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Drivers of Urban Growth: Cellular Automata–Markov–Analytic Hierarchy Process Modeling of Land Use Change in Amman City, Jordan

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ABSTRACT: Over the past two decades, rapid urban growth significantly altered land-use patterns in Amman, raising critical concerns regarding sustainability and food security. This study utilized an integrated Cellular Automata–Markov (CA–Markov) model, in combination with the Analytical Hierarchy Process (AHP), to simulate land-use and land-cover (LULC) changes and project future scenarios for 2031 and 2040. The CA–Markov model quantified temporal land-use transitions and simulated spatial growth patterns, while AHP served as a multi-criteria decision-making tool to determine the relative influence of key driving factors on urban growth. Landsat imagery from 2004, 2013, and 2022 was classified into three main categories: built-up areas, agricultural land, and barren land. The simulation framework incorporated key driving factors, including GDP per capita, population density, road accessibility, elevation, and slope. Model validation against actual 2022 LULC data yielded a high accuracy of 91.4% and a Kappa index of 0.89, demonstrating the reliability of the predictive framework. The results projected that built-up areas would increase from 257.35 km² (32.3%) in 2022 to 309.18 km² (38.9%) in 2031 and 349.17 km² (43.9%) by 2040, accompanied by a consistent decline in both agricultural and barren lands. Spatial analysis revealed that districts with higher population density, intense economic activity, and superior road accessibility were particularly susceptible to rapid urbanization. These findings highlighted the urgent need for proactive urban planning policies to protect agricultural land and manage growing infrastructure demands. While the CA–Markov model effectively replicated historical patterns, its reliance on past trends limited its capacity to anticipate sudden policy shifts or environmental shocks. Future research should prioritize integrating higher-resolution datasets, such as QuickBird imagery and detailed cadastral or infrastructure data, to improve the spatial accuracy of LULC simulations. In addition, the development of policy-driven and scenario-based models should incorporate urban growth boundaries, agricultural land protection policies, and transportation expansion plans. This would enable more realistic forecasting of land-use dynamics and provide stronger decision-support tools for resilient and sustainable urban development.

KEYWORDS: Urban growth; land-use land-cover simulation; CA–Markov model; analytic hierarchy process (AHP); socio-economic.

1. Introduction

Urban expansion was among the most consequential global transformations of the 21st century. Since the mid-20th century, cities experienced remarkable population surges, fundamentally altering land-use patterns and intensifying demands on infrastructure, natural resources, and cultural heritage [1, 2]. This trend was especially pronounced in developing nations and arid environments, where rapid urbanization often occurred at the expense of agricultural and barren lands, raising critical concerns about food security and sustainable development [3, 4]. Land-use and land-cover (LULC) change represented a complex process shaped by the interplay of socioeconomic, environmental, and political drivers operating at multiple spatial and temporal scales [5, 6]. Simulation modeling provided a valuable set of tools for anticipating future scenarios and informing planning and policy, helping researchers and decision-makers design adaptive strategies [7, 8]. However, models based solely on past trends faced limitations, as human interventions and policy decisions could shift developmental pathways and introduce uncertainty [9]. A comprehensive understanding of LULC dynamics therefore required the identification and integration of key driving factors within robust modeling frameworks [10, 11].

Models acted as conceptual abstractions, distilling the essential features of systems and their interactions. In urban studies, modeling provided a means to investigate the causes and consequences of land-use change, capturing the interplay between socioeconomic factors and environmental constraints [12]. Such models were crucial for estimating the impacts of urban expansion and supporting the development of sustainable land management policies. The Cellular Automata (CA)–Markov model emerged as a leading approach for simulating urban growth due to its capacity to incorporate spatial relationships, transition probabilities, and temporal dynamics [7–9]. CA models used cell-based frameworks to simulate complex urban patterns emerging from simple local rules [13], while the Markov chain component estimated land-use transitions over time, albeit without inherent spatial context [14]. The integration of CA and Markov models addressed these individual limitations, supporting both quantitative and spatially explicit projections of LULC change [15]. Recent research underscored the versatility and accuracy of the CA–Markov approach. For example, Gebresellase et al. [7] achieved reliable scenario-based forecasts in Ethiopia's Upper Awash Basin, while Aguejdad [8] highlighted the influence of calibration intervals on model performance. Azabdaftari and Sunar [9] applied the approach for district-level projections in Istanbul, and Jawarneh et al. [3] used it in arid ecosystems in Jordan. These studies collectively demonstrated the CA–Markov model's adaptability across diverse socio-economic and geographic contexts.

To improve predictive realism, CA–Markov models were frequently integrated with multi-criteria decision-making methods such as the Analytical Hierarchy Process (AHP). AHP facilitated the inclusion of diverse drivers like population density, GDP per capita, accessibility, elevation, and slope by assigning weights through expert judgment and consistency checks [10, 11]. Aburas et al. [10] refined CA–Markov outputs by incorporating AHP and frequency ratio analysis, while Nath et al. [11] combined AHP with CA–Markov to assess landscape risk. Mostafa et al. [12] advanced this integration by using fuzzy AHP–CA–Markov to analyze urbanization and its effects on land surface temperature in Egypt, and Sahin et al. [14] demonstrated the value of overlaying CA–Markov with AHP–GIS suitability analysis for urban growth simulation in Türkiye. Beyond methodological innovation, recent work emphasized the importance of identifying and quantifying the drivers of LULC change. Selmy et al. [5] analyzed arid region LULC dynamics (barren lands) using Landsat data and CA–Markov hybrid models, while Xu et al. [15] applied the model to assess land and water resource capacity in Northwest China. Kukuntod and Wijitkosum [16] explored drought vulnerability linked to land-use change through CA–Markov and multi-criteria analysis. Zhang and Li [6] highlighted the role of big data in advancing LULC monitoring, opening new possibilities for integrating diverse datasets into modeling frameworks.

Amman, Jordan, served as a compelling example for the application of CA–Markov–AHP modeling. The city experienced rapid urban expansion in recent decades, fueled by population growth, economic development, and infrastructure investments [1, 17]. This resulted in the transformation of substantial areas of barren and agricultural land into urban spaces, prompting significant concerns regarding sustainable land management and food security. Previous studies used remote sensing indices, entropy measures, and CA–Markov simulations to monitor and forecast urban sprawl in Amman [1, 3, 18]. Building on this foundation, the present study employed an integrated CA–Markov–AHP framework to quantify historical LULC changes, assess the influence of key drivers, and project future scenarios for 2031 and 2040, with emphasis on socio-economic, natural, and physical factors responsible for land-use and land-cover change. As shown in Table 1, hybrid models that integrated Cellular Automata with statistical or machine learning approaches were increasingly preferred due to their ability to capture both spatial and temporal dynamics of land-use change. The frequent application of CA–Markov models in urban growth studies highlighted their suitability for simulating transition probabilities and spatial allocation processes, supporting the selection of the CA–Markov framework in the present study, particularly for modeling urban expansion patterns in Amman.

