OPEN ACCESS
International Journal of Innovations in Science & Technology

Application of Geospatial Approaches for Evaluation of Urban Growth Pattern and Trend Prediction of Multan City, Pakistan

Muhammad Hashim*[1], Atta-ur Rahman[1], Muhammad Qasim[1], Muhammad Umar Farooq[1], Muhammad Dawood[2], Basit Nadeem[2], Shazia Muneer[3]

[1]University of Peshawar, Peshawar, Pakistan

[2]Bahauddin Zakariya University, Multan, Multan, Pakistan

[3]Department of Epidemiology and Public Health, University of Veterinary and Animal Sciences, Lahore

***Correspondence**: hashimgeog@uop.edu.pk

Citation | Hashim. M, Rahman. A. U, Qasim. M, Farooq. M. U, Dawood. M, Nadeem. B, Muneer. S, "Application of Geospatial Approaches for Evaluation of Urban Growth Pattern and Trend Prediction of Multan City, Pakistan", IJIST, Vol. 07 Special Issue. pp 108-120, August 2025

Received | July 17, 2025 **Revised |** July 30, 2025 **Accepted |** August 04, 2025 **Published |** August 06, 2025.

This research aims to evaluate the changes in land use and land cover (LULC) in the study area and scrutinize the urban growth trends in Multan City over a period of 30 years, from 1993 to 2023. Moreover, the research utilizes an Artificial Neural Network (ANN) model to predict urban expansion up to the year 2050. To achieve these goals, geospatial systems and approaches are applied. Satellite imagery and remote sensing data from the years 1993, 2003, 2013, and 2023 are analyzed to detect LULC changes. The classification of these images provides valuable insights into the transformation of Multan's urban landscape over time. A supervised classification technique is primarily utilized to identify specific land cover classes. Landsat 5 data are used for the years 1993 and 2003, Landsat 7 for 2013, Landsat 8 for more recent observations, and Landsat 9 for the latest satellite imagery. The core geospatial model applied in this study is the Cellular Automata–Artificial Neural Network (CA–ANN) model, which is used to simulate and quantify urban expansion. Based on the CA–ANN model results, the urban area in Multan was approximately 154.84 km² in 1993, which expanded to 587.21 km² by 2023. Projections indicate that this urban area will further increase to 992.64 km² by 2030 and could reach 3,184.59 km² by 2050. These findings highlight a significant and rapid urban expansion expected in the coming decades.

Keywords: ANN-Artificial Neural Network, LULC-Land Use Land Cover, RS-Remote Sensing, CA- Cellular Automata

Introduction:

The model of the artificial neural network [1], ANN, is used to simulate urban expansion and obtain better results [2]. Assuming that previous interactions between land use categories affect the future pattern of LULC, this simple and flexible model can mimic urban expansion. [3]. ANN is more effective in estimating future urbanization. The model is dealt with as several layers of interconnected nodes or neurons. It can address complex issues, including nonlinear interactions, urban growth, and land use and land cover shifts [4][2].

This change has exhibited substantial shifts in the last forty years, greatly influenced by anthropogenic activities and natural changes [5]. On the anthropogenic side, the change of land cover is designed for infrastructure development that transforms land cover, which propels urbanization and acceleration of development [6]. In underdeveloped nation state, the urban agglomeration over naturally fragile regions relentlessly forces urban geographers and policy planning experts to address these problems [7]. Further, the urgent problem has also caused increased diversity in the spatial distribution of uses [8]. The amount of land on the earth is continuously being transformed due to the globalization of sprawl [9].

LULC monitoring is of utmost importance to many scientific fields as well as for the effective administration and design of urban land use and its monitoring is of utmost importance to many disciplines [10]. Moreover, RS and GIS technology are stochastic methods for the identification and analysis of spatial patterns and processes of change [11]. The acceleration of urbanization profoundly changes the number, organization, and spatial dispersal of land use and land cover classes [12]. Urbanization causes environmental damage, resource reduction, loss of biodiversity, decrease in natural vegetation cover, loss of cultivable land, and water supply reduction, along with landscape fragmentation [13]. Earth's surface and its data are collected through remote sensing satellite images [14][15]. Both GIS and remote sensing have been widely and successfully used in monitoring the spatial and temporal changes [16][17].

The temporal and spatial changes of land use/land cover have significant impacts on the local environment [18]. Land use (LU) alters land cover (LC) based on human needs and activities. The surface material features of the land, including forests, water bodies, agricultural zones, and urban structures, are termed land cover [5]. The spatio-temporal dynamics of land use and land cover change have long-term impacts on the environment and resources in a particular area [19]. This study aims at analyzing the LULC changes in the region over the years and studying the impacts of anthropogenic activities on the agriculturally significant areas. This study focuses on four specific features selected for their classification: built-up areas, vegetation cover, barren land, and water bodies. It analyzes human encroachment on the shoreline areas and the transformation of sand and soil into construction areas over the years, using geospatial techniques [20]. Remote sensing and GIS techniques offer a powerful infrastructure for classification owing to the many features offered to the user [21]. In decision-making studies related to land use and land cover, remote sensing, along with GIS, helps to fill different portions of feature information at different spatial and temporal scales. Different geographical information systems and remote sensing provide diverse spatial databases with qualitative and quantitative geodata to assess periodic changes in LULC features [22].

This study intends to evaluate the changes in land use and land cover (LULC) in Multan from the year 1993 to 2023, using multi-temporal satellite imagery. Change detection methods in the research evaluate the spatial and temporal aspects of urban development. A combined CA–ANN (Cellular Automata–Artificial Neural Network) model is constructed to predict urban sprawl trends. The effects of both the actual and forecasted sprawl are analyzed within the frameworks of sustainable development and urban spatial planning.

Objectives of the Study:

Map and assess the changes in land use and land cover (LULC) in Multan from 1993 to 2023 using satellite images.

Perform change detection in Google Earth Engine to evaluate the spatial and temporal dynamics of urban growth.

