ISSN: 2634 - 8845

Journal of Earth and Environmental Science Research

Research Article

Open Access

Modeling Urban Growth and Future Scenario Projections for Chinhoyi, Zimbabwe using Cellular Automata

Nobert Tafadzwa Mukomberanwa[1]*, Honest Komborero Madamombe[1], Phillip Taru[1] and Beaven Utete[2]

[1]Chinhoyi University of Technology, Department of Geoinformatics and Environmental Conservation P. Bag 7724, Chinhoyi, Zimbabwe

[2]Chinhoyi University of Technology, Department of Freshwater and Fishery Sciences. P. Bag 7724, Chinhoyi, Zimbabwe

ABSTRACT

Land use land cover (LULC) change processes in less developed countries are typically rapid and extensive, and they often include a considerable proportion of unplanned or informal development. Land use land cover change models can help to understand, analyse and simulate the outcomes of such processes, providing information that can inform policy development. Rapid urbanisation presents a land planning conundrum for town planners and policymakers besides disenfranchising urban green spaces and encroaching into peri urban areas in the developing town of Chinhoyi in Zimbabwe. This necessitates for predicting future urban growth using modern and accurate techniques. This study aims to i) model the urban growth and ii) project future scenarios of a developing town, Chinhoyi in Zimbabwe using Cellular Automata. Landsat satellite images for the interval years 2000, 2013 and 2021 were used for data analysis. Spatial variables comprising rivers, Digital Elevation Model (DEM), slope, Central Business District (CBD) and Euclidean distances of the city roads in tandem with Land Use Land Cover images were analysed using Cellular-Automata model. LULC were significantly different ($p<0.05$) for 2000–2013 with non significant changes between 2013 2021. Cellular Automata prediction model shows marginal growth in Chinhoyi by 2050. This is attributed to fewer land categories which can be converted in the CA model. For broader use the current CA model need more and new parameters (driving factors) to improve its urban growth prediction accuracy. Simulation of future land use can provide decision support for urban planners and decision makers, which is important for sustainable urban expansion in developing countries.

***Corresponding author**
Nobert Tafadzwa Mukomberanwa, Chinhoyi University of Technology, Department of Geoinformatics and Environmental Conservation P. Bag 7724, Chinhoyi, Zimbabwe.

Received: December 26, 2024; **Accepted:** December 30, 2024; **Published:** February 25, 2025

Keywords: Cellular Automata, Spatial Variables, Simulation, Urban Growth

Introduction

Global cities, which are the driving forces behind economic growth, have large populations and are particularly exposed to the impacts of land use land cover change (LULC) [1]. Urbanization is a worldwide process that is dramatically changing landscapes and societies on a global scale [2]. As people move from rural to urban areas in search of improved prospects, the patterns of urban expansion become more intricate and difficult to control, especially in developing towns and cities [3]. Urban areas in these regions frequently experience uncontrolled growth without sufficient planning and infrastructure, resulting in problems such as overcrowding, insufficient services, and environmental deterioration [4]. Anthropic activity has a significant impact on the Earth's surface [5]. Human existence on the Earth and their use of land has had a tremendous effect on the natural environment, resulting in a discernible pattern in LULC across time [6]. Understanding changes in LULC is crucial for selecting, planning, and implementing land use schemes to meet the increasing demands of a growing human population for basic human needs and well-being.

To comprehend the effects of human activities on the natural resource base, it is necessary to observe the Earth from space [7]. Earth satellite observations are essential for gathering important data about the effects of human activities, particularly in cases of rapid changes in land use [8]. Further, earth sensing satellite data has been increasingly significant in mapping the global features and infrastructure, conservation, and monitoring environmental alteration in recent years [6]. Gaining insight into the patterns and factors that influence urban expansion is essential for promoting sustainable development and implementing efficient urban planning. Conventional methods of urban modeling have been constrained by their fixed character and inability to accurately represent the dynamic interactions that influence the development of urban environments over time. In response, computational modeling techniques, such as Cellular Automata (CA), have evolved as powerful tools to simulate and predict urban growth patterns based on a set of established rules guiding cell activity inside a spatial grid [9]. These cells are assigned initial land-use classifications based on existing conditions gathered from satellite imagery, census data, and other sources [10]. Over consecutive iterations, the model adjusts the land-use of each cell according to transition rules that determine how land-use changes based on nearby cells and predefined criteria [11]. Urban growth simulation is a useful tool for decision-makers and urban planners to analyze and contrast different planning scenarios. Moreso, projecting LULC for long-term land use is crucial because of swift changes in operations, mostly, as a result of population development and urbanization, or maybe as a result of changes in a city's dimensions.

Developing towns such as Chinhoyi Town in Zimbabwe are particularly susceptible to rapid and unplanned urban expansion due to reasons such as rural-urban migration, industrialization, and weak regulatory control [12]. The effects of unregulated urban growth in these places include greater demand on infrastructure, environmental deterioration, and socioeconomic inequities [12]. Urban growth in developing towns like Chinhoyi, Zimbabwe, presents a complex challenge, often leading to overcrowding, inadequate services, and environmental degradation. These issues, widely documented in urban development studies, stem from rapid urbanization that outpaces infrastructure development and resource management [13,14]. Addressing such challenges requires predictive modeling to guide sustainable urban planning. Cellular Automata (CA), a computational technique known for its ability to simulate spatial dynamics, is particularly suited for modeling urban expansion due to its flexibility and accuracy in capturing complex urban patterns [15-17]. By leveraging CA, this study not only examines the historical and present urban growth patterns of Chinhoyi but also projects future growth scenarios under different development trajectories.