Table 1. Land Use Land Cover Change (LULCC) models used in recent studies.

Model	Study Area	Dataset	Validation Technique	Reference
CA–Markov	Upper Awash Basin, Ethiopia	Landsat 2000, 2010, 2020	Overall Accuracy, Kappa	[7]
CA–Markov (Calibration interval study)	Harbin, China	Landsat TM/ETM+ 1989–2007	Kappa statistic	[8]
CA–Markov (District evolution)	Istanbul, Turkey	Landsat 1990–2020	Kappa, ROC	[9]
CA–Markov (Arid ecosystems)	Jordan	Landsat/Various	Overall Accuracy	[3]

Table 1 illustrates the versatility of the CA–Markov model, with successful applications reported across diverse regions, including Ethiopia [7], China [8], and Turkey [9]. These studies consistently demonstrate the model's strong performance in simulating land-use and land-cover (LULC) dynamics, as evidenced by high validation scores such as the Kappa statistic and ROC curves. The use of CA–Markov in Jordan's arid ecosystems [3] is especially noteworthy, as it underscores the model's value in semi-arid areas where urban development interacts with vulnerable ecological systems. By positioning Amman within this methodological context, Table 1 provides robust support for employing CA–Markov in the present research and affirms its reliability in comparable environments.

1.1.The concept of urban modeling.

Urban growth models were primarily simulation tools developed to test theories about spatial interactions among different land uses and activities. These models helped analyze the causes and consequences of land-use and land-cover (LULC) changes, offering valuable insights into both the quantitative scale and spatial patterns of urban expansion [5, 6]. Accurate predictions depended on understanding historical and current land-use patterns, which could be projected to estimate future scenarios [7, 8]. A variety of modeling approaches existed, including cellular automata, agent-based, statistical, system dynamics, and hybrid models. Among these, cellular automata (CA) and CA–Markov hybrid models became especially popular in recent research, largely because they were well-suited to capturing spatial relationships and transition probabilities [7–9, 13]. For instance, Gebresellase et al. [7] applied CA–Markov to project LULC changes in Ethiopia, while Jawarneh et al. [3] used it to examine sustainability in Jordan's arid landscapes. Hybrid models that combined CA–Markov with multi-criteria decision-making techniques, such as the Analytical Hierarchy Process (AHP), further enhanced predictive accuracy by integrating socioeconomic and environmental factors [10–12, 14].

The combination of remote sensing and geographic information systems (GIS) became the standard for urban growth analysis, providing precise tools for monitoring spatial change and integrating key drivers such as road accessibility, slope, elevation, population density, and GDP per capita [5, 6, 10–12, 14]. Urban growth resulted from the complex interplay of socio-economic, natural, and built environment factors, which shaped both the scale and spatial patterns of land-use and land-cover (LULC) change [1, 3, 15, 16]. Modeling approaches such as CA–Markov and its hybrid forms, including integration with the Analytical Hierarchy Process (AHP), captured these interactions by weighting multiple drivers and linking quantitative trends with spatial dynamics [5, 7–12, 14].

Indicators commonly applied in previous studies encompassed physical factors like elevation, slope, and proximity to rivers or urban functions, as well as socio-economic drivers including population density, GDP per capita, and access to services. The urban growth indicators and driving factors were organized into natural, built environment, and socio-economic categories. This classification clarifies the mechanisms of urban transformation: natural factors imposed physical limits, built infrastructure facilitated expansion, and socio-economic variables increased demand for urban space [1, 3, 5, 10–12, 14–16]. This framework highlighted the multifaceted nature of urban growth and provided a theoretical basis for interpreting historical LULC changes and projecting future scenarios in Amman. Incorporating these drivers into the CA–Markov–AHP model allowed the study to account for the combined effects of environmental conditions, infrastructure, and socio-economic pressures, supporting more robust and policy-relevant predictions of urban expansion.

1.2. Cellular Automata (C.A) Markov.

The Cellular Automata (CA) model is a cell-based simulation framework widely used in urban growth modeling, as it can represent complex spatial dynamics using straightforward transition rules. CA models effectively capture bottom-up urbanization processes, where local interactions among cells generate larger, emergent spatial patterns [7, 8]. When combined with a Markov chain, which estimates transition probabilities among land-use classes over time, the CA–Markov model integrates both spatial and temporal aspects of land-use and land-cover

(LULC) change [9, 13]. Recent studies have demonstrated the robustness and versatility of the CA–Markov model across diverse contexts. Aguejdad [8] highlighted the importance of temporal resolution in model calibration in Harbin, China, while Azabdaftari and Sunar [9] applied it to predict district-level changes in Istanbul. Other researchers, including Selmy et al. [5] and Mostafa et al. [12], extended the framework by integrating fuzzy AHP and GIS techniques, illustrating the adaptability of hybrid approaches.

Compared to machine learning algorithms such as Random Forest, Support Vector Machines, or Artificial Neural Networks, the CA–Markov model is relatively simple yet highly effective for simulating complex LULC dynamics [12, 14]. Its strengths include flexibility, transparency, and the ability to incorporate multiple driving factors such as slope, elevation, road accessibility, and population density [10, 11, 14]. Additional constraints and suitability factors can be embedded to enhance simulation accuracy, making the model suitable for policy-focused applications [15, 16]. However, CA–Markov primarily captures bottom-up processes and may not fully reflect top-down influences like zoning laws or policy incentives. This limitation is often mitigated by adjusting suitability maps or restricting certain cells within the simulation [14]. Despite this, the CA–Markov model remains widely used and validated, offering a practical balance between methodological simplicity and analytical depth for urban growth prediction.

2. Materials and Methods

2.1.Data source.

