A Deterministic ANN–CA Computational Framework for Spatial Simulation Using Socioeconomic Data

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***Abstract*—Hybrid approaches combining Cellular Automata (CA) and Artificial Neural Networks (ANN) have been widely applied to spatial simulation; however, most implementations rely on stochastic components that limit reproducibility and interpretability. This study proposes a deterministic ANN–CA computational framework in which the stochastic perturbation term of a constrained CA model is replaced by ANN-derived classification values based on socioeconomic variables. The framework integrates data preprocessing, ANN training, transition coefficient generation, and CA-based simulation into a unified workflow. A multilayer perceptron is trained using spatialized socioeconomic indicators (age, education, sex, and income) to generate deterministic transition potentials at the pixel level. Experimental evaluation using multitemporal land-use data shows that the proposed ANN–CA model achieves a moderate improvement in global spatial association (Cramer's V: 0.5622 → 0.6016), while pixel-level agreement (Kappa: 0.6589 → 0.6595) remains nearly unchanged. These results indicate that the proposed approach primarily enhances structural coherence and spatial organization—reducing fragmented growth and improving corridor-oriented expansion—rather than significantly increasing pixel-wise predictive accuracy. By replacing stochastic behavior with data-driven deterministic rules, the proposed framework improves reproducibility and provides a more interpretable linkage between urban growth patterns and socioeconomic drivers. This work contributes a transparent hybrid modeling approach suitable for spatial simulation and planning-oriented applications.**

***Keywords*—Artificial neural networks; cellular automata; spatial simulation; deterministic modeling; hybrid computational framework**

I. Introduction

Urban growth is a complex spatial phenomenon driven by socioeconomic, environmental, and infrastructural interactions that operate across multiple spatial scales. Modeling these processes poses significant computational challenges, as land-use change often emerges from nonlinear relationships and localized interactions among neighboring areas. Accurate representation and forecasting of such dynamics are essential for sustainable urban planning, risk assessment, and effective land management.

Among the available computational approaches, Cellular Automata (CA) have proven particularly effective for simulating spatial processes in which each cell evolves according to local neighborhood rules. Their ability to reproduce emergent spatial patterns has led to widespread adoption in urban growth and land-use change studies [1], [2]. However, conventional CA models typically rely on stochastic perturbation terms to represent uncertainty, which may introduce randomness weakly linked to real-world drivers of urban expansion and reduce model interpretability [3].

To enhance realism and predictive performance, several studies have explored the integration of CA with Artificial Neural Networks (ANNs) [4], exploiting their ability to learn nonlinear relationships from empirical data. Representative applications include the generation of transition probability maps, multi-label land-use classification [5], and scenario-based urban growth forecasting [6]. Although these approaches improve spatial prediction accuracy, most implementations treat ANN outputs as precomputed inputs to CA models rather than embedding them directly into the transition potential formulation.

In recent years, more advanced neural architectures—such as deep convolutional networks and object-detection–oriented models—have been proposed for spatial analysis tasks. Despite their success in computer vision and remote sensing applications, there is currently no consolidated or validated framework that demonstrates how such models can directly and consistently replace the stochastic component in constrained CA formulations, particularly in the context of White's urban growth model. As a result, the stochastic term remains insufficiently addressed in a theoretically grounded and interpretable manner.

Although CA models have demonstrated strong capabilities in simulating urban processes, their reliance on stochastic components limits interpretability and weakens the connection between simulated outcomes and observable socioeconomic variables [3]. Previous studies have attempted to mitigate these limitations through artificial intelligence techniques. For instance, Xu et al. [7] combined ANN with CA–Markov Chain models to improve temporal prediction accuracy, while Zeng et al. [8] introduced hybrid approaches incorporating spatial heterogeneity and nonlinear transition rules. Other recent research has explored GPU-based computational acceleration and convolutional operations [9], as well as ANN–CA applications have been successfully applied across diverse spatial contexts, including cultural and rural environments [10], as well as highly urbanized megacities [11]. More recently, bio-inspired approaches such as Neural Cellular Automata using deep learning techniques have been proposed [12], [13].

Comparable advances have also been reported using Neural Cellular Automata and deep learning–based approaches for spatial modeling and urban dynamics [14], [15].

More broadly, hybrid urban growth modeling has evolved from conventional stochastic Cellular Automata formulations toward data-driven and machine-learning-assisted approaches. Early ANN–CA studies demonstrated that neural networks can capture nonlinear transition behavior and improve land-use simulation when combined with GIS and raster-based CA frameworks. More recent works have extended this idea through CA–Markov models, multi-label land-use transformation models, and machine learning methods designed to estimate transition probabilities from spatial and socioeconomic predictors.

In parallel, alternative deterministic or semi-deterministic approaches have been explored using logistic regression, decision-tree-based models, Random Forest classifiers, and convolutional neural networks. These methods generally aim to improve predictive performance by generating suitability or transition probability surfaces that are subsequently used as external inputs to CA simulations. In CNN–CA and Neural Cellular Automata variants, richer spatial feature extraction has been achieved, particularly from remote sensing imagery, but often at the cost of reduced interpretability in socioeconomic terms [16], [17].

Despite these advances, a common limitation remains: in most hybrid approaches, the learning model operates as a separate upstream component, while the CA transition mechanism itself still depends on externally supplied probability layers or stochastic perturbation terms. Consequently, the interaction between learned socioeconomic patterns and the internal transition logic of constrained CA models remains only partially integrated.

