3.264	8.891	0.042
Observation		decrease	decrease	increase	increase

Table 4 is the State Transition Matrix of 1993 and 2023 study area maps to predict the LU map in 2053. A transition matrix's overall accuracy predicts transitions between states across all possible transitions, calculated by summing the diagonal elements of the transition matrix (no change transitions) and dividing by the total count of observations [22]. In this study, only some state transitions are interpreted as TRUE rather than considered FALSE and discarded. For example, transitions from FOR to AGR and AGR to URB are TRUE, though conventionally treated as FALSE. The overall accuracy assessment included these valid transitions, resulting in improved accuracy. Figure 3 shows the land classification after the reclassification into four for 1993 and 2023.

Table 4. Transition matrix of 1993-2023

2023	1993				
	AGR (%)	FOR (%)	URB (%)	WAT (%)	Total
AGR	41.422	13.505	7.285	0.069	62.283
FOR	9.451	4.095	2.671	0.042	16.267
URB	16.983	1.867	2.437	0.004	21.289
WAT	0.028	0.062	0.067	0.007	0.159
Total	67.882	19.531	12.468	0.117	100



(b) Year_2023 (k=4)
Fig. 3 Land Classification in Gurgaon_1993 vs. Gurgaon_2023

Table 5. Year-wise land cover type % distribution

Year	Source	AGR (%)	FOR (%)	URB (%)	WAT (%)
1993	Landsat7	67.8823	19.5313	12.4687	0.1175
2000	*. Report	69.7991	18.8099	10.9282	0.5818
2008	*. Report	65.5734	19.1887	15.0750	0.1627
2023	Landsat8	62.2839	16.2673	21.2895	0.1595
Observed Trend		Declining	Declining	Increasing	Declining

**Gov. Report: Department of Town and Country Planning, Haryana. The data is consistent for trend comparison for the extrapolated data.*

Table 6. Parameter (ANN – MLP)

Parameter (ANN – MLP)	Value
Neighbourhood (pixel)	1
Learning Rate	0.1
Maximum Iterations	500
Hidden Layers	10
Momentum	0.05
Number of simulation iterations	3

4.4. Validation

The classification outcome is sequenced in Table 5 for a trend comparison. It includes data published by Government Reports* [23] for 2000 and 2008 extrapolated to substantiate data validation.

4.5. Accuracy Assessment

For the LC map prediction in 2053, the Artificial Neural Network – Multiplayer Perceptron (ANN-MLP) algorithm was used to calculate the transition potential matrix required in a Cellular Automata (CA) model of LULC [24], with parametric values in Table 6.

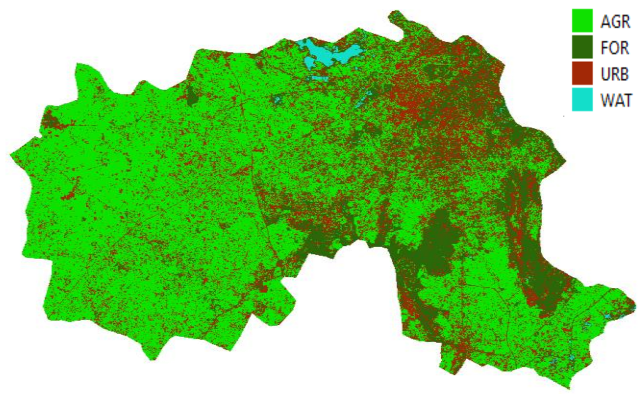
The model performance had (1) Overall Accuracy Δ =-0.00278, (2) Minimum Validation Overall Error = 0.00007, and (3) Validation Kappa = 0.99326. It simulated LU changes for 2053 with the 2023 classification as a reference. Overall accuracy - 0.00278 suggests smaller room for improvement in general. The minimum validation overall error (0.00007) implies prediction accuracy on unseen data.

The Validation Kappa (0.99326) suggests an agreement between the predicted and actual classifications. The ANN-MLP model is robust and suited for predicting land cover in 2053 with the same four classes. Table 7 has the statistical measures between predicted and observed classifications, providing overall accuracy. It has a quantitative analysis of the changes in land use over 30 years, highlighting trends in urbanization, reduction in agricultural and forest lands, and a slight decrease in water coverage.