The gaps in existing literature, particularly regarding the lack of localized urban growth models tailored to small developing towns, underscore the need for this research. Previous studies often focus on large cities, leaving smaller urban centers underrepresented despite their unique drivers of growth, such as population pressure, economic opportunities, and policy frameworks. Understanding these drivers is critical, as urban growth in Chinhoyi may have significant implications for the local economy, potentially influencing employment, housing markets, and service provision. This study aims to fill these gaps by integrating local dynamics into CA-based modeling, providing insights into the interactions between urban growth, socioeconomic factors, and environmental constraints. Ultimately, this research offers a framework for policymakers to anticipate and mitigate urbanization challenges, ensuring balanced and sustainable development for Chinhoyi's future. The objectives of this study were to i) model the urban growth and ii) project future scenarios of a developing town, Chinhoyi in Zimbabwe using Cellular Automata. We hypothesized that the application of Cellular Automata (CA) modelling to the urban growth of Chinhoyi, Zimbabwe, will accurately simulate historical expansion patterns and provide reliable projections of future urban scenarios, revealing that population pressure, economic activities, and policy interventions are the primary drivers of urbanization, with significant implications for land use, infrastructure development, and local economic sustainability.

Materials and Methods

Study Area

Chinhoyi is located in Mashonaland West Province in central northern Zimbabwe, on the western banks of the Manyame River in Makonde District (Figure 1). It is about 116 km northwest of Harare, Zimbabwe's capital and largest city. Chinhoyi is located on the main route, Highway A-1, between Harare and Chirundu, some 240 kilometres northwest of the international border with Zambia. The geographical location is 17°20'59.0"S, 30°11'40.0"E. (Latitude:17.349722; Longitude: 30.194444). The average elevation of Chinhoyi is 1,187 meters (3,894 feet) above mean sea level. Chinhoyi is the provincial capital of Zimbabwe's Mashonaland West Province. The town is located in a predominantly rural community. The main economic activity in the area and its surroundings is farming. There are four relatively old main low-density suburbs i.e. Mzari, Golf Course, Mapako, and Orange Groove, there are nine high-density residential suburbs (Cold Stream, Brundish, Hunyani, Mpata, Gadzema, White City, Ruvimbo, and Chikonohono [18]. The town is home to two universities: Chinhoyi University of Technology and Zimbabwe Open University, as well as the province's largest referral hospital Chinhoyi Provincial Hospital. Orange Groove Motel and Chinhoyi University Hotel are the two hotels in town.

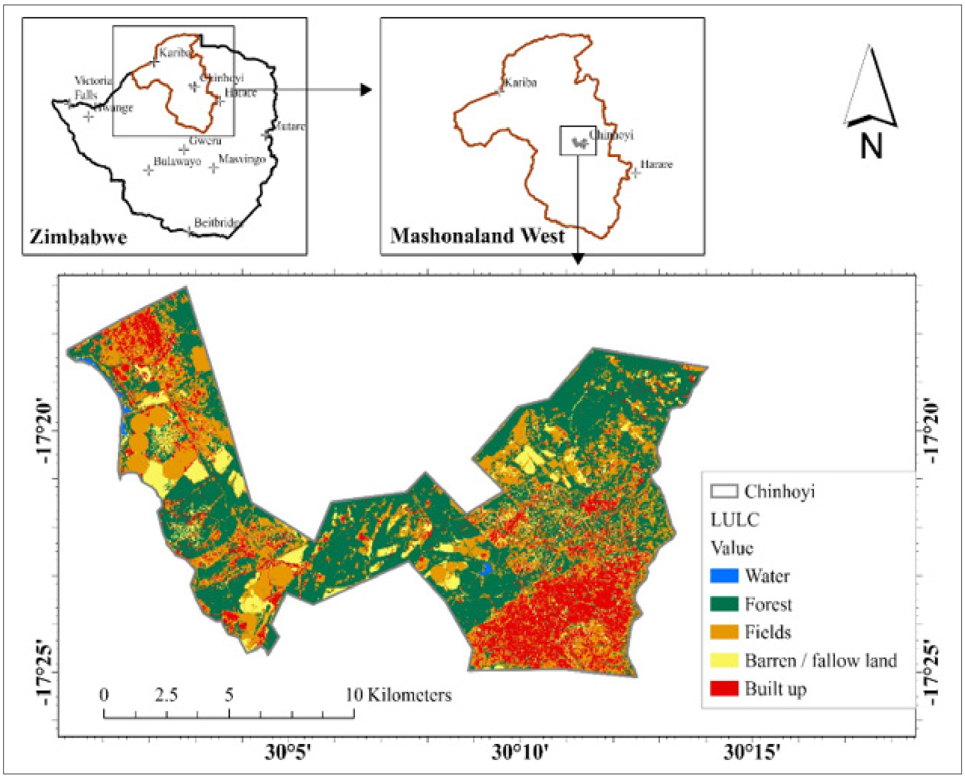


Figure 1: The Location of the study area Chinhoyi (satellite image from Google Earth)

Digital Image Classification and Modelling Future Scenarios

This analysis utilised Landsat images from the years 2000, 2013, and 2021 (Figure 2). Landsat images (Figure 2) with a spatial resolution of 30 m were analysed utilising the Google Earth Engine (GEE) API code editor for Land Use and Land Cover (LULC) classification. All selected images for this study had less than 10% cloud coverage within the study area. Before any analysis, all images were atmospherically corrected to eliminate clouds and provide top-of-atmosphere (TOA) reflectance data. Training samples were obtained directly in the Google Earth Engine via the point drawing tool in the GEE code editor, employing both false colour and natural colour composites. In this study, a random forest (RF) classifier was applied to classify LULC for Chinhoyi. Random forest is noted for its resilience to outliers and noise, and it is less computationally intensive than other decision tree techniques like gradient boosting. The images were divided into five classes including water, forest, grassland, barren ground and built up. Validation samples utilized for the accuracy assessment were gathered in the GEE code editor. One approach of doing accuracy assessment is by constructing a confusion matrix in which different accuracy measures are done. The user accuracy, producer accuracy, total accuracy were accepted to check for categorization accuracy. User accuracy is stated as the tendency that a pixel is tagged as a specific class in the classified image, while producer accuracy is the chance that a certain feature of an area on the ground is categorized as such [19]. The confusion matrix, and Kappa statistic of LULC categorization of each aforementioned years were computed using codes in Google Earth Engine. The total accuracy of 87% and a kappa coefficient of 0.87, showing that the categorization algorithm and images utilised were both excellent.