TABLE I. CONCEPTUAL COMPARISON OF URBAN GROWTH SIMULATION APPROACHES

Approach	Integration with CA	Determinism	Interpretability
Stochastic CA	Internal stochastic term	Low	Low
CA–Markov	External transition probabilities	Moderate	Low
ML–CA (LR / RF)	External suitability maps	Moderate–High	Moderate
CNN–CA	External feature-based probabilities	Moderate	Low
Proposed ANN–CA	Direct embedding in the transition potential	High	High

Table I summarizes representative urban growth modeling approaches, highlighting their differences in terms of integration with Cellular Automata, level of determinism, and interpretability. As shown, most prior approaches rely on externally generated transition probabilities or suitability maps, while maintaining either stochastic behavior or limited interpretability within the CA framework. In contrast, fewer studies address the methodological question of whether a learned deterministic mechanism can directly replace the stochastic term in a constrained CA model.

In contrast, the approach proposed in this study does not use the ANN as an external probability-map generator. Instead, ANN-derived class coefficients are embedded directly into White's transition potential formulation, allowing socioeconomic information to participate internally in the CA decision process. This distinction is central to the present work, whose contribution lies less in maximizing pixel-level accuracy than in advancing a reproducible, deterministic, and interpretable hybrid modeling framework.

In light of these limitations, the central research question of this study is:

Can the stochastic perturbation term in a constrained Cellular Automata model be replaced by ANN-derived deterministic transition coefficients while preserving spatial modeling performance?

This study addresses this gap by replacing the stochastic perturbation term in White's constrained CA model with an ANN-generated classification value derived from spatialized socioeconomic variables. A multilayer perceptron trained via the backpropagation algorithm is employed as a first step, given its robustness, interpretability, and proven capacity to approximate complex nonlinear functions from limited datasets. This choice allows for a controlled and transparent evaluation of ANN-driven transition potentials within the CA framework.

The proposed framework is applied to the city of Culiacán, Mexico, a rapidly expanding urban area characterized by the availability of detailed geostatistical and socioeconomic datasets, making it a suitable case study for evaluating the proposed approach. Specifically, this study:

- Designs and trains a multilayer perceptron ANN to process spatialized socioeconomic variables—age, education, sex, and income—at the basic geostatistical area level.
- Integrates ANN outputs directly into White's constrained CA model to compute pixel-level transition potentials.
- Evaluates predictive performance using historical land-use maps from 1997, 2004, and 2011, employing spatial agreement metrics such as Cramer's V and the Kappa index.

By embedding ANN-derived socioeconomic drivers into the CA transition mechanism, this work advances a more deterministic and data-driven approach to urban growth modeling. The proposed integration improves the explicit linkage between spatial patterns and demographic or economic factors and facilitates future extensions toward hybrid simulation frameworks, including Agent-Based Models (ABM).

The principal methodological contribution of this study lies in directly replacing the stochastic term in White's model with classification values generated by a multilayer perceptron trained on spatialized socioeconomic variables. This integration reinforces the deterministic character of the model, enhances spatial coherence, and enables a more interpretable linkage between urban growth patterns and underlying socioeconomic drivers.

Future work will explore the integration of more recent neural architectures—such as convolutional and detection-based networks—once a stable methodological bridge between these models and constrained CA dynamics is established. In this way, the present study lays the groundwork for progressively incorporating more advanced ANN models into urban growth simulation, while maintaining methodological rigor and interpretability.

In summary, this work presents a novel and computationally grounded methodology for integrating socioeconomic data into land-use change simulation through a deterministic ANN–CA framework, demonstrated through a case study of Culiacán, Mexico. The remainder of the study describes the proposed model, its implementation, and its validation.

II. Materials and Methods

A. Overall Workflow of the ANN CA Model

Fig. 1 presents the overall workflow integrating Artificial Neural Networks (ANN) with Constrained Cellular Automata (CA) for urban growth modeling, providing an overview of the methodological process from data acquisition and preprocessing to model simulation, validation, and interpretation.

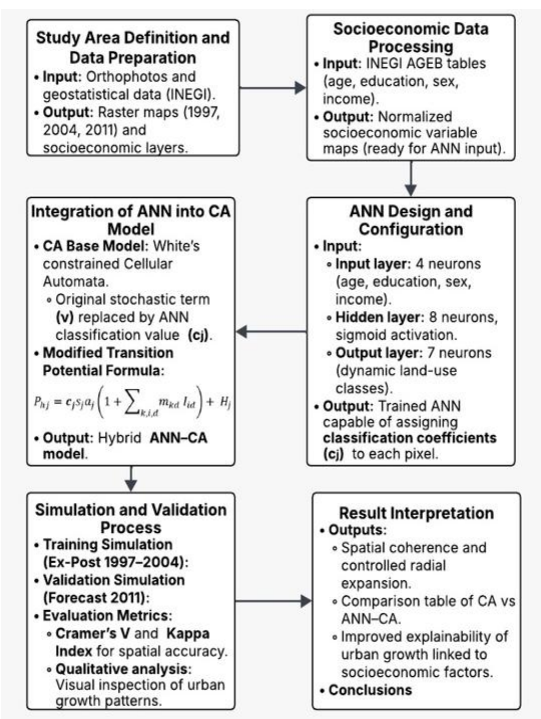


Fig. 1. Overall workflow of the hybrid artificial neural network and cellular automata model.

The methodology consists of five main stages:

1) Study area definition and data preparation: Orthophotos and geostatistical data provided by the National Institute of Statistics and Geography (INEGI) were processed to generate raster land-use maps for 1997, 2004, and 2011.

2) Socioeconomic data processing: Socioeconomic variables at the Basic Geostatistical Area (AGEB) level—age, education, sex, and income—were normalized and spatialized to generate raster layers suitable for ANN input.