Construct a CA-ANN (Cellular Automata-Artificial Neural Network) model to forecast future urban expansion.

Evaluate the impacts of the growth on sustainable development and urban spatial planning.

Novelty Statement:

This research describes the first use of a hybrid Cellular Automata-Artificial Neural Network (CA-ANN) model for predicting urban expansion in Multan, Pakistan. While earlier research in the region used traditional statistical or single-method models, this paper proposes an AI-driven approach capable of capturing complex spatial-temporal trends in urban expansion. By combining multi-temporal satellite imagery with auxiliary geographic data, the model increases the accuracy and interpretability of Land Use/Land Cover (LULC) change estimates. The findings propose a unique decision-support framework for urban planners and policymakers in rapidly emerging cities, filling a crucial research gap in Pakistan's urban growth modeling literature.

Study Area:

The case study is located in Multan city, which is the focus of this study. The region is experiencing rapid urbanization. Multan is, in terms of population, the seventh largest city in Pakistan, and the third largest in area. As per the Pakistan Bureau of Statistics (GoP, 2017), the population of the district Multan was 4.745 million, out of which 2.1 million resided in Multan city, which is 44% of the district population. Multan, sometimes referred to as the "City of Sufis," is a historic city in the Punjab region. Multan city is situated between latitudes 29.792° and 30.457° North and longitudes 71.265° to 71.835° East Figure 1.

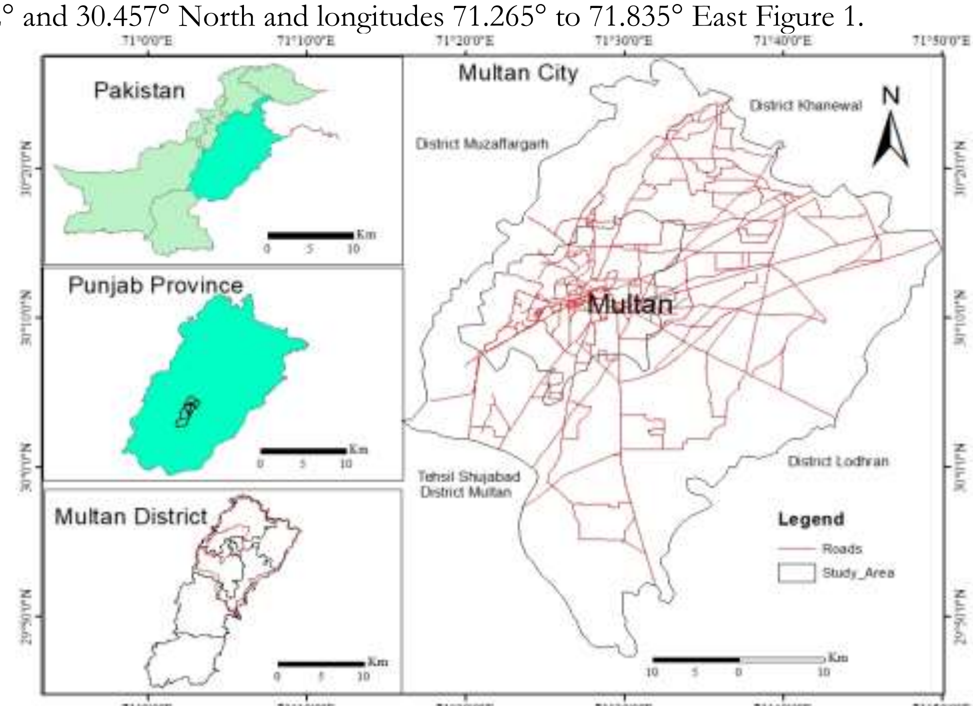

Figure 1. Location of the Study Area

Methodology:

Data Sourcing:

Using the CA-ANN models requires different steps involving collecting, preparing, and standardizing the data, as well as selecting the relevant input parameters from the classified

Land Use and Land Cover (LULC) maps. After the data set was put into the neural network, which was structured with input, hidden, and output layers. Through repeated training, the optimal network architecture was identified and refined for enhanced predictive accuracy. This study used secondary data from multiple sources, such as satellite images, DEMs, and spatial vector layers. Photographs of periods empty of clouds free images of a similar seasons were collected. The raster layers have a 30 m resolution Table 1; Figures 2 to 10.

Table 1. Data preparation for CA-ANN.

Data Types	Years of Data	Data Source	Resolution
Landsat 5	15- March, 1993	USGS	30 meters
Landsat 7	19- March, 2003	USGS	30 meters
Landsat 8	30- March,2013	USGS	30 meters
Landsat 9	21 – March, 2023	USGS	30 meters
DEM	2023	USGS	30 meters
The slope layer	Not available	Extracted from DEM	Not available
Hill shade layer	Not available	Extracted from DEM	Not available
Excluded Layer	Not available	MDA Multan	Not available
Administrative boundary	Not available	MDA Multan	Not available

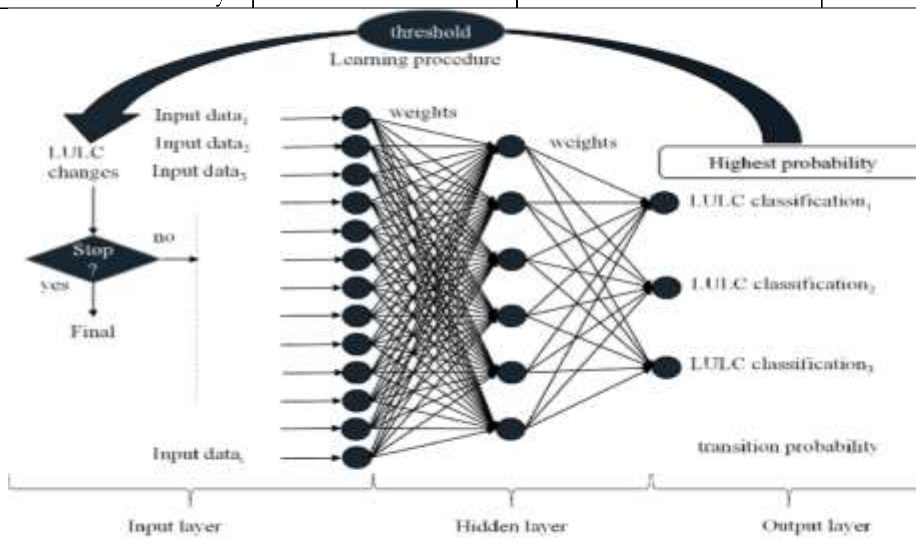

Figure 2. ANN Network

Flow Diagram of the Study:

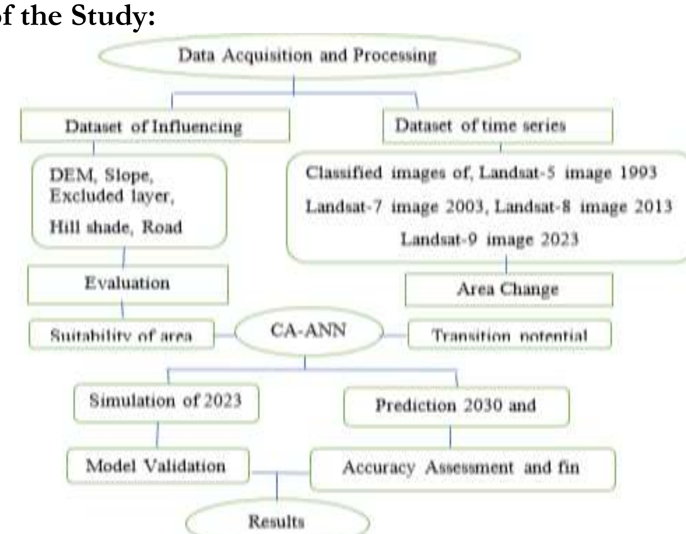

Figure 3. Plan of work

Input Variables:

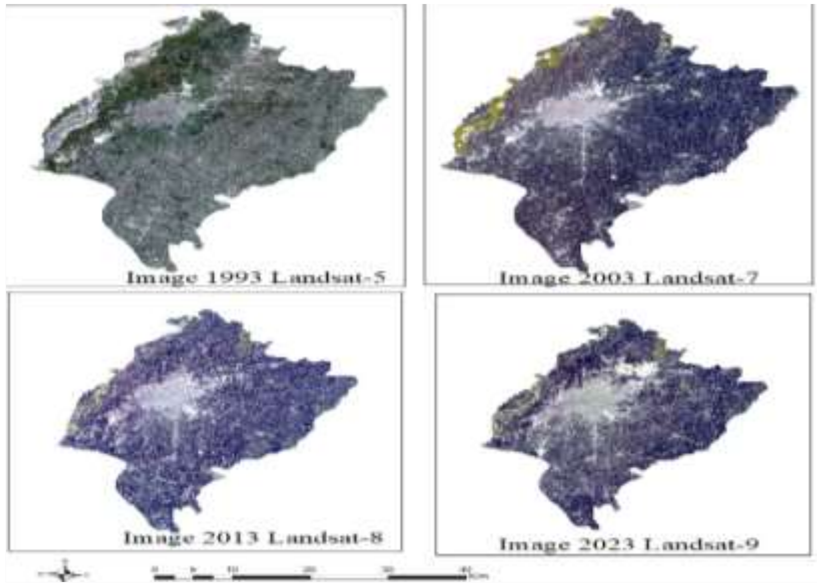

Figure 4. Urban Prediction2030 map

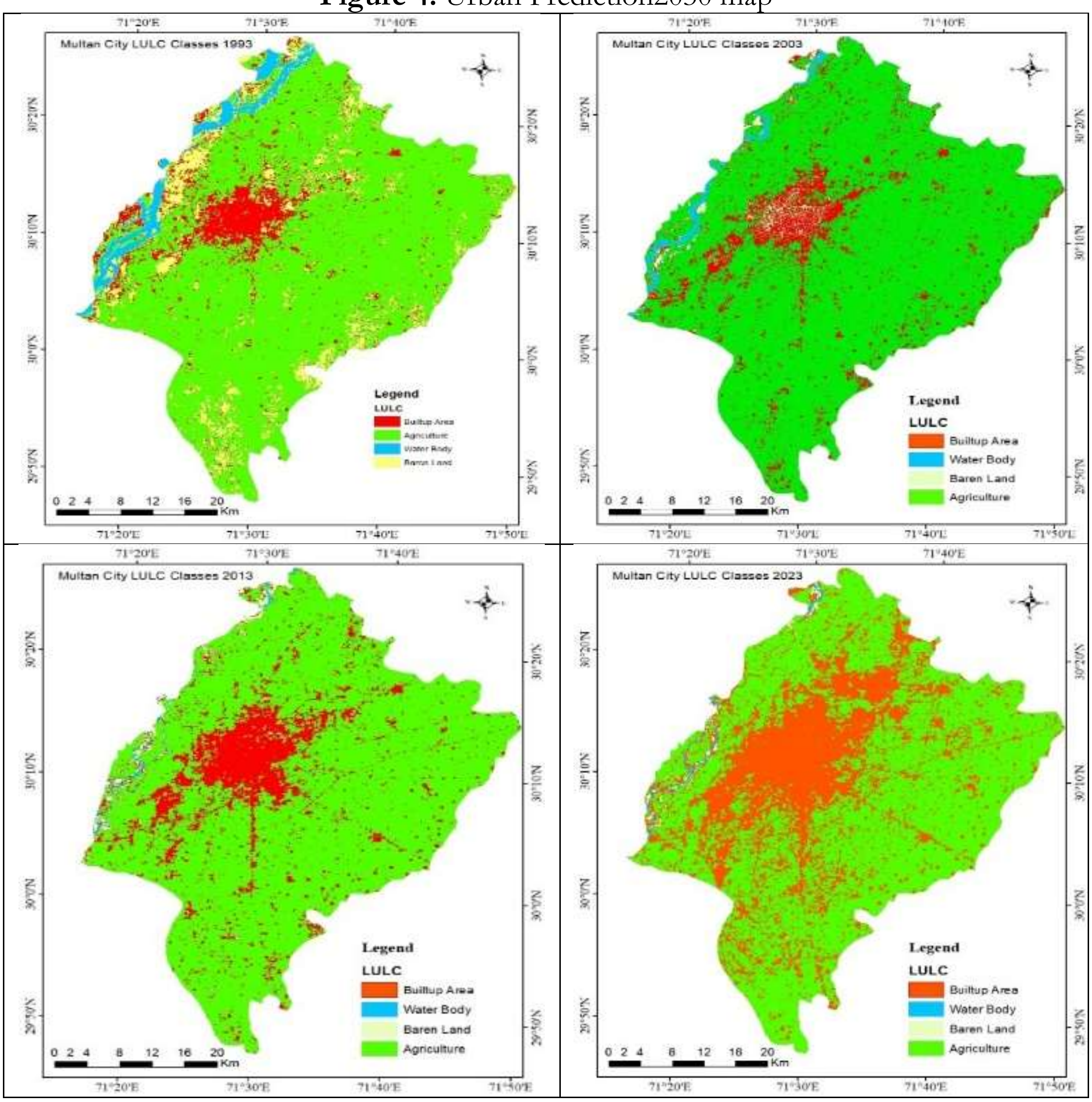

Figure 5. LULC map for 1993, 2003, 2013, and 2023

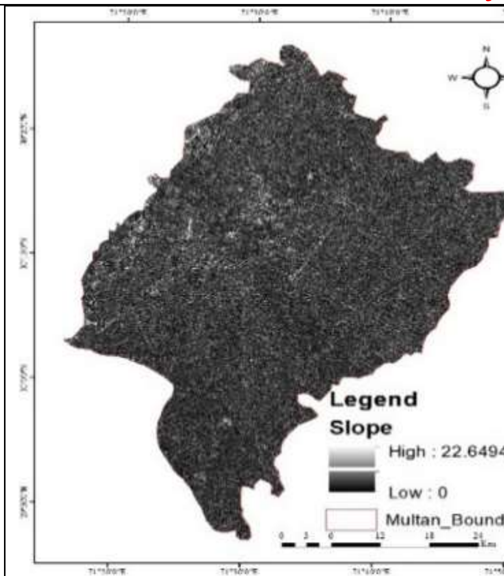

Figure 6. Slope map

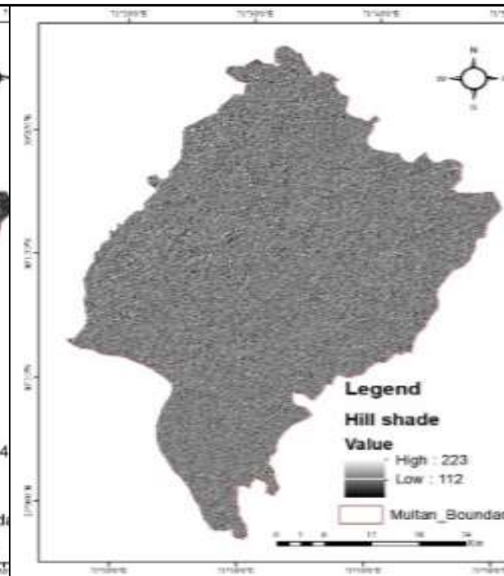

Figure 7. Hill shade map

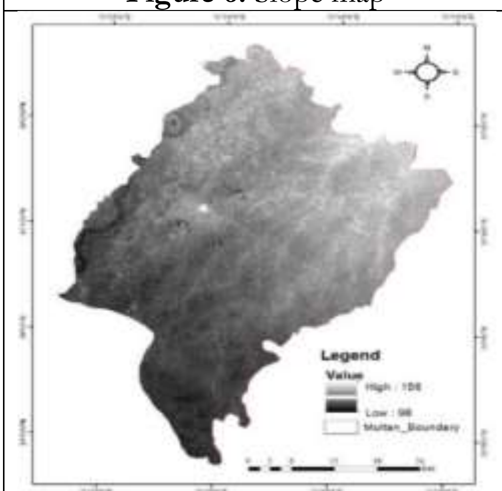

Figure 8. DEM map

Figure 9. Excluded area map

Figure 10. Road network map

Artificial Neural Network (ANN):

The first step of the project is to apply a Cellular Automata (CA) model for simulating the Land Use and Land Cover (LU/LC) change using transition probabilities which were obtained from training of an Artificial Neural Network (ANN). The first step focuses on the predictive LU/LC change modeling by spatially allocating a pixel for the neural network input layer attributes. This predictive modeling is done at the pixel level. Each pixel is tied to n attributes as inputs for the neural network. The neural network is summarized with the equations below.

$$x = [x_1, x_2, x_3, x_4, x_n]^T \text{ Equation 1}$$

The attributes defined as x1, x2, and x3 represent elements. The transposition of the layer is observed with the symbol T. The input layers consist of the LULC maps for the years (1993, 2003, 2013, 2023) together with 8 other conditioning layers. To maintain reliability, all layers were interpolated to a spatial resolution of 30 m, converted to raster (TIFF) format, and then processed to extract relevant attributes.

The next stage involves using a raster evaluation, where the first raster is taken from one attribute, while the second raster is drawn from another attribute. In this step, the changes in the size of each land use and land cover class are compared to the first one.

The first step of the project is to apply a Cellular Automata (CA) model for simulating the Land Use and Land Cover (LU/LC) change using transition probabilities which were obtained from training of an Artificial Neural Network (ANN). The first step focuses on the predictive LU/LC change modeling by spatially allocating a pixel for the neural network input layer attributes. This predictive modeling is done at the pixel level. Each pixel is tied to n attributes as inputs for the neural network. The neural network is summarized with the equations below.