Projection of future changes in LULC for Chinhoyi for the year 2050 was done using Cellular automation (CA-ANN). Several studies have revealed that the CA-ANN technique is more robust when doing future projection of LULC [20-23]. For the goal of developing future simulation maps the classified maps of 2000, 2013 and 2021 (Figure 2) were utilised as inputs, and combined with spatial variables (slope, DEM, CBD, roads and rivers) (Figure 3). A change map for the years 2003–2013 (Figure 4) was constructed to indicate the transition from one class to another. A simulated map for the year 2021 was also developed from the model (Figure 6) and then coupled with the actual or observed 2021 map to construct projection for the year 2050 (Figure 8). The projected LULC map alterations were validated using the Kappa statistics. Digital elevation model (DEM), distance to central business area (CBD), distance to roads, slope, and rivers (Figure 3) were used as inputs for LULC prediction. Slope and DEM are important inputs for LULC simulation because they provides information on topography of the land, and determines the distribution of forests, grasslands, and water resources across the terrain [24]. Other spatial variables considered include distance to road, distance to Central Business District (CBD), distance to rivers (which has a strong link to population increase and urban development). The most recent data used includes DEM and slope data (height data has a significant link to settlements, and many people wish to dwell in low-slope locations) [25]. The Geospatial Information Agency (GIA) supplies road, elevation, and slope data in the form of Geographic Information System (GIS) digital data. Slope is one of the most fundamental variables determining land cover changes. A steep slope may become a limiting factor for development [25]. Because of the simplicity of structure and building development, the majority of built-up land is found on relatively level places. Furthermore, a steep slope is vulnerable to mass movement, which can trigger a landslide, which is another reason why slope is a limiting factor for developed areas [26]. In the case of a built-up area invasion, proximity becomes a critical concern. Built-up area will occupy the property which is close to critical infrastructure like roadways, core business centers, and highway gates. Because the highway is the most significant infrastructure for inhabitants to reach the city, calculating the proximity of highway gates as a driving factor is critical.

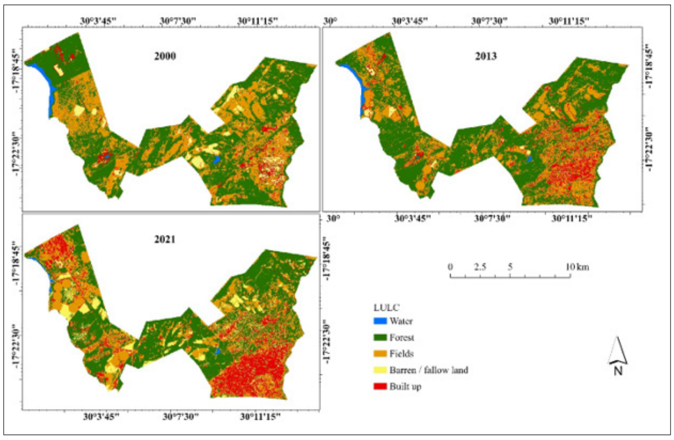


Figure 2: Classified Images for the Year 2000, 2013 and 2021

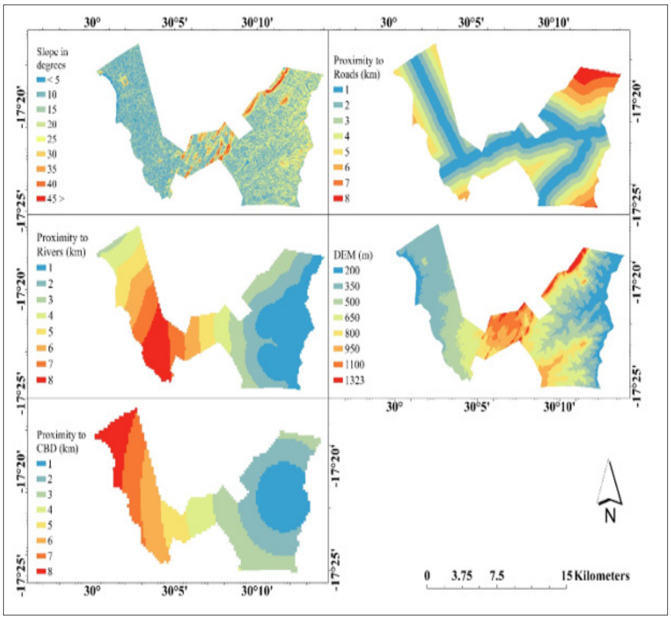


Figure 3: Spatial Variables (driving factors) for the Model (slope in degrees, proximity to roads, Proximity to Rivers, Proximity to CBD and Digital Elevation Model)

Evaluating Correlation

The evaluating correlation model contains three techniques for performing correlation. We used the Pearson's correlation as shown in Table 1. A correlation of a variable with itself is always 1. From the results obtained (Table 1), the degree of association ranges from weak (near to 0.1 or -0.1) to moderate (close to 0.3 or -0.3). Positive correlations show that as one variable increases, the other tends to increase as well. Negative correlations show that while one variable increases, the other tends to decrease. There is a weak positive association (0.118) between the existence of roads and the slope of the land. This shows that places with greater slopes might have slightly more roadways, possibly due to road development considerations. There is also a weak negative connection (-0.195) between highways and waterways. This would indicate that highways prefer to avoid or are less likely to be constructed near waterways. Moreso, a weak negative connection (-0.172) between roads and DEM was detected. Areas with lower DEM values (lower elevation) may have slightly more roadways. To add, there is also a modest negative connection (-0.114) between roads and proximity to the CBD. This means that roadways might be less concentrated in or near the CBD. On a different observation, there is a moderate negative correlation (-0.231) between slope and rivers. Higher slopes are less likely to be near rivers. Under the same circumstance, there is a moderate positive correlation (0.302) between slope and DEM. Higher slopes correspond to higher DEM values (higher elevation). Finally, is a weak positive association (0.154) between rivers and DEM was also detected. Areas with rivers tend to have slightly higher DEM values (elevated terrain). Understanding these linkages helps in urban planning and growth modeling. For example, understanding that roads avoid higher slopes or are less concentrated near rivers might inform infrastructure development decisions. Similarly, correlations with DEM and CBD can inform decisions relating to terrain suitability and urban center development.