3) ANN design and training: A multilayer perceptron was configured to process socioeconomic variables and generate classification coefficients for dynamic land-use classes.

4) Integration of ANN into the CA model: The stochastic perturbation term in White's constrained CA model was replaced by ANN-derived classification values, yielding a deterministic transition potential.

5) Simulation and validation: Ex-post and forecast simulations were performed, and model outputs were evaluated using spatial agreement metrics and qualitative visual inspection.

This hybridization enables the CA framework to integrate socioeconomic information directly into the transition mechanism, improving interpretability and spatial realism.

B. Study Area and Spatial Data

The geographical location of the study area, corresponding to the municipality of Culiacan, Mexico, is shown in Fig. 2. The geographic coordinates are 24°48′15″ N and 107°25′52″ W, with an average altitude of 54 m above sea level.

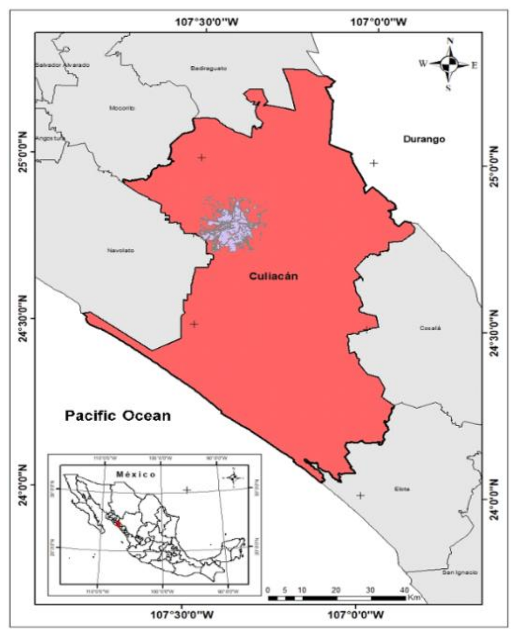


Fig. 2. Location of the study area in Culiacan, Sinaloa, Mexico.

Urban land-use maps were generated through vector digitization over orthophoto mosaics. Orthophotos from 1997 (scale 1:20,000) and 2004 (scale 1:10,000) were projected in the WGS 84 / UTM Zone 13N coordinate system. ArcMap® was used for vector cartography, while IDRISI Selva® was employed for raster processing.

All vector layers were converted to raster format using the Database Workshop module in IDRISI. The resulting raster maps (Fig. 3 and Fig. 4) serve as input matrices for the CA model [18].

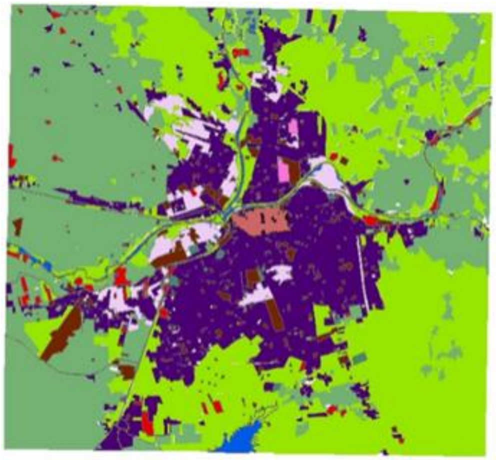


Fig. 3. Raster land use map of Culiacan for 1997.

Fig. 4. Raster land use map of Culiacan for 2004.

Urban land-use categories used in the simulations are summarized in Table II.

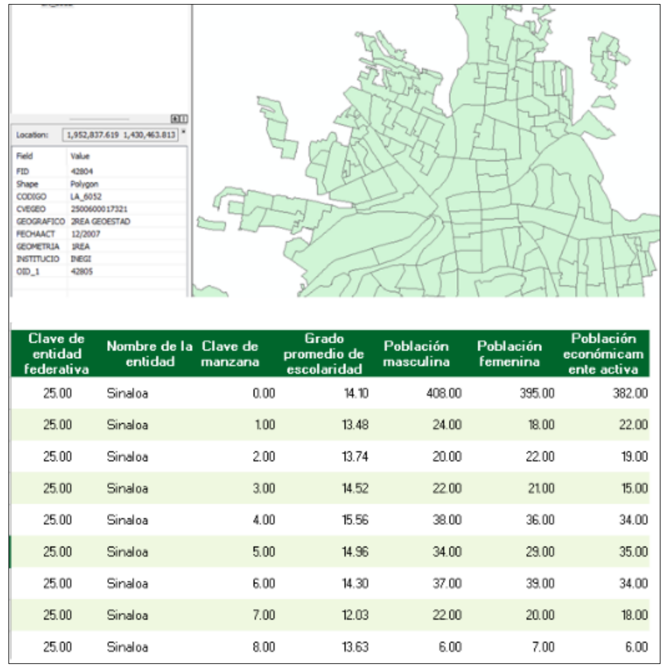
TABLE II. CLASSIFICATION OF URBAN USES

Num	Quantity
1	Urban Voids
2	Services
3	Agricultural Zone
4	Commercial Zone
5	Forestry Zone
6	Industrial Zone
7	Housing
8	Water Bodies
9	Equipment
10	Undeveloped

C. Socioeconomic Data Processing

Socioeconomic information was obtained from INEGI at the AGEB level, which provides tabular demographic and economic data for the Mexican territory. The selected variables—age, education level, sex, and income—were identified as relevant indicators of urban development dynamics.

Since AGEB data are provided in tabular format, spatialization was performed by linking attribute tables to AGEB polygon layers using the Joins and Relates functionality in ArcMap. The resulting spatial layers were converted to raster format and resampled to match the spatial resolution of land-use maps (Fig. 5 and Fig. 6).