The attributes defined as x1, x2, and x3 represent elements. The transposition of the layer is observed with the symbol T. The input layers consist of the LULC maps for the years (1993, 2003, 2013, 2023) together with 8 other conditioning layers. To maintain consistency, all layers were resampled to a spatial resolution of 30 m, converted to raster (.tiff) format, and then processed to extract relevant attributes.

The next step involves using two-way raster comparison, where the first raster is taken from one attribute, while the second raster is drawn from another attribute. In this step, the changes in the size of each land use and land cover class compared to the first one, a trial-and-error strategy was applied in the third phase to find the best arrangement of 12 neurons in one hidden layer of the neural network. The neural network's output layer has the same number of neurons as the classes of the target or dependent variable and, therefore, in this case, has six neurons corresponding to the six LU/LC classes. Furthermore, the neuron "l" in the output layer computes a rate which indicates the conversion possibility flowing from the LU/LC category "l." This probability is derived from the output of the neural network.

In the fourth phase, the workflow consists of simulating the changes in LU/LC using a Cellular Automata (CA) model. This CA model consists of spatially organized grids made up of cells, which can adopt several different states based on their proximity to other cells. The CA analyzes the arrangement of cells near a particular cell. This is then followed by verification of the replicated LU/LC maps and evaluation of the predicted and actual LU/LC maps for 2023. Having completed this validation, the forecasts for LU/LC in 2030 and 2050 were developed

Train Model:

In evaluating the model, the data set was randomly partitioned into training and test sets at a ratio of 70% and 30% respectively. This ensured that the ANN model was evaluated neutrally, as it was tested using data that the model had not encountered prior. Model evaluation was executed at the agreed criteria by the overall accuracy, the Kappa coefficient, and the confusion matrix, which calculated the diverse multi-class confusion matrix, thus enabling a holistic evaluation of the classification and the prediction performance.

Table 2. Calculation correlation

Hill shade	Slope Values	Road Values	Excluded Values
------	-0.00515589789967	-0.000745616409643	-0.0041840949647
------	-----	-0.0008835520663773	-0.00549046788596
------	-----	-----	-0.0918218772615
------	-----	-----	-----

Evaluation correlation is the procedure of determining the relationship between the target values and the expected outputs of an artificial neural network (ANN) model. It is a very important step of the model's presentation and accuracy processing. Evaluation correlation offers a comparison between the predicted outputs and the ground truth, so much so that it can shed some light on how well the ANN model has managed to capture the existing patterns and relationships in the dataset. It is also important to note that a high evaluation correlation means that there is a high comparability between the model's predictions and the real-world phenomena.

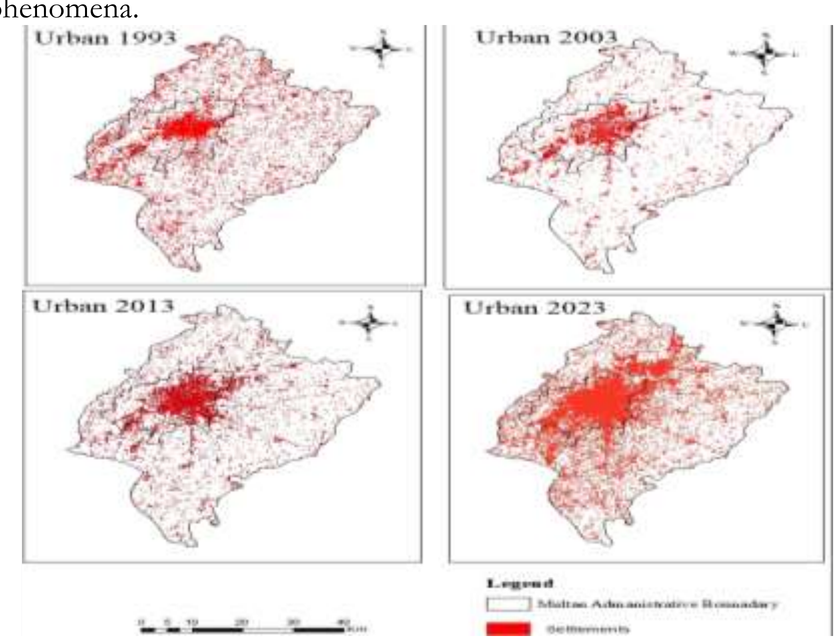

Figure 11. Settlements map

Table 3. Area Change

Classes	1993 Area	2023 Area	Δ	1993 %	2023 %	Δ%
Non-Urban	4137.90 sq.km	3705.53 sq.km	-432.37sk.km	96.39	86.32	-10.072
Urban	154.84 sq.km	587.21 sq.km	432.37sk.km	3.607	13.67	10.072

Figure 12. Area Change

The table illustrates the land cover change between non-urban and urban areas between the years 1993 and 2023. In 1993, non-urban areas had an area of 4137.90 sq.km, which is about 96.39 of the total land, while urban areas covered only 154.84 sq.km, which is 3.61 of the total land. By 2023, non-urban land decreased to 3705.53 sq.km, which is a reduction of 432.37 sq.km (10.07% decline in share). On the other hand, urban areas grew considerably to 587.21 sq.km, which is an increase of 432.37 sq.km which increasing their share to 13.67% of the total area (10.07% increase). The data shows a significant movement of non-urban land to urban land.