To simulate land-use and land-cover (LULC) change in the study area, Landsat satellite imagery for 2004, 2013, and 2022 was obtained from the United States Geological Survey (USGS; http://glovis.usgs.gov/) at a spatial resolution of 30 × 30 meters. The imagery was pre-processed using spectral band combination and scanline error correction. The processed images were then classified into three LULC categories namely; built-up area, agricultural land, and barren land using a supervised pixel-based classification method. The classification outputs served as primary inputs for the simulation. Supplementary datasets included a 12.5-meter resolution ALOS PALSAR digital elevation model (DEM) obtained from the Alaska Satellite Facility (http://asf.alaska.edu/), as well as socio-economic data on population density and GDP per capita provided by the Greater Amman Municipality.

2.2. Determined driving factors for LULC simulation using CA-Markov model.

A growing body of research has highlighted that land-use change is influenced by multiple factors, including socio-economic conditions, existing land-use patterns, physical constraints, and climate variability [10–13]. Because these influences vary by region, it is essential to include both natural and human-driven variables for accurate simulations. For this study, five key drivers were selected for Amman based on expert input and local context: population density, GDP per capita, distance to road networks, elevation, and slope. These variables were identified through consultations with urban planning and geospatial specialist’s familiar with the area, considering Amman’s specific development patterns, infrastructure, and topography. This approach ensured that the selected factors reflected real-world urban growth dynamics rather than generic modeling assumptions. Abdeljawad et al. [1] emphasized that the expansion of road networks has played a pivotal role in Amman’s land development. All selected factors were processed using ArcGIS Pro 2.5, and the MOLUSCE extension in QGIS 2.18 was employed to generate transition probabilities, analyze land-cover changes, perform simulations and validations.

2.3. Analytic hierarchy process (AHP).

The AHP is a structured decision-making method that simplifies complex problems by decomposing them into a series of pairwise comparisons [24]. This approach accommodates both subjective and objective judgments and incorporates a consistency check to minimize potential bias. In this study, AHP was applied to assess the relative importance of each selected driving factor. Pairwise comparisons were performed using an online AHP calculator, and the resulting weights were incorporated into the CA–Markov model through a multi-criteria evaluation framework. Judgments were assigned using Saaty's fundamental scale [19−24], with a consistency ratio (CR) of 0.1 or less considered acceptable. A value of 1 indicated equal importance, with both factors contributing equally to the objective. A value of 2 represented moderate importance, reflecting slight preference based on experience and judgment. A value of 3 denoted strong importance, where one factor was clearly favored over another. A value of 4 signified very strong importance, indicating the dominance of one factor supported by practical evidence. A value of 5 represented extreme importance, reflecting the highest degree of preference for one factor over another.

2.4. Simulation of future LULC change.

Accurate simulation of future land-use and land-cover (LULC) change requires a thorough understanding of past transformation trends [18]. The Markov model estimates the likelihood of transitions between land-cover classes over time based on observed changes from two periods [19]. In this study, transition matrices were generated for 2004–2013 and 2013–2022. Transition probabilities from 2004–2013 were combined with Cellular Automata (CA) through a multi-criteria evaluation to produce a simulated LULC map for 2022, using one iteration to project nine years ahead. The CA–Markov model integrates the spatial capabilities of CA with the probabilistic framework of Markov chains, addressing the limitations of each model when applied separately. Gebresellase et al. [7] demonstrated that this hybrid approach effectively simulates complex LULC dynamics. In the present study, the model was further applied to project future LULC for 2031 (two iterations, 18-year projection) and 2040 (three iterations, 27-year projection), assuming that historical transition probabilities remain constant. While this assumption facilitates structured long-term forecasting, it may reduce projection reliability because it does not account for unexpected policy changes, economic fluctuations, infrastructure expansion, or environmental shifts. Consequently, forecast uncertainty increases with longer simulation periods, particularly for 2040, where cumulative effects of unmodeled drivers could lead to over- or underestimation of urban growth and agricultural land conversion. The CA–Markov model incorporated transition probabilities alongside selected urban growth drivers, using a multi-criteria evaluation framework informed by the Analytical Hierarchy Process (AHP). Transition rules were calibrated to prioritize the conversion of barren land to built-up areas, reflecting observed urban expansion patterns in Amman. Classified land-cover data from 2004 (starting year) and 2013 (ending year) were used to simulate the LULC distribution for 2022 as a single nine-year projection.

2.5.Model validation.

Validation is a crucial step for establishing the reliability of simulated land-use and land-cover (LULC) maps. In this study, the MOLUSCE extension in QGIS 2.18 was used to calculate overall accuracy and Kappa statistics by comparing the simulated 2022 LULC map with a reference map derived from actual Landsat imagery. A Kappa value of 0.81 or higher was considered to indicate almost perfect agreement [25]. After achieving satisfactory validation results for 2022, the CA–Markov model was adopted to simulate future LULC scenarios for 2031 and 2040.

2.6. Urban growth series Markov model.

To assess the spatial extent of predicted urban growth, built-up areas were extracted from the simulated LULC maps for 2031 and 2040 and overlaid as a post-simulation spatial analysis step rather than a separate model. This approach enabled visualization and quantification of projected urban expansion. In addition to producing maps showing the direction and pattern of Amman's future growth, the analysis calculated the total area of built-up land for each forecast year and measured the magnitude and rate of urban increase between periods. These quantitative outputs provided a clear basis for evaluating the scale of anticipated urban expansion and facilitated objective comparison of future development scenarios.

3. Results and Discussion

3.1 Land-use land-cover change from 2004 – 2022.

The Landsat images for 2004, 2013, and 2022 were classified using the Support Vector Machine (SVM) algorithm in ArcGIS Pro 2.5 into three major land-use and land-cover classes: built-up areas, agricultural land, and barren land (Figures 1). The classification results reveal a sustained expansion of built-up areas throughout the study period, reflecting the rapid pace of urbanization in Amman. Built-up land increased from 22.39% (178.18km^2) in 2004 to 25.63% (204.03 km^2) in 2013, and further to 32.33% (257.35km^2) in 2022 representing a net gain of approximately 79km^2 over 18 years. This consistent growth trend underscores increasing development pressure and the need for predictive spatial planning tools to manage future expansion sustainably. Agricultural land exhibited fluctuations over time, declining from 3.59% (28.55km^2) in 2004 to 2.63% (20.92km^2) in 2013 before recovering slightly to 3.57% (28.39km^2) in 2022. These variations suggest that agricultural areas in Amman remain vulnerable to urban encroachment but may also experience localized recovery, potentially linked to land management practices or classification dynamics. In contrast, barren land showed a steady and substantial decline, decreasing from 74.03% (589.24 km^2) in 2004 to 64.10% (510.23 km^2) in 2022. The reduction of nearly 79 km^2 closely corresponds to the increase in built-up areas, indicating that barren lands have served as the primary source for urban expansion. This pattern highlights the progressive consumption of available open land, reinforcing concerns about land scarcity and the importance of forward-looking urban growth modelling for sustainable planning in Amman. These trends align with findings from Al-Bilbisi [26], who reported rapid urban area increases in Amman from 149.08 km^2 in 1987 to 237.86 km^2 in 2017 using multitemporal Landsat data, highlighting long-term expansion along transport routes into vegetation and open spaces. Similarly, a long-term analysis of the Amman-Zarqa Basin over four decades (1980–2020) showed that urban expansion was the dominant driver of LULC change, converting agricultural lands and open soils into built-up areas, with accelerating growth particularly in the last two decades [27]. These comparisons indicate that Amman's urban growth pattern is not only persistent but also structurally similar across multiple temporal scales and methodologies, reinforcing broader concerns about land scarcity and the need for spatially explicit planning tools to support sustainable urban development in the context of rapid urbanization.