Clave de entidad federativa	Nombre de la entidad	Clave de manzana	Grado promedio de escolaridad	Población masculina	Población femenina	Población económicamente activa
25.00	Sinaloa	0.00	14.10	408.00	395.00	382.00
25.00	Sinaloa	1.00	13.48	24.00	18.00	22.00
25.00	Sinaloa	2.00	13.74	20.00	22.00	19.00
25.00	Sinaloa	3.00	14.52	22.00	21.00	15.00
25.00	Sinaloa	4.00	15.56	38.00	36.00	34.00
25.00	Sinaloa	5.00	14.96	34.00	29.00	35.00
25.00	Sinaloa	6.00	14.30	37.00	39.00	34.00
25.00	Sinaloa	7.00	12.03	22.00	20.00	18.00
25.00	Sinaloa	8.00	13.63	6.00	7.00	6.00

Fig. 5. Raw socioeconomic data at the basic geostatistical area level.

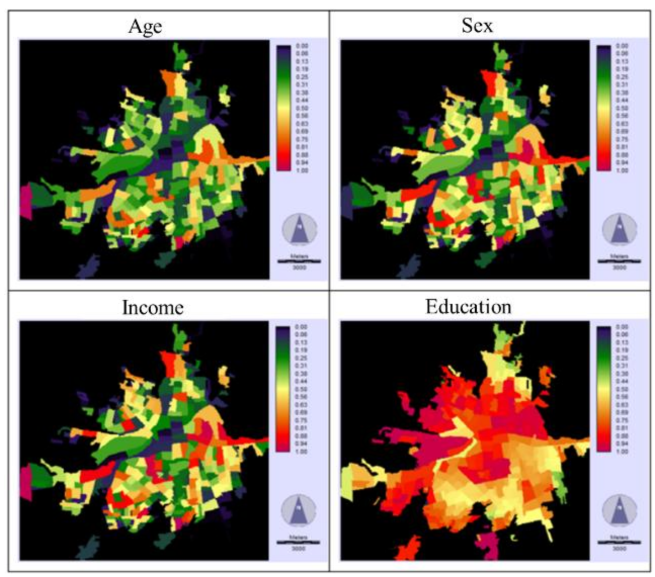


Fig. 6. Spatialized socioeconomic variables used as ANN inputs.

To ensure numerical stability and efficient ANN training, all socioeconomic variables were normalized to a [0,1] range. This preprocessing step reduces scale bias among variables and improves convergence during network training.

D. Computational Environment and Validation Metrics

Model implementation was accelerated using NVIDIA CUDA architecture to optimize matrix operations and ANN training. GPU-based parallelization was applied to ANN computations and CA simulations to handle large raster datasets efficiently [19].

Model performance was evaluated using both quantitative and qualitative criteria. Quantitative validation employed Cohen's Kappa index and Cramer's V coefficient to measure spatial agreement between simulated and observed land-use maps. Qualitative evaluation focused on the visual coherence of urban growth patterns, particularly radial expansion and the reduction of fragmented urban clusters.

E. Cellular Automata Model

The CA model used in this study is based on White's constrained cellular automaton for high-resolution urban land-use modeling [2]. The transition potential from state h to state j is defined as:

$$P_{hj} = v s_j a_j \left(1 + \textstyle\sum_{k,i,d} m_{kd}\, I_{id}\right) + H_j \quad (1)$$

where v is the stochastic perturbation term, s_j represents suitability, a_j is the Euclidean distance to the nearest road, and m_{kd} is the calibration matrix modeling neighborhood influence with a distance decay effect [1].

Transition potentials are computed only when $s_j > 0$. Neighborhood influence accounts for attractive or repulsive effects depending on cell state and distance, filtered by the indicator I_{id}.

F. Artificial Neural Network Design

The ANN was implemented as a multilayer perceptron consisting of three layers: an input layer with four neurons (age, education, sex, income), a hidden layer with eight neurons using sigmoid activation, and an output layer with seven neurons corresponding to dynamic land-use classes (Fig. 7).

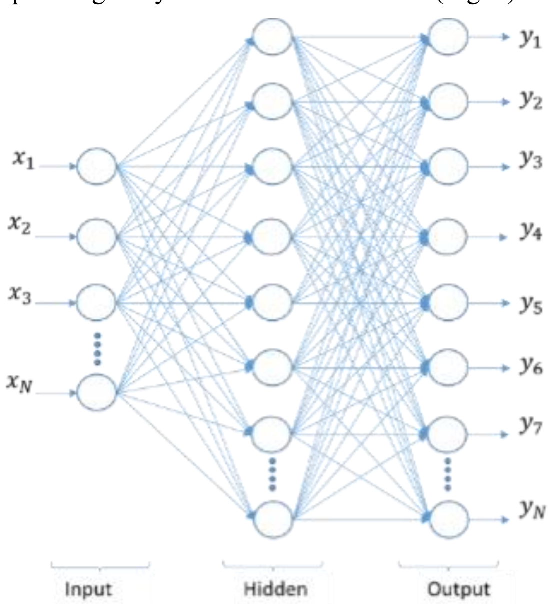


Fig. 7. Artificial neural network architecture used in the experiments.

The network was trained using the backpropagation algorithm with a learning rate of 0.01, momentum of 0.9, and a stopping criterion defined by a mean squared error (MSE) of 0.1. Ten percent of the dataset was randomly selected for validation during training.

Unlike conventional ANN–CA approaches, the proposed framework embeds ANN outputs directly into the CA transition potential equation. The stochastic term v in White's model is replaced by the ANN-derived classification coefficient c_j, ensuring deterministic pixel transitions driven by socioeconomic context (Fig. 8).