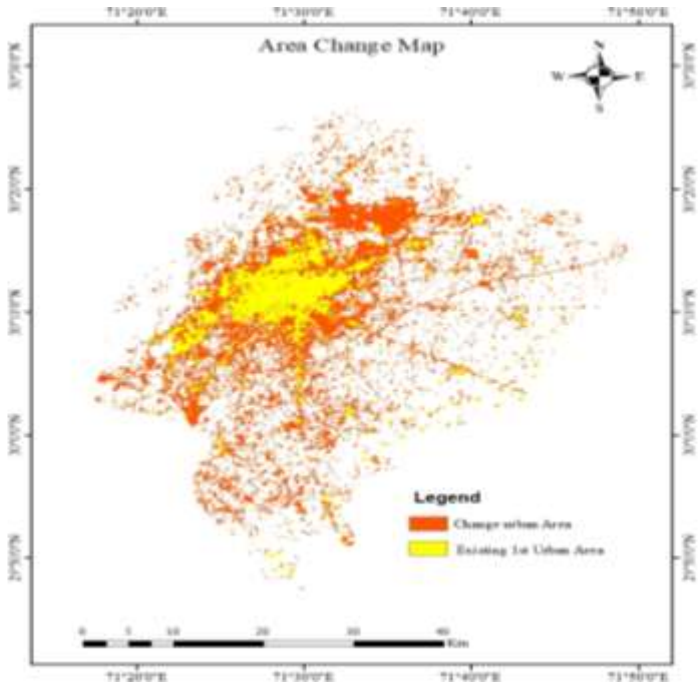

Figure 13. Change and Existing Urban Area

Transition Potential Modeling:

Transition potential modeling is a method applied within artificial neural network (ANN) frameworks aimed at capturing and analyzing the dynamics of state changes within a system. It is centered on the system's potential energy surface and the likelihoods of transitioning from one energy state to another. Through the use of ANNs, transition potential modeling can learn and represent intricate relationships that exist among the system's parameters, thus allowing for the forecasting and even the simulation of state changes. as profound understanding of the mechanisms and behaviors of the system is made possible. With an ANN trained on transition potential models, one is able to appreciate the dynamic factors that drive state changes and apply this understanding across disciplines like physics, chemistry, and biology to investigate and anticipate changes at the molecular, cellular, and systemic levels.

Cellular Automata Simulation:

Artificial neural networks (ANNs) are employed to capture learnable rules for intricate patterns, interactions, and behaviors, allowing for simulative processes within the self-exciting cellular automata model systems. By the use of ANNs, researchers are able to train models on historical and observed data, thus accurately simulating the observed behaviors of the systems under study. Cellular automata simulations are applicable across disciplines, including, but not limited to, physics, biology, social science, and even computer science. The interdisciplinary synergy of ANN models and cellular automata provides a robust framework to study complex wonders, understand the dynamics of a given system, and predict its future situations and performances.

Validation and Accuracy:

Endorsement and accuracy imitation is a key step in measuring the effectiveness and trustworthiness of models of artificial neural networks. Validation is the evaluation of the model's performance and simplification capabilities on new data. This is done by intense the accessible data into a preparation and a validation set, where the training set is used to train the ANN model, and the validation set is used to assess its performance. Accuracy simulation is the measurement of the model's predictions in comparison to known or labeled data and determining its accuracy.

Accuracy simulation gives insights into the model's classifying or predicting capabilities while also shedding light on the possible metrics of the model's performance, such as accuracy, precision, and recall. Researchers can validate the model's performance and identify issues such as over-/under fit, tune model parameters, and make model selection decisions through validation and accuracy simulation.

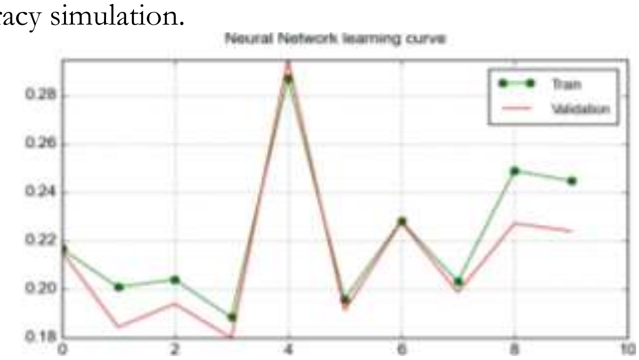

Figure 14. Train the ANN model

Table 4. Validation of Kappa

Sr-No	Kappa Types	Validation
1	Correctness	95.5 %
2	Kappa (overall)	0.93 %
3	Kappa (histogram)	0.93 %
4	Kappa (location)	0.87 %

The table shows validation results of an urban area simulation model based on the accuracy assessment and the metrics provided. The model's accuracy is documented as 95.5%, which is the agreement rate between the simulated and actual urban areas. The value of the Kappa coefficient, which is used to measure the level of agreement, reflects accuracy in model performance as well, since it gives an overall Kappa of 0.93, which is statistically excellent. The Kappa histogram value, which is also 0.93, indicates strong agreement in the consistency of distribution of the classified categories. On the other hand, the Kappa location value of 0.87 indicates that the distribution of predicted urban areas in comparison to the actual observation is correct, but not as precisely as the histogram-based measure. All of these indicators point to the simulation model's high degree of accuracy in both quantitative and spatial forecasting patterns of urban expansion.

Urban area changes in km^2:

Table 5. Prediction results for 2030 and 2050

No	Class	2023 Area	2030	2050
1	Non-Urban	3705.53 km^2	3300.1 km^2	1408.15 km^2
2	Urban	587.21 km^2	992.64 km^2	3184.59 km^2

The table gives the timeline for the transition of land use from non-urban to urban for the years 2023, 2030, and 2050. Non-urbanized areas occupied 3705.53 km^{2}of land, and urban areas 587.21 km^2. In the year 2030, the projections show that non-urban land would reduce to 3300.1 km^2 and urban areas would increase to 992.64 km^2. This increasing trend extends till

2050, where non-urban areas are expected to reduce massively to 1408.15 km^2, and urban areas would increase to 3185.59 km^2. It can be interpreted from the data that there is an increase in the rate of urban expansion and an overall change in Land Use, which indicates that urban areas are likely to outnumber non-urban areas by 2050. This further paints a picture that there is a growing need for Urban Planning to be able to efficiently take care of managing land resources due to population growth.