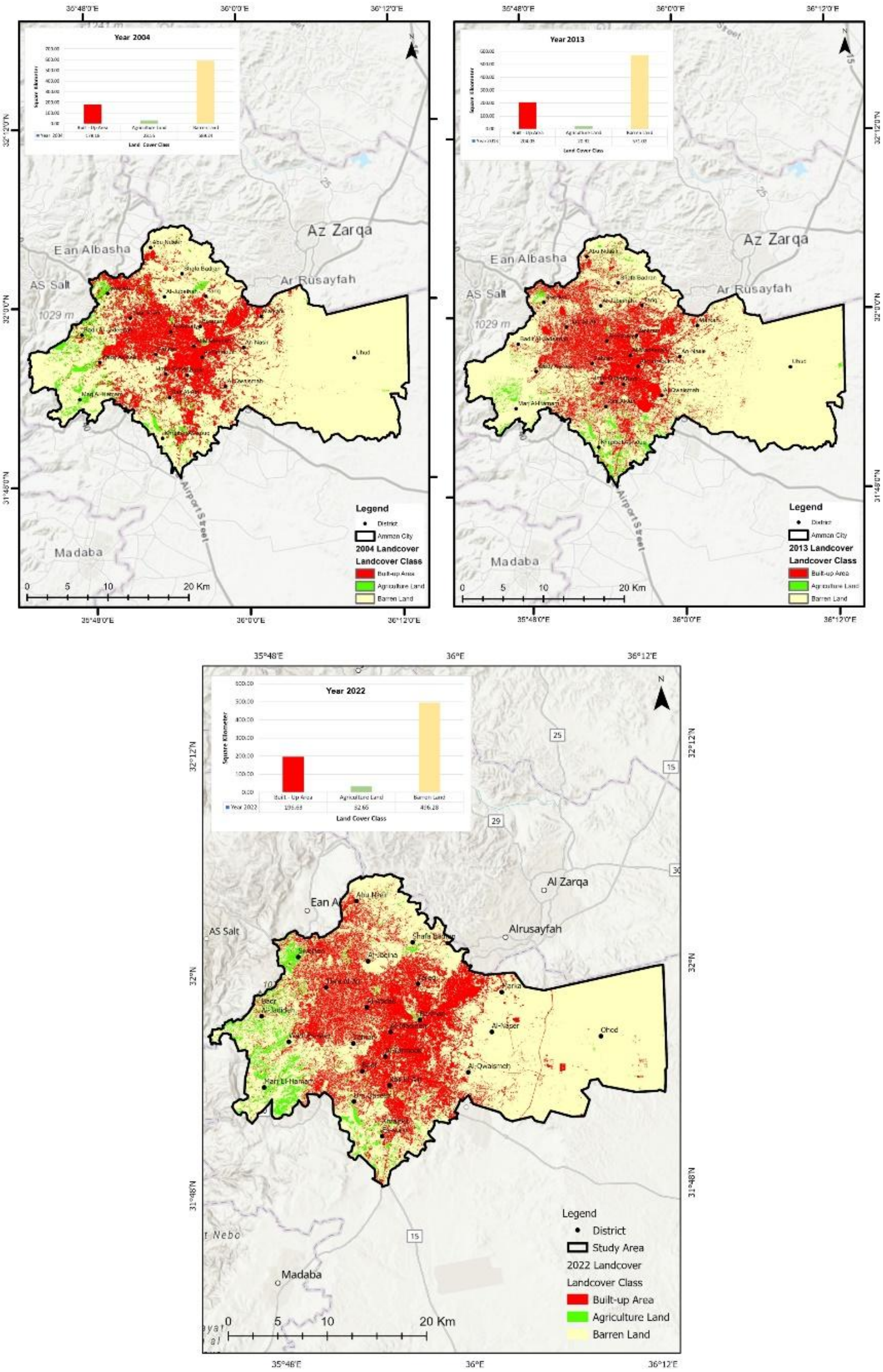


Figure 1. 2004, 2013 & 2022 LULC Map.

As shown in Figure 1, built-up areas expanded progressively outward from the city core between 2004 and 2013, accompanied by a noticeable reduction in surrounding barren lands. This pattern indicates the early stages of horizontal urban sprawl driven by population growth and infrastructure development. By year 2022, the expansion had become substantially more pronounced, with built-up areas covering more than 32% of the study area. This accelerated outward growth reflects increasing development pressure on available land and underscores the urgency for predictive urban growth modelling to guide sustainable land-use planning in Amman, particularly in the context of land scarcity and long-term food security concerns.

The change analysis (Table 2) reveals that between 2004 and 2013, built-up areas increased by 3.25%, whereas agricultural and barren lands declined by 0.96% and 2.29%, respectively. In the subsequent period, between 2013 and 2022, built-up areas expanded by 6.70%, agricultural land saw a modest gain of 0.94%, and barren land decreased by 7.64%. These results clearly demonstrate a consistent pattern of urban growth in Amman, primarily driven by the conversion of barren land into built-up areas. Agricultural land, meanwhile, has experienced periods of both decline and recovery. These findings are consistent with previous research, which has highlighted road expansion, population growth, and economic development as key drivers of urbanization in Jordan [1, 3, 13].

Table 2. Distributions of LULC classes from 2004-2022.