The selected ANN architecture (4–8–7) was intentionally designed as a compact multilayer perceptron to balance model interpretability and computational efficiency. Given the limited number of input features and the objective of embedding the ANN directly into the CA transition mechanism, a shallow architecture was preferred over deeper models to avoid overfitting and preserve transparency in the learned relationships [20]. Preliminary experiments with larger hidden layers showed no significant improvement in spatial performance metrics, supporting the choice of a minimal yet sufficient network capacity.

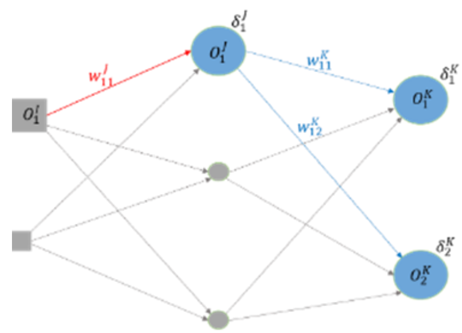


Fig. 8. Conceptual representation of the three-layer perceptron.

G. Training Algorithm and Data Selection

ANN training followed the standard backpropagation algorithm. Socioeconomic raster layers served as input, while the 2004 land-use map was used as the target output. The training dataset consisted of randomly selected pixels representing 10 % of the study area (Table III).

TABLE III. SOCIOECONOMIC VARIABLES USED FOR ANN TRAINING

Variable	Type
Sex	Discrete
Age	Discrete
Education	Discrete
Income	Continuous

The backpropagation process iteratively adjusted network weights to minimize classification error. Although the algorithm may converge to local minima, achieving a predefined error threshold was sufficient for stable and reliable classification performance in the context of urban growth simulation.

The training dataset was constructed using a random sampling strategy covering approximately 10% of the total raster cells. This proportion was selected as a trade-off between computational efficiency and representativeness of spatial patterns. Although random sampling is commonly used in pixel-based classification tasks, it may introduce spatial autocorrelation effects, where neighboring pixels share similar characteristics.

To mitigate this limitation, the sampled pixels were distributed across the entire study area, ensuring coverage of different land-use classes and socioeconomic conditions. However, it is acknowledged that spatial leakage cannot be fully eliminated under random sampling. Future work will explore spatial cross-validation strategies and geographically stratified sampling to further improve model robustness.

H. Implementation Details

The proposed ANN–CA model was implemented using a custom computational pipeline integrating raster processing and neural network training. The Cellular Automata model follows a Moore neighborhood configuration, considering local spatial interactions within a fixed window.

ANN training was performed using a backpropagation algorithm with a learning rate of 0.01 and momentum of 0.9. The stopping criterion was defined based on mean-squared error convergence. GPU acceleration was employed using NVIDIA CUDA to optimize matrix operations and reduce computation time during both training and simulation stages.

All simulations were conducted using consistent spatial resolution and aligned raster datasets to ensure comparability across temporal scenarios. Additional implementation details are available upon request to facilitate reproducibility.

III. Results

A. Experimental Setup and Comparative Summary

Two model configurations were evaluated to quantify the effect of replacing the stochastic term in White's constrained Cellular Automata (CA) formulation:

- Baseline CA: White's constrained CA using the original stochastic perturbation term v.
- Proposed ANN–CA: the stochastic term v replaced by an ANN-derived classification coefficient c_j computed from socioeconomic variables.

The ANN was implemented as a multilayer perceptron with 4 input neurons (age, education, sex, income), 8 hidden neurons, and 7 output neurons corresponding to the dynamic land-use categories. The network was trained using a random 10 % pixel sample, taking the 2004 land-use raster map as the target output. A sigmoid activation function was used, and training stopped when the mean squared error (MSE) reached 0.1.

1) Ex-post simulation (1997–2004): Fig. 10 and Fig. 11 summarize the training process and the ANN configuration used to generate the classification coefficients incorporated into the CA transition potential. Ex-post urban growth simulations for the period 1997–2004 are shown in Fig. 13 (baseline CA) and Fig. 14 (ANN CA).

Quantitative spatial agreement metrics are:

- Baseline CA: Cramer's V = 0.5622, Kappa = 0.6589
- Proposed ANN–CA: Cramer's V = 0.6016, Kappa = 0.6595

Table IV summarizes the comparison between the two configurations.

TABLE IV. COMPARISON BETWEEN BASELINE CA AND ANN CA CONFIGURATIONS

Model Configuration	Cramer's V	Kappa Index	Spatial Pattern Description
Baseline CA (White's Model)	0.5622	0.6589	Irregular clusters and scattered patches
Proposed ANN–CA Model	0.6016	0.6595	Coherent radial expansion along transport corridors
Forecast (2011 Validation)	0.5626	0.5726	Structured growth, slight accuracy drop

Note: Forecast results correspond only to the ANN–CA model. Direct comparison with the baseline CA model for the 2011 scenario is beyond the scope of this study and will be addressed in future work.

a) Quantitative takeaway: The ANN–CA configuration increases Cramer's V by 6.98% relative to the baseline, indicating a stronger global spatial association between simulated and observed land-use patterns. The observed behavior of the evaluation metrics highlights an important distinction between pixel-level accuracy and structural spatial consistency. While the Kappa index shows only a marginal increase, this metric is highly sensitive to local misalignments and does not fully capture the organization of spatial patterns. In contrast, Cramer's V reflects overall spatial association and indicates an improvement in the structural coherence of the simulated urban dynamics.