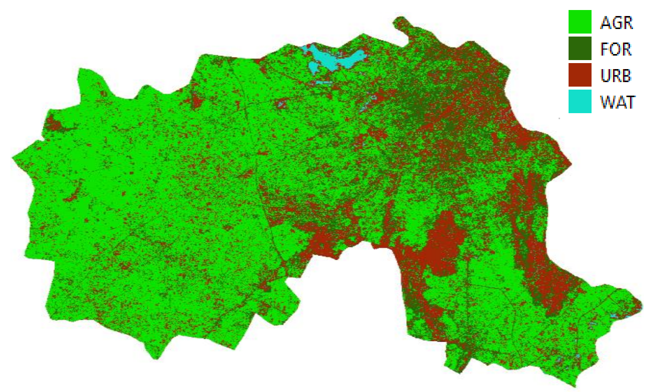
The kappa coefficient (K) measures the agreement between two assessments on the same subjects. It ranges between –1 and 1 [4]. It is also rare. An 'Acceptable' or 'Good' kappa value is subjective. However, per the 'Fleiss' arbitrary guidelines, K= 0.75 is excellent [25]. The predicted map of 2053 using the reference to 2023 is in Figure 4.

Table 7. Transition matrix of (1) prediction_2053, (2) reference_2023

2053	2023 AGR (%)	FOR (%)	URB (%)	WAT (%)	Total
AGR	62.256	0.028	0.007	0.0021	62.294
FOR	0.018	14.533	0.031	0.0024	14.584
URB	0.007	1.701	21.249	0.0182	22.976
WAT	0.002	0.001	0.0006	0.141	0.145
Total	62.283	16.264	21.287	0.164	100
PA [%]	99.971	89.5299	99.9647	88.889	
UA [%]	99.951	99.774	99.966	98.298	
f1-Score	0.996	0.943	0.996	0.933	
Overall accuracy [%]	98.253%				
Kappa hat	0.9676 (Probability of chance agreement)				



(a) Reference_Year_2023 (k=4)



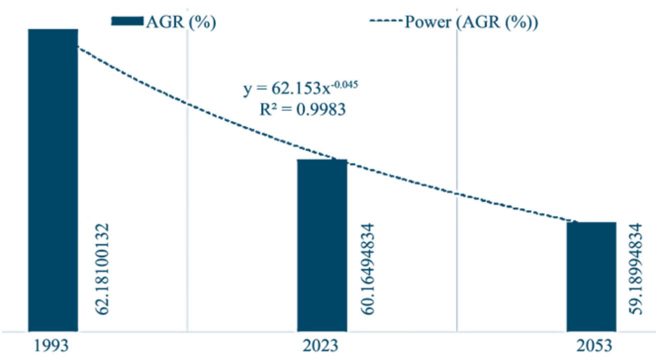
(b) CA MC Simulated_Year_2053 (k=4)

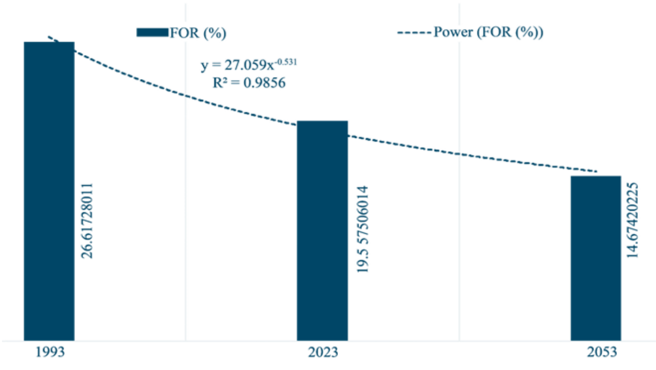
Fig. 4 Reference_Gurgaon_2023 vs. Simulated_Gurgaon_2053

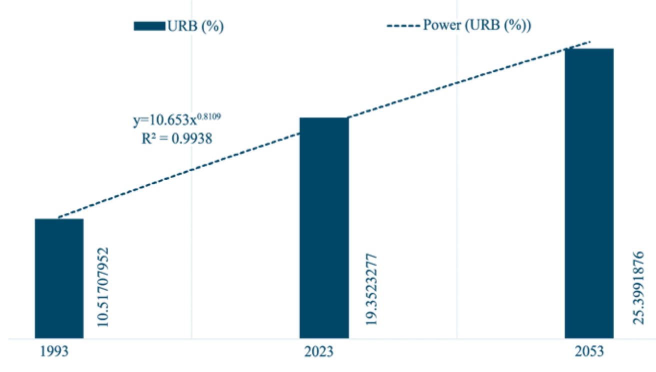
High accuracy in LC classification ensures that resources such as water, soil, and biodiversity are correctly identified and managed. It can also avoid improper resource allocation due to misclassification, which can harm ecosystems and reduce the sustainability of land use.