Land Cover Class	Year 2004		Year 2013		Year 2022		2004 - 2013	2013 - 2022
	Area (Km^2)	%	Area (Km^2)	%	Area (Km^2)	%	% Change	% Change
Built - Up Area	178.18	22.39	204.03	25.63	257.35	32.33	+3.25%	+6.70%
Agriculture Land	28.55	3.59	20.92	2.63	28.39	3.57	-0.96%	+0.94%
Barren Land	589.24	74.03	571.02	71.74	510.23	64.10	-2.29%,	-7.64%
Total	**795.97**	**100.00**	**795.97**	**100.00**	**795.97**	**100.00**		

3.2 Transition matrix.

Land-use land-cover (LULC) simulation is based on estimating the probability that one land class will transition to another over a given time period, and these probabilities are summarized in a transition matrix. In this matrix, diagonal elements represent the likelihood of a land class remaining unchanged, while off-diagonal values indicate the probability of conversion to other classes. These transition probabilities directly influence future simulations by determining both the quantity and direction of projected land-use change in the Markov process, which then guides the Cellular Automata allocation of changes across space. As a result, higher probabilities of transition from barren or agricultural land to built-up areas increase the model's projected urban expansion, whereas high persistence values for a class promote its spatial stability in future scenarios. Tables 3 shows the transition probabilities for the periods 2004–2013 and 2013–2022, respectively. Between 2004 and 2013 (Table 3), barren land and built-up areas exhibited the highest probabilities of persistence 88.46% and 67.41%, respectively, suggesting relative stability in these categories. However, a notable 32.21% of barren land and 9.00% of agricultural land transitioned into built-up areas, underscoring the ongoing urban expansion. In contrast, built-up areas had just a 0.38% chance of reverting to agriculture and a 2.40% probability of becoming barren land, indicating that once land is urbanized, it rarely changes back. Significantly, 68.41% of agricultural land converted to barren land, highlighting its susceptibility to degradation or abandonment.

Table 3. Transition probabilities of LULC classes from 2004 to 2013.

Transition Probability (2004 - 2013)			
Landcover Class	Built - Up Area	Agriculture Land	Barren Land
Built-up Area	0.674096	0.003762	0.091426
Agriculture Land	0.089997	0.225920	0.684083
Barren Land	0.322142	0.024006	0.884569
Transition Probability (2013 - 2022)			
Landcover Class	Built - Up Area	Agriculture Land	Barren Land
Built - Up Area	0.850725	0.018129	0.131146
Agriculture	0.089141	0.302668	0.608192
Barren Land	0.182979	0.027548	0.789473

The 2013–2022 transition probability matrix (Table 3) reveals strong persistence of built-up and barren land classes, alongside high instability in agricultural land. Built-up areas show an 85.07% probability of remaining built-up, confirming the structural permanence of urban development once land is converted. Only small proportions transition to agriculture (1.81%) or revert to barren land (13.11%), indicating that urban land rarely returns to non-urban uses. This high persistence directly supports the model's projection of continued outward urban expansion in Amman, as existing developed areas act as stable nuclei for future growth. Agricultural land, in contrast, appears highly vulnerable, with only a 30.27% probability of persistence. A substantial 60.82% probability of transition to barren land suggests either land degradation, fallowing, or misclassification linked to seasonal variability, while 8.91% converts directly to built-up areas, reflecting ongoing urban encroachment on productive land. Barren land demonstrates relative stability (78.95% persistence) but also shows a notable 18.30% probability of conversion to built-up areas, confirming that open and unused lands constitute the primary reserve for urban growth. Together, these probabilities indicate that future simulations will likely project continued expansion of built-up areas mainly at the expense of barren land, with agricultural areas remaining under pressure an outcome that reinforces concerns about land scarcity and the need for sustainable urban planning strategies in Amman.

These transition dynamics are further illustrated in Figure 2, which presents the spatial probability of land-cover change across the study area. The map highlights zones with a high likelihood of conversion, particularly along the urban fringe where development pressure is most intense. The results confirm that barren land constitutes the principal land reserve fueling urban expansion, as large portions of open land exhibit strong probabilities of transitioning into built-up areas. In contrast, agricultural land emerges as the most volatile category, showing unstable transition behavior and heightened susceptibility to both degradation and urban encroachment. Moreover, the increasing persistence of built-up areas over time reflects the consolidation and densification of established urban zones, underscoring the largely irreversible nature of land conversion once urbanized. This pattern suggests that future urban growth in Amman will likely follow a path-dependent trajectory, expanding outward from existing developed cores into adjacent open lands. Such dynamics reinforce concerns about land scarcity and highlight the importance of proactive, spatially informed planning strategies to manage growth sustainably and reduce pressure on environmentally and economically valuable land resources.