This suggests that the proposed ANN–CA model primarily enhances spatial organization and transition consistency rather than exact pixel-by-pixel agreement, which is consistent with the deterministic and pattern-oriented nature of the proposed framework. From an applied perspective, such improvements in structural coherence are particularly relevant for urban planning and spatial decision-making, where the overall configuration of growth patterns is often more informative than strict local accuracy.

Qualitative analysis of the simulated maps further supports this interpretation. The ANN–CA model produces more coherent and structured spatial patterns, characterized by controlled radial expansion, reduction of fragmented or isolated urban patches, and the emergence of corridor-oriented growth aligned with underlying socioeconomic gradients. These characteristics are not fully captured by pixel-based metrics but are particularly relevant for urban planning and spatial decision-making, where the overall configuration and consistency of growth patterns are more informative than strict local accuracy.

2) Forecast validation (2011): To evaluate model generalization beyond the calibration interval, a forecast simulation targeting 2011 was generated using the same configuration employed for the 1997–2004 experiment. The ANN–CA model achieved:

- Cramer's V = 0.5626
- Kappa Index = 0.5726

a) Forecast takeaway: Although both indices decrease relative to the ex-post simulation, the values remain within a comparable range to the baseline ex-post performance. This indicates that the ANN–CA model maintains structural stability over longer simulation horizons, despite increased uncertainty in socioeconomic and spatial dynamics.

As expected in land-use forecasting tasks, predictive accuracy decreases with time due to evolving drivers that are not explicitly modeled. However, the ANN–CA configuration preserves coherent growth structures and avoids the erratic expansions typically induced by purely stochastic perturbations under identical CA settings.

3) Interpretation of ANN outputs: The ANN generates, for each pixel, a classification vector assigning a weight to each dynamic land-use category. For example, a given socioeconomic profile may produce the following output:

- Housing (Class 7): 0.806
- Services (Class 2): 0.125
- Industrial (Class 6): 0.041

These values represent deterministic transition preferences derived from socioeconomic context. When incorporated into the CA transition potential, they replace the random perturbation term of White's original model, ensuring that simulated land-use changes are systematically informed by demographic and economic conditions rather than stochastic variability.

B. Simulation Procedure and Output Mapping

To perform the simulations, White's constrained CA model was modified by replacing the stochastic coefficient v with a classification coefficient c_j, where c_j is produced by the trained ANN for each target land-use state j. Fig. 9 illustrates the role of socioeconomic inputs and ANN outputs within the hybrid simulation pipeline.

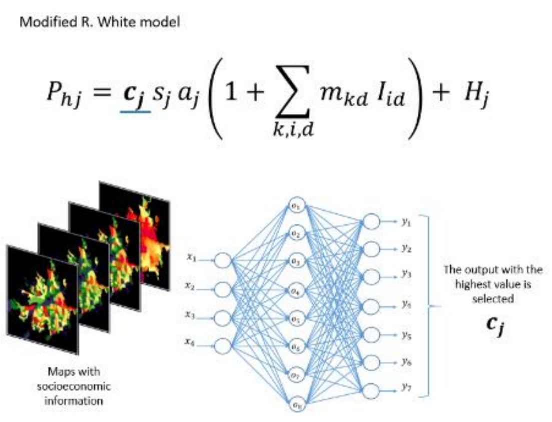


Fig. 9. Integration of ANN outputs into the cellular automata transition mechanism.

1) Training sample and convergence: The ANN training dataset consisted of randomly selected pixels from the four socioeconomic raster layers, with the corresponding land-use class in the 2004 raster map used as the target output. Training proceeded until the predefined error threshold (MSE = 0.1) was reached. Although this MSE threshold may appear high for conventional classification tasks, in this context, it was used as a convergence criterion to obtain stable class preference patterns rather than precise probability estimates. This is consistent with the role of the ANN within the proposed framework, where outputs are not interpreted as exact class probabilities but as relative transition preferences embedded in the CA transition mechanism. The pixel-level training scheme is illustrated in Fig. 10.

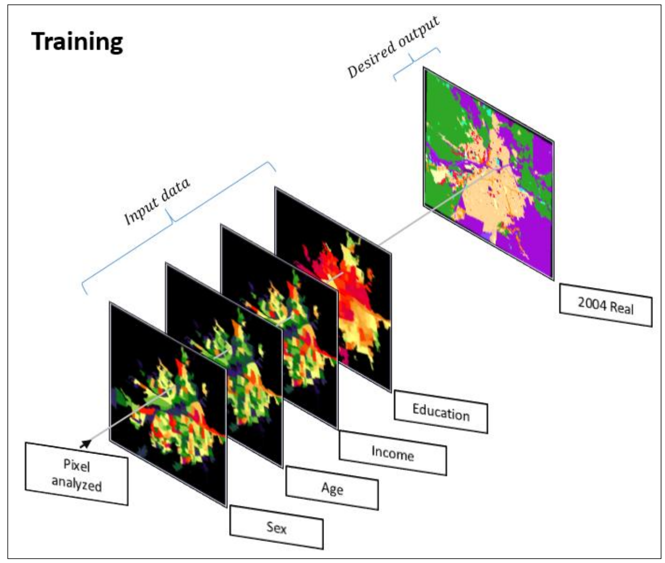


Fig. 10. Pixel-based training scheme for the ANN.

2) ANN configuration used in the hybrid simulation: The final ANN configuration used in the experiments is shown in Fig. 11, consisting of four input neurons, eight hidden neurons, and seven output neurons with sigmoid activation. Output values are constrained to the interval $[0,1]$, where higher values indicate stronger class affinity.