Table 1: Pearson's Correlation for Evaluation of Spatial Variables Used

	Road	Slope	River	DEM	CBD
Road		0.118	-0.195	-0.172	-0.114
Slope			-0.231	0.302	-0.334
River				0.154	0.779
DEM					-0.146
CBD					

Land Use Land Cover Change 2000-2013

The data presented illustrates the original (2000) and final (2013) hectares (ha) of distinct land use and land cover (LULC) classifications in Chinhoyi Town (data 2). There was a drop-in water area from 180.90 ha in 2000 to 136.53 ha in 2013. This reduction could be due to reasons such as water management methods, changes in water bodies (e.g., drying up), or land use changes (e.g., conversion to built-up areas or agricultural fields). There was an increase in forest cover from 8017.20 ha in 2000 to 8256.69 ha in 2013. The increase of forested areas reflects attempts towards afforestation, reforestation, or natural regeneration, which can contribute to biodiversity protection and ecosystem services. There was a decline in agricultural fields from 5268.51 ha in 2000 to 5008.41 ha in 2013. This reduction could reflect land use changes such as urbanization, conversion to other land uses (e.g., built-up areas or forest), or changes in farming operations. There was a significant decline in barren or fallow land from 859.23 ha in 2000 to 210.06 ha in 2013. The decline in barren or fallow land may reflect land reclamation, agricultural intensification, or conversion to other land uses. There was a large rise in built-up areas from 718.92 ha in 2000 to 1433.07 ha in 2013. The rise of built-up regions indicates urban expansion, population growth, infrastructural development, and economic activities. This can impact natural habitats, agriculture, and water resources.

Table 2: Class Statistics of area Changes (2000-2013) for Chinhoyi

LULC Classes	2000ha (Initial)	2013ha (Final)
Water	180.90	136.53
Forest	8017.20	8256.69
Fields	5268.51	5008.41
Barren/fallow	859.23	210.06
Built up	718.92	1433.07

Transition Probability Matrix

The transition matrix provides insights into the dynamics of land use and land cover changes in Chinhoyi Town. It illustrates the proportion of pixels changing from a land use type to another. It also gives probability of stability (diagonal elements) and transitions between distinct LULC classes (off-diagonal components). High transition probabilities suggest large shifts in particular LULC classifications, such as forests transitioning to fields or built-up areas. This matrix is constructed by multiplying each column in the transition probability matrix by the number of cells in the later image that correspond to the relevant land use. The rows in the 5 by 5 matrix table (Table 3) show earlier land cover classifications, whereas the column indicates modern land cover categories. Despite the fact that this matrix can be utilized as a straight input for determining the prior probabilities in maximum likelihood classification of remotely sensed data, it was employed to estimate land use and land cover of 2050. Understanding these transitions is vital for urban planning, conservation initiatives, and sustainable land management in Chinhoyi, assuring balanced development and environmental stewardship.

Table 3: Transition Probability Matrix (The Probability that one land Cover Category will Change to the other is Represented in the Transition Probability Matrix)

	Water	Forest	Field	Barren/Fallow	Built up
Water	0.731841	0.19204	0.029851	0	0.046269
Forest	0.000471	0.703267	0.246026	0.001426	0.04881
Field	0.000034	0.445002	0.444592	0.013529	0.096841
Barren/Fallow	0	0.131141	0.470724	0.131245	0.26689
Built up	0.00025	0.176014	0.394717	0.02028	0.408738

Cellular Automata Model and Map Overlays

After observing LULC changes, we created the change map for2000-2013 which was used to create a simulated map for 2021. The simulated map 2021 was used in conjunction with the Actual map of 2021 to predict LULC change in Chinhoyi by 2050. Map overlays were also performed to compare the changes in the Built-up area class since our study was mainly focussed on this class. Comparisons were made for the year 2000-2013, 2013-2021 and 2021-2050.

Results

Land use Land Cover Change

These findings illustrate changes in land use and land cover (LULC) for Chinhoyi Town throughout different time periods. The area covered by water has decreased over time, with modest changes between 2000 and 2021 (Table 4). The models and predictions show a further modest decline by 2050. The forested area has exhibited an overall growth from 2000 to 2021. Both simulated and forecasted data indicate a continued trend of increase in forest cover by 2050. Agricultural fields have shrunk steadily from 2000 to 2021. Simulated and forecasted statistics suggest this trend will continue with a modest decline by 2050 (Table 4). Barren or fallow land has reduced dramatically from 2000 to 2021, but models and estimates suggest a modest increase by 2050. The built-up area has showed a substantial rise over time, particularly between 2000 and 2013. While there was some stabilization after 2013, simulations and estimates anticipate a progressive increase by 2050. Overall trends show that there is a general tendency of decreasing water and agricultural fields (Table 4), indicating likely urbanization or land conversion for other uses. Forest cover has generally risen, showing efforts towards conservation or reforestation. Barren or fallow land has declined but might witness a minor increase in the future. The built-up area has risen consistently, reflecting urban expansion and infrastructure development. These changes emphasize the dynamic character of land use in Chinhoyi town, impacted by variables like as urbanization, agricultural techniques, and conservation measures.