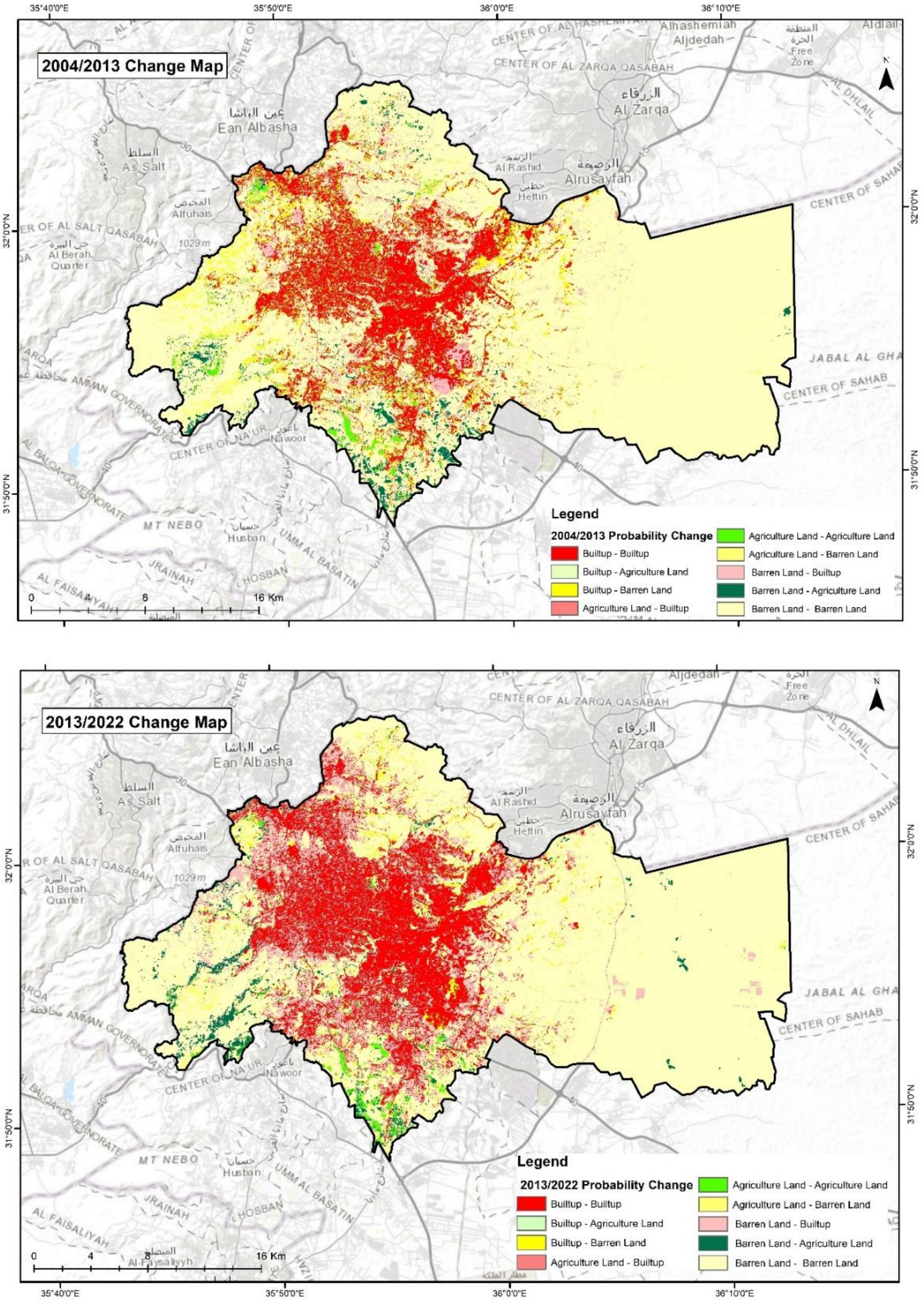


Figure 2. Probability Change Map between 2004/2013, 2013/2022.

Table 4 provides a detailed statistical analysis of land-use and land-cover (LULC) changes in Amman over two key periods, 2004–2013 and 2013–2022. It quantifies the extent of land transitions between built-up areas, agricultural land, and barren land, highlighting both the persistence of each class and the magnitude of conversions among them. Table 4 offers critical insights into the dynamics of urban growth, land degradation, and agricultural land vulnerability, serving as a foundation for understanding spatial development patterns and informing sustainable planning strategies in the region.

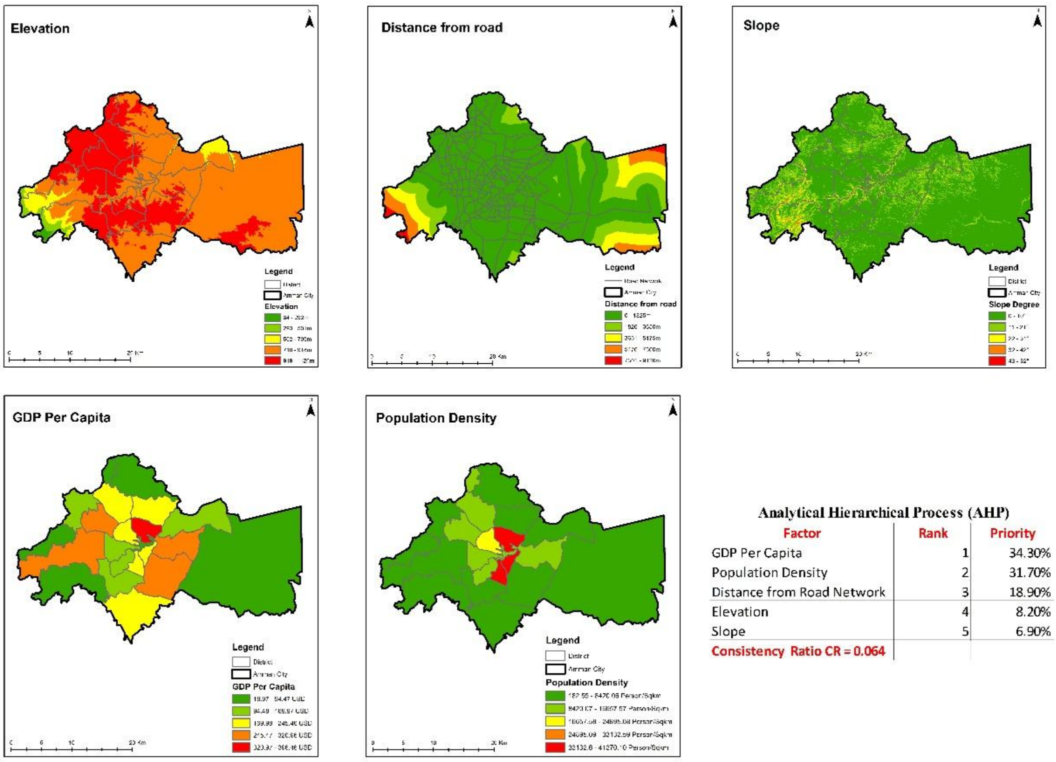
Table 4. Statistical Analysis of LULC change.

Change	2004 -2013 (km^2)	2013 - 2022 (Km^2)
Built-up Unchanged	111.91	144.2
Built-up → Agriculture	0.62	3.07
Built-up → Barren Land	2.54	1.91
Agriculture → Built-up	53.48	22.23
Agriculture Land Unchanged	6.37	6.49
Agriculture → Barren Land	19.28	13.04
Barren land → Built-up	54.94	110.66
Barren land → Agriculture	14.43	16.66
Agriculture Unchanged	531.55	477.46

The statistical analysis in Table 4 highlights significant shifts in land-use and land-cover (LULC) patterns in Amman over two distinct periods: 2004–2013 and 2013–2022. The data reveal a marked increase in the stability of built-up areas, with the area of unchanged built-up land growing from 111.91 km² to 144.2 km², reflecting ongoing consolidation and densification of urban zones over time. Transitions from agriculture to built-up land decreased from 53.48 km² in the first period to 22.23 km² in the second, indicating a slowing but still notable urban encroachment on agricultural areas. Meanwhile, conversions from barren land to built-up land more than doubled, increasing from 54.94 km² to 110.66 km², confirming that barren lands continue to serve as the primary source for urban expansion, consistent with the observed reduction in open land availability. The relatively stable areas of unchanged agricultural land (6.37 km² and 6.49 km²) suggest localized pockets of persistence, yet the net agricultural land area declined notably, mirroring the overall trend of vulnerability highlighted in previous analyses. Conversions between agricultural land and barren land also show dynamic interactions, with agriculture-to-barren transitions decreasing slightly (19.28 km² to 13.04 km²) and barren-to-agriculture conversions rising (14.43 km² to 16.66 km²), potentially indicating shifts in land management, fallowing, or land degradation processes. Overall, these transitions emphasize the accelerating urban growth pressure on both barren and agricultural lands, underscoring the urgent need for integrated spatial planning approaches that balance urban development with land conservation to mitigate land scarcity and support sustainable urban growth in Amman.