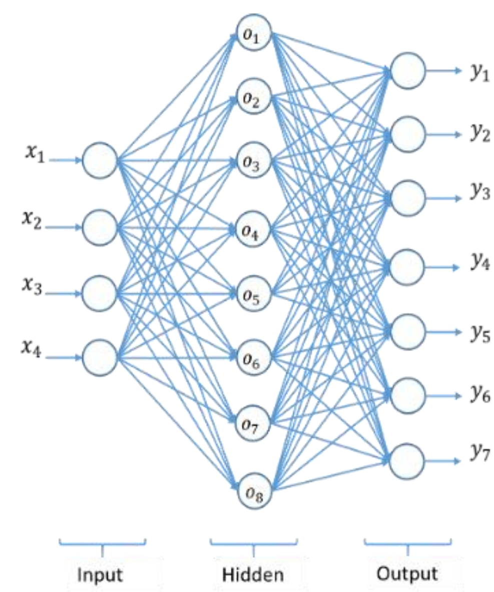


Fig. 11. Final configuration of the artificial neural network.

During simulation, the ANN processes socioeconomic inputs at each pixel coordinate and directly outputs classification vectors without requiring a target map. The per-pixel inference process is illustrated in Fig. 12.

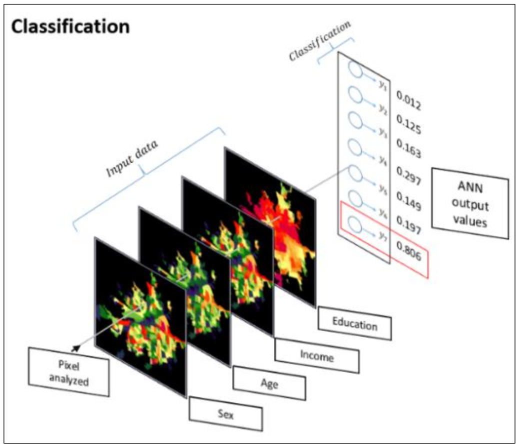


Fig. 12. Pixel-level classification scheme during simulation.

3) Ex-post simulation maps (1997–2004): Using identical CA parameters, two ex-post simulations were generated: one using the baseline CA and one using the proposed ANN–CA integration. Results are shown in Fig. 13 and Fig. 14, respectively.

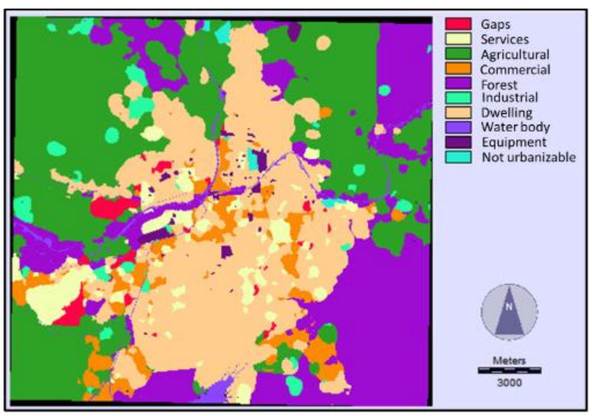


Fig. 13. Ex post simulation from 1997 to 2004 using cellular automata only.

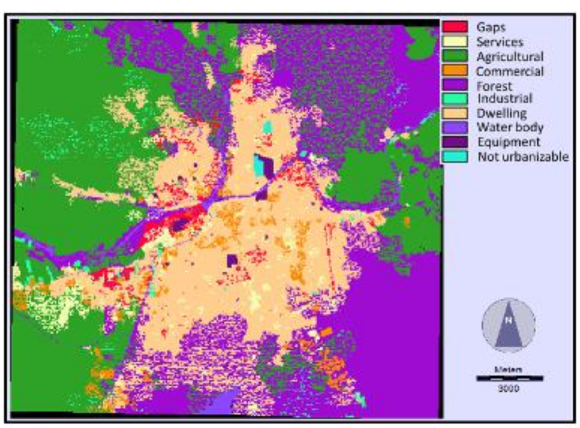


Fig. 14. Ex post simulation from 1997 to 2004 using the proposed ANN CA model.

The ANN–CA model exhibits improved spatial regularity and corridor-oriented expansion, consistent with socioeconomic-driven transition potentials.

4) Forecast simulation (2011): A forecast simulation was generated for 2011 using the same configuration applied to reproduce the 2004 map. The resulting simulated map is shown in Fig. 15.

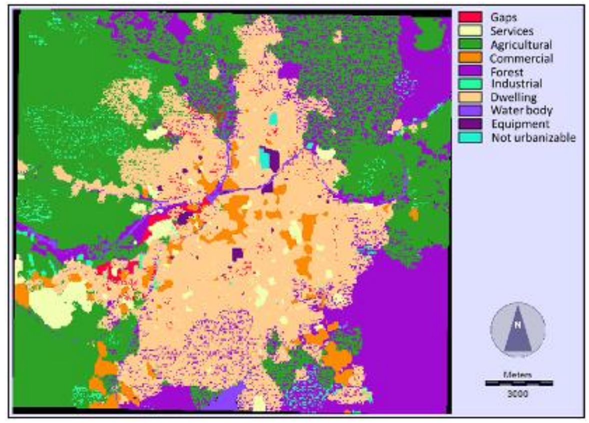


Fig. 15. Forecast simulation of urban growth for 2011 using the ANN CA model.

The decrease in agreement indices relative to the ex-post experiment is consistent with the increasing uncertainty associated with longer simulation horizons. Nevertheless, the ANN–CA model maintains coherent spatial structures, supporting its suitability for medium-term urban growth analysis.

Overall, the results indicate that the proposed ANN–CA framework provides a more structured and consistent spatial simulation, even when improvements in traditional accuracy metrics remain limited. This reinforces the role of deterministic, data-driven transition mechanisms in improving the interpretability and stability of urban growth models.