Table 4: Summary of Land use Land Cover (ha) Changes from 2000-2050

LULC Class	2000	2013	2021	Simulated 2021	Predicted 2050
Water	180.90 ha	136.53 ha	103.95 ha	128.79 ha	106.47 ha
Forest	8017.20 ha	8256.69 ha	8440.07 ha	9303.27 ha	9078.16 ha
Fields	5268.51 ha	5008.41 ha	4857.93 ha	3879.45 ha	3915.90 ha
Barren/fallow	859.23 ha	210.06 ha	124.74 ha	275.13 ha	396.09 ha
Built up	718.92 ha	1433.07 ha	1518.07 ha	1458.12 ha	1548.14 ha

Cellular Automata (CA) Model Development

The LULC change map for Chinhoyi in between 2000-2013 demonstrated significant transitions (Figure 4). The results show that many land use classes were converted to built up area as this increased in coverage in the period under study. Artificial Neural Network was used to model LULC Transition Potential Modelling potential (Figure 5). Five inputs were used to customize the area: land modelling the neighbourhood learning rate momentum next iterations number and hidden layers. The minimum validation overall error contains information about the minimum wrist error on validation set of samples. The delta overall accuracy contains differences between minimum wrist error and current error. The current validation Kappa coefficient shows the Kappa value of 0.87. The neural network learning curve (Figure 5) shows errors of training and validation sets. After preparing the actual map for the year 2021, we created a simulated map for the year 2021. The simulation result produces a land use cover map for the year 2021 (Figure 6). The validation tab allows checking, validating and comparing the simulation results. The reference map (actual 2021) and simulated land use land cover map 2021 were loaded in order to start the validation process. The multiple resolution budget result shows a Kappa value of 0.87 (Figure 7). After simulating for the year 2021, we then continue with our desired prediction for the year 2050 using five iterations. The results of the prediction show a trifling growth in Chinhoyi by the year 2050 (Figure 8).

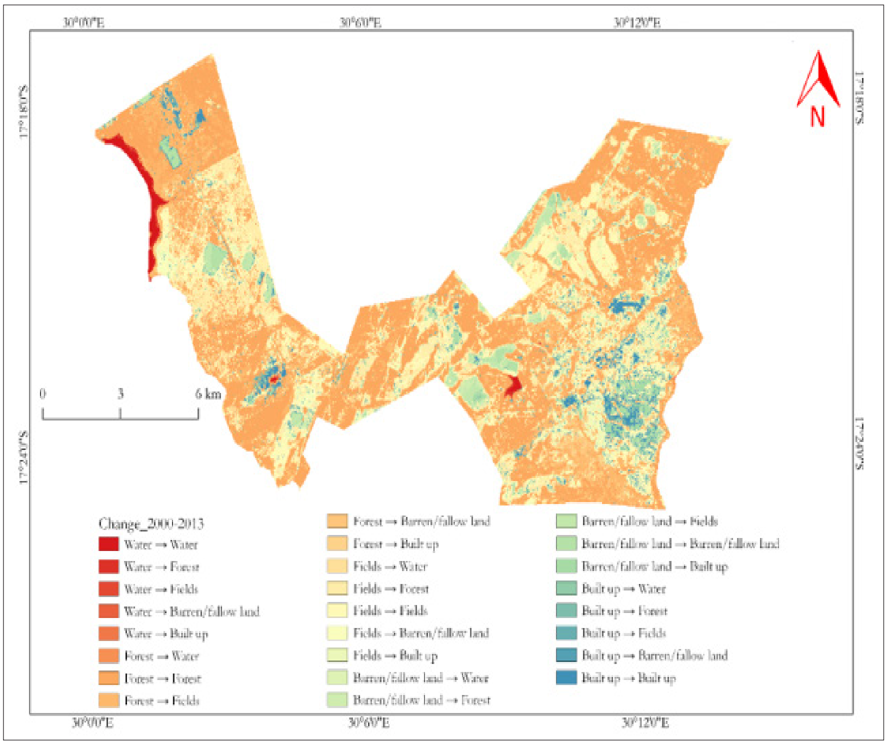


Figure 4: Change Map (2000-2013) showing Transitions from one Class to Another

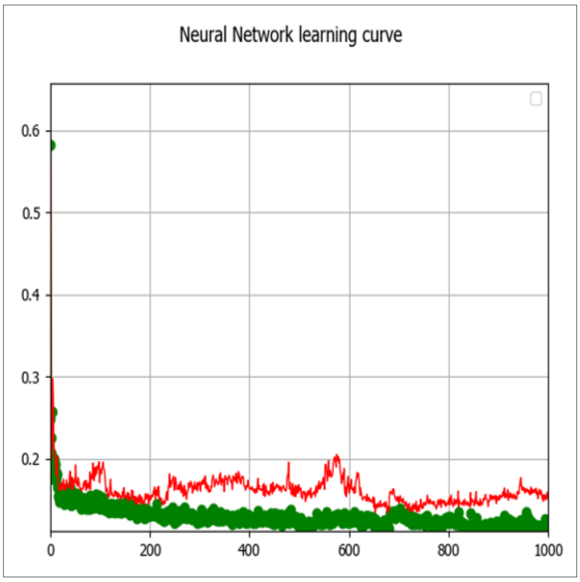


Figure 5: Neural Network Learning Curve showing errors of Training x-axis and Validation sets y-axis