Prediction 2030 and 2050:

The data gives the land area estimates for the years 2023, 2030, and 2050 for the Non-urban and Urban classes. Now, let's analyze the observed features. The Non-urban Class describes the areas that do not fall under an urban area, are under development. The data further demonstrates that it is expected that these areas will keep decreasing over the years. The land area decreased from 3705.53 km^2 to 3300.1 km^2 between 2023 and 2030, suggesting a loss of non-urban land. Additionally, it is anticipated that the predicted land area will drop even more to 1408.15 km^2 by 2050. This implies that non-urban areas have undergone a significant shift, either as a result of changes in land use practices, infrastructural development. Developed or urbanized areas are represented by the Urban class. Data indicates that the area of urban land is expected to grow over time. Urban areas significantly expand from 587.21 km^2 to 992.64 km^2 between 2023 and 2030. This suggests that urbanization was accelerating at the time. The estimated urban land area is predicted to rise to 3184.59 sq km by 2050, indicating increased urban expansion and growth.

Table 6. ANN Model results

Area Years	Non-Urban area	Land conversion in Urban
Area in 2023	3705.53 km^2	587.21 km^2
Land conversion in Urban 2030	3300.1 km^2	992.64 km^2
Land conversion in Urban 2050	1408.15 km^2	3184.59 km^2

These findings suggest that the terrain is changing, with a considerable increase in urban regions and a decrease in non-urban territory. In addition to highlighting the significance of sustainable urban planning, controlling urban sprawl, and protecting non-urban areas for ecological and environmental reasons, this trend points to the growing impact of urbanization on land use patterns. Effective land management, resource allocation, and the creation of plans to guarantee sustainable and balanced urban development can all be facilitated by keeping an eye on and comprehending these changes. Figure,15,16.

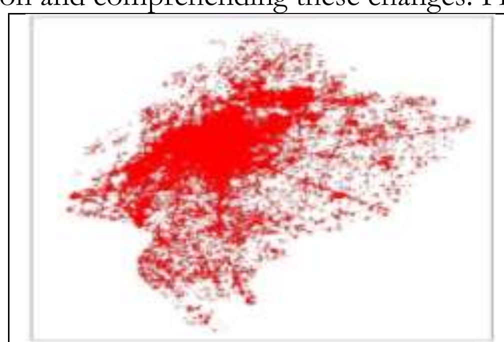

Figure 15. CA-ANN-Prediction 2030

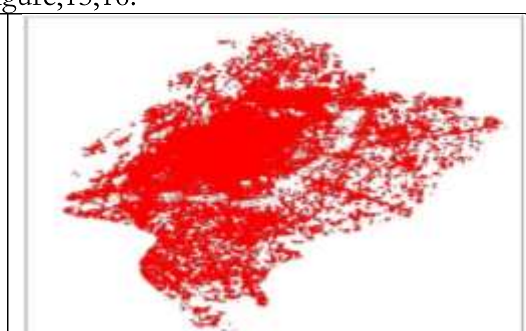

Figure 16. CA-ANN-Prediction 2050

Result and Discussion:

The analysis of satellite imagery from 1993 to 2023 in Multan City shows significant urban growth, with urban land increasing from 154.84 km² (3.6% of the area) in 1993 to 587.21 km² (13.7%) in 2023, while non-urban land decreased by 432.37 km². Predictions using the CA–ANN model indicate urban land could expand to 992.64 km² by 2030 and 3184.59 km² by 2050, with non-urban areas contracting significantly. The model demonstrated high accuracy, with a correctness of 95.5% and a Kappa coefficient of 0.93. These trends highlight the urgent need for sustainable urban planning to mitigate environmental impacts, ensure resource management, and preserve agricultural areas, advocating for integrated approaches using technologies like remote sensing and GIS.

Conclusion:

For the first time, this research innovatively utilized the hybrid Cellular Automata–Artificial Neural Network (CA–ANN) model to predict urban growth in Multan City. The findings showed significant changes in land use from 1993 to 2023, including urban expansion by more than 10% in land share at the expense of non-urban areas. The model demonstrated exceptional predictive accuracy, achieving 95.5% correctness and an overall Kappa coefficient of 0.93, which confirms its trustworthiness for spatial–temporal urban change analysis. This study's AI-based projections for 2030 and 2050 demonstrate the ability of modern technology to model complicated urban changes as compared to more traditional approaches.

The expected projections also suggest that by 2050, urban regions are expected to surpass non-urban regions, which would create immense challenges in achieving sustainable development, resource distribution, and environmental protection. This information highlights the necessity of immediate integrated urban frameworks that approach urban infrastructure expansion while striving to uphold ecological balance. The methodology and findings presented in this paper can also assist policymakers, urban planners, and researchers by providing a decision-support framework to take proactive actions to manage uncontrolled urban growth while protecting the agricultural sustainability of the region.

References:

[1] Z. H. A. Maher Milad Aburas, Yuek Ming Ho, Mohammad Firuz Ramli, "The simulation and prediction of spatio-temporal urban growth trends using cellular automata models: A review," *Int. J. Appl. Earth Obs. Geoinf.*, vol. 52, pp. 380–389, 2016, doi: https://doi.org/10.1016/j.jag.2016.07.007.

[2] R. C. X. Yang, "Simulating land use change by integrating ANN-CA model and landscape pattern indices," *Geomatics, Nat. Hazards Risk*, vol. 7, no. 3, 2016, [Online]. Available: https://www.tandfonline.com/doi/full/10.1080/19475705.2014.1001797

[3] S. Ali, A. U. Rahman, and S. Ali, "Spatio-Temporal Analysis of Land Use Land Cover, Dynamics in Built-up Area and Its Trend Predictions in Peshawar Vale, Pakistan," *Rev. Appl. Manag. Soc. Sci.*, vol. 5, no. 2, pp. 177–192, Jun. 2022, doi: 10.47067/RAMSS.V5I2.226.