5. Discussion and Analysis

The projection of LC changes in Gurgaon by 2053 provides insights to policymakers for informed strategies to balance human needs and ecological sustainability. With such predicted shifts, Gurgaon can strive to meet the needs of the growing population while preserving its natural resources and environmental health. Urban growth often leads to converting agricultural and natural lands for urban use. Agricultural land (AGR) reduction indicates a possible shift into urban expansion or reforestation. It may also reflect changes in farming practices or land management policies aimed at sustainability [26]. The decrease in predicted forests has concerns about deforestation or conversion of forests to other land uses like urban or agricultural, minimizing the effects of biodiversity, climate regulation, and ecosystem services [27]. The substantial increase in urban expansion, likely driven by population growth, economic development, and urbanization, can bring economic benefits but challenge infrastructure, cause the loss of green spaces, and cause potential environmental degradation. Though minor in absolute terms, the reduction in water bodies indicates issues in water resource depletion, drying up lakes or rivers, or conversion of water bodies for other land uses. Such a trend will impact water availability and aquatic ecosystems. The encroachment on water reserve areas for agriculture will lead to a decrease in water bodies, indicating a shift towards other land uses [28]. Figure 5 represents the AGR, FOR, URB, and WAT percentages in 1993, 2023, and predicted 2053. The dotted lines represent a power function trend line fitted to the data points given by a linear equation in intercept form.







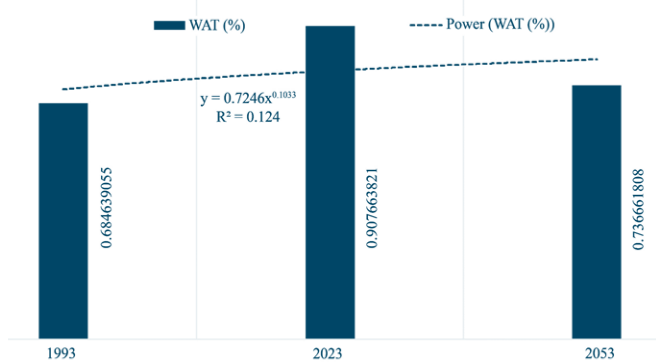


Fig. 5 (a, b, c, d): Comparative 1993, 2023, predicted 2053

The prediction accuracy may decline with an increase in the prediction interval, likely due to the consistent application of a uniform transition rule across the simulation period [29]. Implementing the interplay of social, human, and economic elements into the simulation is also challenging. CA MC simulated the system dynamic based on local rules and a probabilistic model predicting future states based on current conditions [30]. The trends highlight the importance of sustainable land management practices and the need for policies that balance development with environmental conservation. Addressing the predicted loss of forests and water bodies should be a priority to ensure ecological balance and long-term sustainability. Urban planning should also focus on creating sustainable cities that minimize environmental impacts.

6. Conclusion

The accuracy measurement of CA MC modeling assesses the model's effectiveness in predicting land change dynamics. The model trained a thirty-year interval LC changes between 1993 and 2023 to predict 2053, with qualitative factors and regulations on protected areas, pollution control measures, people migration, community attitudes, local cultural values, public awareness of environmental conservation, etc. These factors influence the simulated long-term predictions, which are assumed to remain unchanged during the period. The study witnessed land change transformations, drawing attention to the degrading ecosystems and biodiversity.

Agricultural land needs to focus on sustainable practices as the available agricultural land is diminishing. The increased urban areas necessitate effective urban planning to manage growth and minimize environmental impacts. Reduced forest cover calls for conservation to protect forested areas and restore degraded lands. Strategies to preserve agricultural land within urban expansion are necessary to ensure food security and retain agricultural productivity. Monitoring and managing water resources will ensure availability for various needs, including industrial and agricultural usage.

Given the ecological challenges, an environmental sustainability framework can assess the impacts of LC changes to analyze the loss of natural habitats, depletion of groundwater resources, and increased pollution levels associated with urbanization and industrialization [31]. The development processes should address socio-economic disparities and promote inclusive development as a central goal for adopting equitable land use practices in the district.

The LC change dynamics open the futuristic expansion trends for urban planners and policymakers to manage infrastructure development relating to roads, housing, utilities, public amenities, etc., to accommodate the growing population. It needs to minimize the environmental impacts, promote reforestation, and enhance carbon sequestration in natural and managed ecosystems as practices within urban planning. The changed map in 2053 provides early caution to protect the ecosystem, as substantiated by the model's accuracy and reliability in prediction.

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