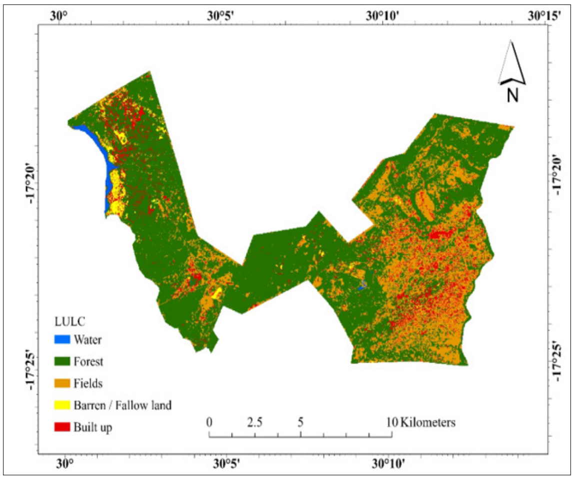


Figure 6: Simulated map for Chinhoyi Town in 2021

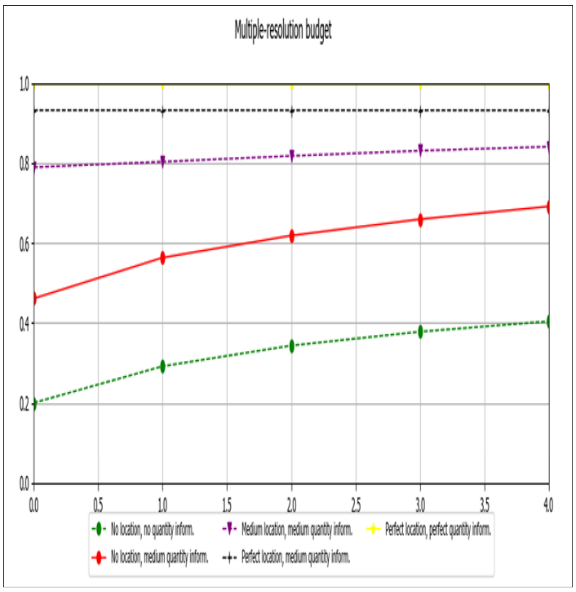


Figure 7: Multiple Resolution Budget for Validating Simulated Map 2021 with Actual Map of 2021 with a Kappa value of 0.87

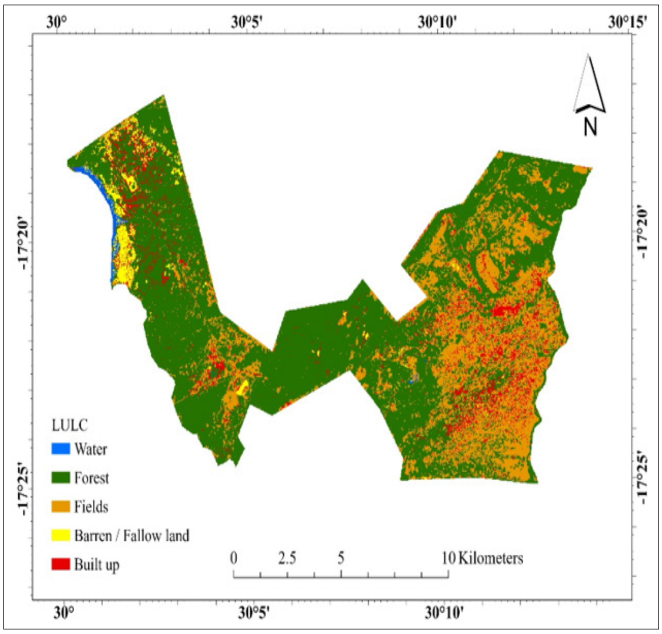


Figure 8: Predicted map for 2050 for Chinhoyi Town

Map Overlays to show Changes in Built up Class (2000, 2013, 2021, and 2050)

We created an overlay of built up land to show the location of changes from 2000-2013 (Figure 9). In the year 2000, built up land had 718.92 ha and in the year 2013 it had 1433.7 hectares. This shows that the built-up area had gained 714.15 ha in between. In the year 2013, built up land had 1433.7 ha and in the year 2021 in had 1518.07 ha (Figure 9). This shows that the built-up area had gained 85 ha in between. Finally, we then created an overlay of built up land to show the location of changes from 2021-2050 (Figure 9). In the year 2021, built up land had 1518.07 ha and in the year 2050 it had 1548.14 ha. This shows that the built-up area had gained 30.7 ha. The results of the prediction show a trifling (trivial or less important) growth in Chinhoyi by the year 2050.

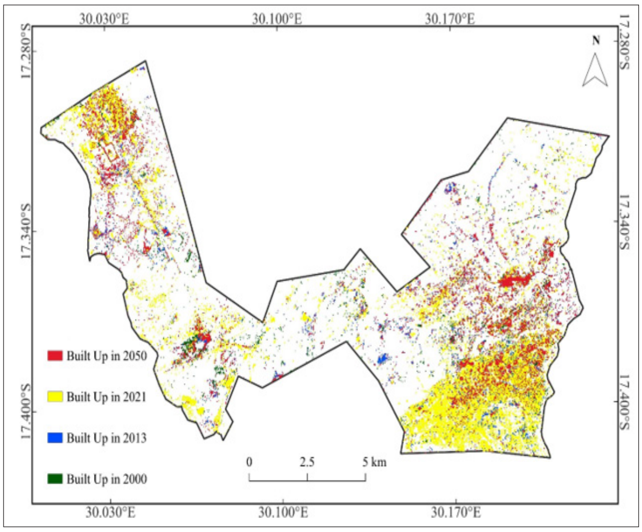


Figure 9: Overlay of Built up Land to show the Location of Change from 2000, 2013, 2021 and 2050 for Chinhoyi Town

Discussion

The results of the land change modeling for Chinhoyi, Zimbabwe, highlight notable trends in Land Use and Land Cover (LULC) changes, offering insights into the dynamics of urban growth and their implications for the local environment and communities. The study, spanning from 2000 to projected scenarios in 2050, reveals patterns that underscore the interplay between urbanization, agricultural land use, and natural resource management. These findings, derived using Cellular Automata (CA) and the Artificial Neural Network (ANN) model, provide a foundation for evaluating future urbanization scenarios and their socioeconomic and environmental effects.

The modeling indicates marginal growth in the built-up area, increasing from 718.92 ha in 2000 to a predicted 1548.14 ha by 2050. This gradual expansion, though less pronounced than in larger cities, reflects consistent urban sprawl into surrounding areas. The term “marginal growth” aptly describes this slow but impactful development, emphasizing the significant challenges it poses to land-use planning and resource allocation [12,15]. The shift from fields, which are projected to decline from 5268.51 ha in 2000 to 3915.90 ha by 2050, to built-up areas highlights the encroachment of urban growth on agricultural lands, raising concerns about food security and rural livelihoods.