3.3 Percentage influence of selected urban growth factor.

To assess the relative impact of key drivers influencing urban growth in Amman, the Analytical Hierarchy Process (AHP) was conducted using Saaty's pairwise comparison scale [24]. Five primary factors (Figure 3) were selected based on expert knowledge and local context: GDP per capita, population density, distance to road networks, elevation, and slope. Expert judgments guided the assignment of relative importance scores, with calculations performed via an online AHP tool to ensure methodological consistency. The Analytic Hierarchy Process (AHP) pairwise comparison matrix was used to determine the relative importance of key urban growth factors influencing land-use change in Amman. The results show that GDP per capita is the most influential factor, with the highest priority weight of 34.3%, indicating that economic growth and increased income levels significantly drive urban expansion and land development. Population density ranks second with a priority value of 31.7%, reflecting the strong role of demographic pressure in shaping urban land demand and settlement patterns. Distance from the road network occupies the third position with 18.9%, suggesting that accessibility to transportation infrastructure plays an important role in guiding where development occurs. In contrast, physical environmental factors such as elevation (8.2%) and slope (6.9%) have relatively lower influence, implying that socio-economic and accessibility factors are more dominant than topographic constraints in determining urban land-use change in the study area. Overall, the ranking highlights that economic conditions, population concentration, and infrastructure accessibility are the primary drivers of urban growth in Amman.



Analytical Hierarchical Process (AHP)

Factor	Rank	Priority
GDP Per Capita	1	34.30%
Population Density	2	31.70%
Distance from Road Network	3	18.90%
Elevation	4	8.20%
Slope	5	6.90%
Consistency Ratio CR = 0.064		

Figure 3. Urban growth factor map.

These weights directly shaped the spatial patterns observed in the CA–Markov simulations by influencing the suitability maps used for allocating future land-use changes. Areas characterized by strong economic activity and high population concentration were assigned higher development suitability, leading to intensified urban expansion in and around existing urban cores. Similarly, proximity to road networks guided growth along transportation corridors, reinforcing linear and clustered expansion patterns. In contrast, higher elevation and steeper slopes acted as relative constraints, limiting development in topographically challenging areas. As a result, the weighted factors collectively produced simulation outputs that reflect both the socio-economic drivers of growth and the moderating influence of physical landscape features on Amman's projected urban form. The consistency ratio (CR) is a crucial measure used in the Analytical Hierarchy Process (AHP) to evaluate the logical consistency of judgments made during the pairwise comparison of factors. It quantifies the degree to which the comparisons are free from contradictions, ensuring that the assigned relative weights reflect a coherent and rational decision-making process. A CR value below 0.1 (or 10%) is generally considered acceptable, indicating that the expert assessments are consistent enough to produce reliable and valid results. By calculating the CR, researchers can validate the trustworthiness of the priority rankings derived from AHP, thereby strengthening the robustness of multi-criteria analyses in complex spatial and urban planning studies. The consistency ratio (CR) for the matrix was calculated at 0.064 (6.4%), which is well below the acceptable threshold of 0.1. This indicates that the expert judgments used in the analysis were both consistent and reliable [24]. This low CR value validates the consistency of expert judgments in the pairwise comparison matrix, indicating that the assigned weights are logically coherent and dependable for guiding urban growth analysis and planning decisions.

3.3.1. Validation of CA–Markov model.

Validation is essential to ensure the reliability of future LULC simulations. For this study, the actual 2022 LULC map generated from Landsat imagery served as the reference for evaluating the simulated 2022 map. Validation involved comparing the spatial distribution and area of each land-cover class between the two maps. The model achieved a correctness rate of 91.4% and an overall Kappa index of 0.89, which indicates almost perfect agreement according to standard interpretation criteria [25]. The Kappa histogram score was also high, at 0.92, reinforcing the robustness of the simulation. These results demonstrate that the CA–Markov model is highly effective in replicating observed land-use changes and can be confidently used for future scenario projections. A visual comparison of the simulated and actual 2022 maps is provided in Figure 4, illustrating strong alignment across all three land-cover classes.

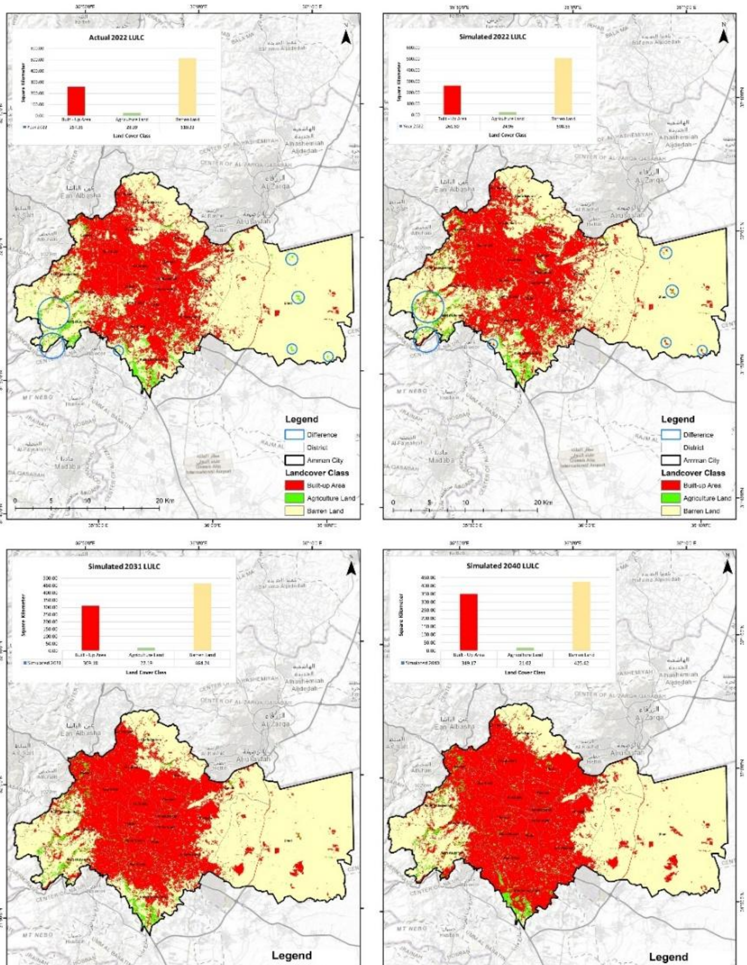


Figure 4. Actual 2022 LULC, Simulated LULC map for 2022, 2031 and 2040.