IV. Discussion

The results obtained in this study are consistent with recent advances in hybrid urban growth modeling that combine data-driven learning techniques with spatial simulation frameworks. Xu et al. [7] demonstrated that integrating Artificial Neural Networks with CA–Markov Chain models improves temporal prediction performance, while Zeng et al. [8] highlighted the importance of accounting for spatial heterogeneity and nonlinear transition rules in urban CA formulations. In comparison with these approaches, the proposed ANN–CA model introduces a direct and internal embedding of ANN outputs into the CA transition potential, rather than relying on externally generated probability maps. This design yields a deterministic and socioeconomically interpretable simulation mechanism.

Relative to CNN–CA integrations such as the vector-based framework proposed by Zhai et al. [13], and to Neural Cellular Automata approaches explored by Catrina et al. [14], the proposed model prioritizes explainability over deep spatial feature abstraction. While deep architectures excel at learning complex spatial patterns from imagery, their internal representations are often difficult to interpret in socioeconomic terms. In contrast, the multilayer perceptron used in this work produces class-specific coefficients that can be directly associated with demographic and economic variables, enabling clearer interpretation of urban growth drivers.

Although global agreement metrics—particularly the Kappa index—show limited variation between the compared models, the proposed ANN–CA framework produces structurally more coherent spatial patterns and improved transition consistency. This outcome is expected given that Kappa is highly sensitive to local misalignment, while Cramer's V captures global spatial association. For urban growth analysis and planning support, structural coherence and pattern realism are often more relevant than strict pixel-wise accuracy.

From a practical perspective, embedding socioeconomic variables directly into the CA transition mechanism enhances the transparency and interpretability of simulated outcomes. Urban planners and decision-makers can relate simulated expansion patterns to observable demographic and economic factors, rather than to stochastic variability. This characteristic represents a key advantage of the proposed approach when compared with purely stochastic CA models or black-box deep learning alternatives.

A detailed ablation analysis of the ANN architecture and the contribution of individual socioeconomic variables is beyond the scope of this study, as the primary objective is to evaluate the feasibility of embedding ANN-derived deterministic coefficients directly into the CA transition mechanism. Nevertheless, future work will explore the sensitivity of the model to network configuration, input variable selection, and their impact on spatial simulation performance.

Future work may extend the proposed framework by incorporating additional predictors, such as environmental constraints, transportation infrastructure, or policy-related variables, to further improve predictive performance. From a computational standpoint, the ANN–CA formulation provides a stable methodological foundation for exploring more advanced architectures, including Convolutional Neural Networks (CNNs) and Graph Neural Networks (GNNs), once robust strategies for integrating these models into constrained CA dynamics are established. Such extensions could enhance feature extraction while preserving the interpretability and deterministic behavior demonstrated in this study.

V. Conclusions

This study demonstrated the advantages of directly embedding an Artificial Neural Network (ANN) into a Cellular Automata (CA) framework for urban growth simulation by replacing the stochastic perturbation term in White's constrained model with ANN-derived classification values computed from spatialized socioeconomic data.

The main contributions of this work can be summarized as follows:

- Novel methodological integration: ANN outputs are incorporated directly into the CA transition potential formulation rather than being used as precomputed probability layers. This design enables a dynamic, context-aware, and internally consistent influence on pixel-level transitions.
- Socioeconomic grounding of urban dynamics: Demographic and economic variables—age, education, sex, and income—are explicitly embedded in the transition mechanism, strengthening the interpretability of simulated patterns and improving their relevance for planning and policy analysis.
- Improved spatial pattern coherence: Although improvements in global agreement metrics are modest, the ANN–CA model produces more coherent and realistic urban growth structures than the baseline CA model, particularly by reducing fragmented clusters and enhancing corridor-oriented expansion.

From a practical standpoint, the proposed approach supports urban planners and decision-makers by directly linking simulation outcomes to observable socioeconomic indicators. This characteristic enables more transparent interpretation of growth dynamics and facilitates targeted interventions in urban development and land-use management.

Future research directions include:

- Integrating the proposed ANN–CA framework with Agent-Based Models (ABM) to capture agent-level decision-making processes.
- Applying the methodology to cities with different urban growth patterns to evaluate robustness and generalizability [1].
- Incorporating additional spatial predictors, such as environmental constraints and transportation infrastructure, to further enhance predictive performance.
- Exploring advanced neural architectures, including Convolutional Neural Networks (CNNs) [9], [12], for improved feature extraction from remote sensing data, once stable integration strategies with constrained CA models are established.
- Extending the evaluation framework by incorporating per-class performance analysis, including confusion matrices and class-specific accuracy metrics, to better assess the model's ability to distinguish among different land-use categories.
- Incorporating statistical significance tests, such as McNemar's test, to complement the analysis of spatial agreement and provide a more comprehensive evaluation of model performance.

Overall, this study provides a methodological foundation for future hybrid approaches that combine explainable artificial intelligence with geospatial simulation frameworks in support of sustainable urban development planning. By strengthening the deterministic component of CA models, the proposed ANN–CA integration represents a step toward more data-driven, interpretable, and transferable approaches to land-use change modeling.

The presented framework contributes to the broader adoption of explainable AI in geospatial sciences and encourages further interdisciplinary collaboration between urban planning, computer science, and spatial modeling communities.

Conflict of Interest

The authors declare no conflict of interest.

The authors further declare that generative artificial intelligence tools were used exclusively for language editing and figure description refinement. All generated content was reviewed, validated, and approved by the authors, who take full responsibility for the final version of the manuscript.

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