The ANN model employed for LULC transition potential modeling utilized key parameters to simulate these changes accurately. These include proximity to central business district (CBD), road networks, and water sources, which influence accessibility and land desirability [24]. Topographical factors like slope and DEM were also considered, ensuring the model captured the spatial constraints and opportunities of Chinhoyi’s landscape. The integration of such diverse parameters enhanced the model’s ability to predict LULC changes under various scenarios [20].

Local regulations and governance significantly influence land-use patterns, particularly in balancing urban growth and agricultural preservation [17]. Weak enforcement of zoning laws and unregulated development often lead to the loss of fertile agricultural lands to urban sprawl, as evidenced by the projected decline in fields [16]. Conversely, strong policy frameworks that prioritize sustainable development, such as enforcing urban growth boundaries and incentivizing vertical development, can mitigate these effects. The introduction of protected agricultural zones, combined with policies promoting urban agriculture, can sustain food production while accommodating urban expansion.

The decline in agricultural land and changes in LULC have profound implications for local communities. Reduced access to fields can limit livelihood opportunities for farming households, leading to economic displacement and increased poverty. Additionally, declining agricultural productivity may exacerbate food insecurity and increase dependence on costly food imports. These shifts could also affect resource availability, such as water and land for subsistence farming, further marginalizing vulnerable populations. To counter these challenges, diversification of livelihoods through skill development programs and support for non-agricultural industries could provide alternative income sources. Urban agriculture initiatives could also play a vital role in sustaining local food supplies and reducing community reliance on external markets.

Comparing Chinhoyi’s urbanization trends to other Zimbabwean towns reveals similarities and distinctions that underscore its unique dynamics. Like many secondary towns, Chinhoyi experiences moderate urbanization driven by population growth, economic activity, and rural-urban migration. However, its smaller scale and location within a rich agricultural region differentiate it from cities like Harare, where rapid urban growth often leads to uncontrolled sprawl and informal settlements. Chinhoyi’s slower growth trajectory presents an opportunity to implement proactive urban planning measures that can avoid the challenges faced by larger urban centers.

The socioeconomic effects of agricultural land loss on nearby communities cannot be overstated. As fields give way to urban development, farming communities may face reduced income, limited employment opportunities, and disrupted traditional lifestyles. These changes could widen economic disparities and lead to rural depopulation. To mitigate these effects, targeted interventions such as investments in sustainable agricultural practices, compensation for displaced farmers, and the promotion of agribusiness could help preserve economic stability. Establishing farmer cooperatives and introducing land-use policies that prioritize agricultural productivity can further enhance resilience.

To effectively manage urban sprawl while maintaining environmental health and community well-being, several strategies are essential. Urban planning must prioritize compact and mixed-use development to reduce the spatial footprint of urbanization. Protecting natural ecosystems, such as forests, which have shown a slight increase in area from 8017.20 ha in 2000 to a predicted 9078.16 ha by 2050, is vital for maintaining ecological balance and supporting biodiversity. Green infrastructure, such as urban parks and sustainable drainage systems, can mitigate the environmental impacts of urban growth. Community engagement in decision-making processes is also critical, ensuring that development aligns with the needs and aspirations of local residents.

Conclusion

In conclusion, the results of the land change modeling for Chinhoyi underscore the complex dynamics of urban growth and its far-reaching implications for land use, community livelihoods, and environmental sustainability. The study highlights the need for robust policies and targeted interventions to balance urban expansion with agricultural preservation and resource management. By learning from the experiences of other Zimbabwean towns and leveraging proactive planning measures, Chinhoyi can chart a sustainable path for its urban future, ensuring both environmental health and the well-being of its residents.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work the author(s) used Quillbot in order to correct grammar. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Acknowledgements

We express our gratitude to the anonymous reviewers who contributed to enhancing the quality of our work.

Funding

There was no funding associated with this study.

Conflict of Interest Statement

The authors declare no conflict of interest associated with this paper.

Data Availability Statement

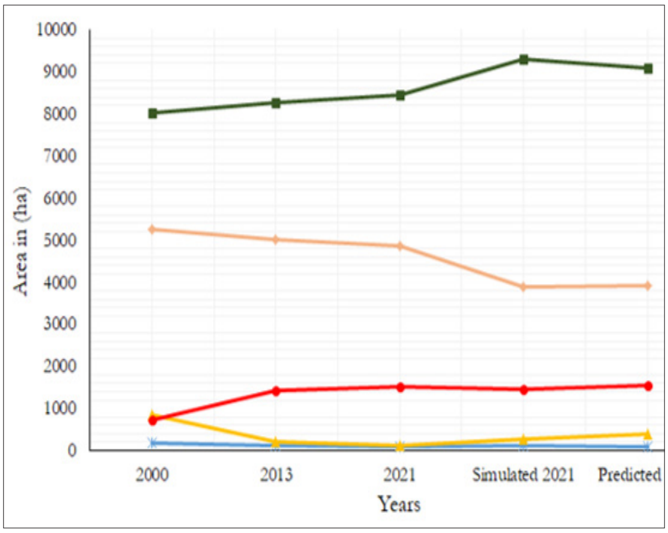
There is data available for this paper.

List of Appendices

Appendix 1: Changes in LULC classes (2000-2013)

Classes Changes (2000-2013)	No. of Hectares	% Change
water → water	132.39	0.87997
water → forest	34.74	0.23091
water → fields	5.40	0.03589
water → barren/ fallow land	8.37	0.05563
water → built up	3.78	0.02513
forest →water	5638.23	37.4764
forest → forest	1972.44	13.1105
forest →fields	11.43	0.07597
forest →barren/ fallow	391.32	2.60104
forest →built up	0.18	0.0012
fields → water	2344.50	15.5835
fields → forest	2342.34	15.5691
fields → fields	71.28	0.47379
fields →barren/ fallow	510.21	3.39128
fields → built up	112.68	0.74897
barren/fallow land →water	404.46	2.68838
barren/fallow land →forest	112.77	0.74956
barren/fallow land →fields	229.32	1.52425
barren/fallow land →barren/fallow	0.18	0.0012
barren/fallow land →built up	126.54	0.84109
Built up →water	283.77	1.88617
Built up →forest	14.58	0.09691
Built up →fields	293.85	1.95317