[4] S. M. Muhammad Hashim , Atta-ur-Rahman , Muhammad Qasim, Muhammad Umar Farooq, Basit Nadeem, "Determination Of Demographic Change And Urban Settlement Pattern In Multan City, Pakistan," *J. Posit. Sch. Psychol.*, vol. 7, no. 6, p. 6, 2023, [Online]. Available: https://journalppw.com/index.php/jpsp/article/view/17522

[5] A. J. Munahzah Meraj, "Land Use/Land Cover (LULC) Dynamics in a Semi-Arid Watershed in Eastern Rajasthan, India Using Geospatial Tools," *J. Geogr. Inf. Syst.*, vol. 14, no. 6, p. 12, 2022, [Online]. Available: https://www.scirp.org/journal/paperinformation?paperid=122078

[6] Z. Hassan *et al.*, "Dynamics of land use and land cover change (LULCC) using geospatial techniques: a case study of Islamabad Pakistan," *Springerplus*, vol. 5, no. 1, pp. 1–11, Dec. 2016, doi: 10.1186/S40064-016-2414-Z/FIGURES/6.

[7] M. F. Baqa *et al.*, "Monitoring and Modeling the Patterns and Trends of Urban Growth Using Urban Sprawl Matrix and CA-Markov Model: A Case Study of Karachi, Pakistan," *L. 2021, Vol. 10, Page 700*, vol. 10, no. 7, p. 700, Jul. 2021, doi: 10.3390/LAND10070700.

[8] D. Dutta, A. Rahman, S. K. Paul, and A. Kundu, "Estimating urban growth in peri-urban areas and its interrelationships with built-up density using earth observation datasets," *Ann. Reg. Sci.*, vol. 65, no. 1, pp. 67–82, Aug. 2020, doi: 10.1007/S00168-020-00974-8/METRICS.

[9] M. O. S. Iman Rousta, "Spatiotemporal Analysis of Land Use/Land Cover and Its Effects on Surface Urban Heat Island Using Landsat Data: A Case Study of Metropolitan City Tehran (1988–2018)," *Sustainability*, vol. 10, no. 12, p. 4433, 2018, doi:

https://doi.org/10.3390/su10124433.
[10] N. A. Kashif Ali, "Impact of Urbanization on Vegetation: a Survey of Peshawar, Pakistan," *Polish J. Environ. Stud.*, vol. 28, no. 4, 2019, [Online]. Available: https://www.pjoes.com/Impact-of-urbanization-on-vegetation-A-survey-of-Peshawar-Khyber-Paktunkhaw-Pakistan,89609,0,2.html
[11] P. K. & E. S. Raziyeh Teimouri, Rasoul Ghorbani, "Investigation of land use changes using the landscape ecology approach in Maragheh City, Iran," *J. Environ. Stud. Sci.*, vol. 13, pp. 271–284, 2023, [Online]. Available: https://link.springer.com/article/10.1007/s13412-023-00822-z
[12] S. T. Maomao Zhang, Abdulla - Al Kafy, Pengnan Xiao, Siyu Han, Shangjun Zou, Milan Saha, Cheng Zhang, "Impact of urban expansion on land surface temperature and carbon emissions using machine learning algorithms in Wuhan, China," *Urban Clim.*, vol. 47, p. 101347, 2023, doi: https://doi.org/10.1016/j.uclim.2022.101347.
[13] C. Ahmed, A. Mohammed, and A. Tahir, "Geostatistics of strength, modeling and GIS mapping of soil properties for residential purpose for Sulaimani City soils, Kurdistan Region, Iraq," *Model. Earth Syst. Environ.*, vol. 6, no. 2, pp. 879–893, Jun. 2020, doi: 10.1007/S40808-020-00715-Y/METRICS.
[14] A. Jana, M. K. Jat, A. Saxena, and M. Choudhary, "Prediction of land use land cover changes of a river basin using the CA-Markov model," *Geocarto Int.*, vol. 37, no. 26, pp. 14127–14147, Dec. 2022, doi: 10.1080/10106049.2022.2086634.
[15] P. A. Parvaiz A. Bhat, Mifta ul Shafiq, Abaas A. Mir, "Urban sprawl and its impact on landuse/land cover dynamics of Dehradun City, India," *Int. J. Sustain. Built Environ.*, vol. 6, no. 2, pp. 513–521, 2017, doi: https://doi.org/10.1016/j.ijsbe.2017.10.003.
[16] M. Burke, A. Driscoll, D. Lobell, and S. Ermon, "USING SATELLITE IMAGERY TO UNDERSTAND AND PROMOTE SUSTAINABLE DEVELOPM," *Natl. Bur. Econ. Res.*, 2020, [Online]. Available: https://www.nber.org/system/files/working_papers/w27879/w27879.pdf
[17] M. Hashim *et al.*, "The spatio-temporal analysis of land use land cover changes in Multan city, Pakistan," *Nat. Appl. Sci. Int. J.*, vol. 4, no. 1, pp. 120–134, Jun. 2023, doi: 10.47264/idea.nasij/4.1.8.
[18] N. Kayet *et al.*, "Spatiotemporal LULC change impacts on groundwater table in Jhargram, West Bengal, India," *Sustain. Water Resour. Manag.*, vol. 5, no. 3, pp. 1189–1200, Sep. 2019, doi: 10.1007/S40899-018-0294-9/METRICS.
[19] S. Nayak and M. Mandal, "Impact of land use and land cover changes on temperature trends over India," *Land use policy*, vol. 89, p. 104238, 2019, doi: https://doi.org/10.1016/j.landusepol.2019.104238.
[20] N. K. Msofe, L. Sheng, and J. Lyimo, "Land Use Change Trends and Their Driving Forces in the Kilombero Valley Floodplain, Southeastern Tanzania," *Sustain. 2019, Vol. 11, Page 505*, vol. 11, no. 2, p. 505, Jan. 2019, doi: 10.3390/SU11020505.
[21] V. P. T. Peter Zeilhofer, "GIS and ordination techniques for evaluation of environmental impacts in informal settlements: A case study from Cuiabá, central Brazil," *Appl. Geogr.*, vol. 28, no. 1, pp. 1–15, 2008, doi: https://doi.org/10.1016/j.apgeog.2007.07.009.
[22] A. Saxena and Mahesh Kumar Jat, "Land suitability and urban growth modeling: Development of SLEUTH-Suitability," *Comput. Environ. Urban Syst.*, vol. 81, p. 101475, 2020, doi: https://doi.org/10.1016/j.compenvurbsys.2020.101475.