Appendix 2: The Trend of Changes in LULC for Chinhoyi from 2000-2050 (predicted)



References

1. Mushore TD, Mutanga O, Odindi J, Dube T (2017) Linking major shifts in land surface temperatures to long term land use and land cover changes: A case of Harare, Zimbabwe. Urban Climate 20: 120-134.
2. Dube T, Sibanda M, Bangamwabo V, Shoko C (2018) Establishing the link between urban land cover change and the proliferation of aquatic hyacinth (Eichhornia crassipes) in Harare Metropolitan, Zimbabwe. Physics and Chemistry of the Earth 108: 19-27.
3. Kamusoko C, Aniya M, Adi B, Manjoro M (2009) Rural sustainability under threat in Zimbabwe–simulation of future land use/cover changes in the Bindura district based on the Markov-cellular automata model. Applied Geography 29: 435-447.
4. Ghalehteimouri KJ, Shamsoddini A, Mousavi MN, Ros FBC, Khedmatzadeh A (2022) Predicting spatial and decadal of land use and land cover change using integrated cellular automata Markov chain model-based scenarios (2019–2049) Zarriné-Rūd River Basin in Iran. Environmental Challenges 6: 100399.
5. Al Ahmadia K, Heppenstallb A, Seeb L, Hoggb J (2008) Modeling urban growth dynamics using cellular automata and GIS.http://www.saudigis.org/FCKFiles/File/47_E_KhalidAlahmadi_KSA.pdf.
6. Yang J, Gong J, Tang W, Shen Y, Liu C, et al. (2019) Delineation of urban growth boundaries using a patch-based cellular automata model under multiple spatial and socio-economic scenarios. Sustainability 11: 6159.
7. Khan F, Das B, Mohammad P (2022) Urban growth modeling and prediction of land use land cover change over Nagpur City, India using cellular automata approach. Geospatial technology for landscape and environmental management: sustainable assessment and planning 261-282.
8. Rienow A, Mustafa A, Krelaus L, Lindner C (2021) Modeling urban regions: Comparing random forest and support vector machines for cellular automata. Transactions in GIS 25: 1625-1645.
9. Jadawala S, Shukla SH, Tiwari PS (2021) Cellular automata and markov chain based urban growth prediction. International Journal of Environment and Geoinformatics 8: 337-343.
10. Otgonbayar M, Ranatunga T, Onishi T, Hiramatsu K (2018) Cellular automata modelling approach for urban growth. Reviews in Agricultural Science 6: 093-104.
11. Marondedze AK, Schütt B (2019) Dynamics of land use and land cover changes in Harare, Zimbabwe: a case study on the linkage between drivers and the axis of urban expansion. Land 8: 155.
12. Fitawok MB, Minale AS (2024) A review of the application and implications of cellular automata-based urban growth model in africa. South African Geographical Journal 01-19.
13. Jones MO, Allred BW, Naugle DE, Maestas JD, Donnelly P, et al. (2018) Innovation in rangeland monitoring: annual, 30 m, plant functional type percent cover maps for US rangelands, 1984–2017. Ecosphere 9: e02430.
14. Smith A (2010) Image segmentation scale parameter optimization and land cover classification using the Random Forest algorithm. Journal of Spatial Science 55: 69-79.
15. Batty M (2007) Cities and complexity: understanding cities with cellular automata, agent-based models, and fractals: The MIT press.
16. Mukomberanwa NT, Taru P, Utete B, Madamombe HK (2024) Predicting the Dry Season Habitat Occupancy of African Savannah Elephant Using Vegetation Indices and Modelling

Landscape Variability in a Mesic Protected Area. African Journal of Ecology 62: e13318.

17. White R, Engelen G (1993) Cellular automata and fractal urban form: a cellular modelling approach to the evolution of urban land-use patterns. Environment and planning A 25: 1175-1199.
18. Musademba D (2011) Municipality solid waste (MSW) management challenges of Chinhoyi town in Zimbabwe: Opportunities of waste reduction and recycling. Journal of sustainable development in Africa 13: 168-180.
19. Parida BR, Mandal SP (2020) Polarimetric decomposition methods for LULC mapping using ALOS L-band PolSAR data in Western parts of Mizoram, Northeast India. SN Applied Sciences 2: 1049.
20. Asori M, Adu P (2023) Modeling the impact of the future state of land use land cover change patterns on land surface temperatures beyond the frontiers of greater Kumasi: A coupled cellular automaton (CA) and Markov chains approaches. Remote Sensing Applications: Society and Environment 29: 100908.
21. Fetene DT, Lohani TK, Mohammed AK (2023) LULC change detection using support vector machines and cellular automata-based ANN models in Guna Tana watershed of Abay basin, Ethiopia. Environmental Monitoring and Assessment 195: 1329.
22. Girma R, Fürst C, Moges A (2022) Land use land cover change modeling by integrating artificial neural network with cellular Automata-Markov chain model in Gidabo river basin, main Ethiopian rift. Environmental Challenges 6: 100419.
23. Tariq A, Mumtaz F (2023) A series of spatio-temporal analyses and predicting modeling of land use and land cover changes using an integrated Markov chain and cellular automata models. Environmental Science and Pollution Research 30: 47470-47484.
24. Mashapa C, Gandiwa E, Muboko N, Mhuriro Mashapa P (2021) Land use and land cover changes in a human-wildlife mediated landscape of save valley conservancy, south-eastern lowveld of Zimbabwe. JAPS: Journal of Animal & Plant Sciences 31.
25. Saputra MD, Joyoatmojo S, Wardani DK, Sangka KB (2019) Developing critical-thinking skills through the collaboration of jigsaw model with problem-based learning model. International Journal of Instruction 12: 1077-1094.
26. Mustafa G, Arif R, Atta A, Sharif S, Jamil A (2017) Bioactive compounds from medicinal plants and their importance in drug discovery in Pakistan. Matrix Sci. Pharma 1: 17-26.