With successful validation, the model was then used to project future LULC scenarios for 2031 and 2040, based on transition dynamics observed from 2004 to 2022. These projections offer valuable insight into the likely trajectory of urban growth in Amman and support strategic planning for sustainable land management. The comparison between actual and simulated land-use land-cover for 2022 (Figure 4) reveals a close alignment between observed and modelled spatial patterns, underscoring the effectiveness of the integrated Cellular Automata–Markov (CA–Markov) modelling approach in capturing the urban growth dynamics of Amman. The actual built-up area was recorded at 257.35km² (32.33%), while the model projected a slightly higher extent of 261.80km² (32.91%). This minor overestimation of approximately 4.45km² (0.58%) suggests the model successfully simulates the expansion trends of urban areas with high spatial accuracy, reflecting the strong influence of key driving factors such as population density and GDP per capita identified through AHP analysis.

Agricultural land showed a larger discrepancy, with the actual area at 28.39km² (3.57%) compared to the simulated 24.96km² (3.14%), indicating an underestimation of about 3.43km² (0.43%). This underprediction may stem from the inherent volatility of agricultural land observed in previous analyses, where fluctuations are driven by complex socio-economic and environmental factors, including land management practices and seasonal variations, which are challenging to fully capture in the model. The slightly lower simulated agricultural area suggests the model may overrepresent conversion to barren or built-up classes in some locations, highlighting a potential limitation in capturing fine-scale agricultural land persistence or recovery.

For barren land, the actual extent was 510.23km² (64.10%) versus the simulated 508.85km² (63.96%), demonstrating a close match with a minimal underestimation of 1.38km² (0.14%). This result aligns with earlier findings that barren land is the primary source for urban expansion and confirms the model's ability to accurately represent the depletion of open lands over time. Overall, the small differences between observed and predicted LULC distributions affirm the robustness of the CA–Markov modelling framework, especially when combined with weighted driver factors from AHP. However, the slight mismatches, particularly in agricultural land, underscore the importance of continuous model calibration and the integration of additional local data or dynamic socio-economic variables to enhance predictive precision, supporting sustainable urban planning efforts in Amman amidst rapid urbanization and land scarcity challenges.

3.4 Future simulation of LULC.

Future land-use land-cover scenarios for Amman in 2031 and 2040 were projected using the integrated CA–Markov model, leveraging historical land-cover change data from 2004 to 2022 alongside the weighted influence of key urban growth drivers identified through the Analytical Hierarchy Process (AHP). The model applied transition probabilities derived from observed changes and incorporated socio-economic and physical factors such as population density, GDP per capita, proximity to road networks, elevation, and slope to simulate spatial dynamics of urban expansion and land conversion. Two simulation iterations were conducted: the first projecting land-use conditions for 2031, representing an 18-year forecast from the 2013 baseline, and the second extending the projection to 2040, corresponding to a 27-year forecast from the same baseline.

Figure 4 presents the simulated LULC maps for both projection years, visually capturing anticipated patterns of urban growth, agricultural land fluctuations, and the reduction of barren land. These maps illustrate an intensified outward expansion of built-up areas, particularly along major transportation corridors and flatter terrains, consistent with the spatial influence of accessibility and topographic constraints highlighted in previous analyses. Table 5 complements this visual data by providing a quantitative summary of land-cover distributions, comparing projected changes against the 2022 reference year. The statistical overview reveals expected increases in built-up areas, continued pressure on agricultural lands, and further depletion of barren lands, emphasizing the trajectory of ongoing urbanization and land transformation. These future scenarios not only highlight the spatial and temporal dimensions of Amman's urban growth but also underscore critical planning challenges related to land scarcity, environmental sustainability, and food security. The projections serve as valuable decision-support tools for policymakers, urban planners and developers, enabling proactive strategies to manage growth, protect vital agricultural zones, and mitigate adverse impacts on the natural landscape. However, it is important to recognize that these forecasts rely on the assumption that historical transition probabilities and driving factor influences remain stable over time, which may not fully account for unforeseen socio-economic shifts, policy changes, or environmental events. Therefore, continual model calibration with updated data and incorporation of scenario-based variables will be essential to refine future predictions and support resilient urban development in Amman.

Table 5. Statistical analysis of simulated 2031and 2040 with reference to 2022 LULC.

Land Cover Class	**Reference 2022**		**Simulated 2031**		**Simulated 2040**	
	Area (Km^2)	**%**	**Area (Km^2)**	**%**	**Area (Km^2)**	**%**
Built - Up Area	257.35	32.33	309.18	38.86	349.17	43.89
Agriculture Land	28.39	3.57	22.19	2.79	21.02	2.64
Barren Land	510.23	64.10	464.24	58.35	425.42	53.47
Total	795.97	100.00	795.61	100.00	795.61	100.00

The projected land-use changes in Amman carry significant implications for the city's environmental sustainability, food security, and urban planning challenges. The substantial increase in built-up areas from 32.33% in 2022 to nearly 44% by 2040 signals continued and accelerated urban expansion driven largely by population growth and economic development. This expansion predominantly consumes barren and agricultural lands, with barren land shrinking from 64.10% to just over 53% and agricultural land declining from 3.57% to 2.64% over the same period. The loss of agricultural land, although numerically smaller, is particularly concerning given its crucial role in local food production and ecosystem services, which are vital for a city facing land scarcity and environmental constraints.

The encroachment on barren lands, which have historically served as buffer zones and potential reserves for future development, further exacerbates land availability issues, reducing open spaces that could otherwise support ecological functions or future urban needs. This trend underscores the increasing pressure on finite land resources and highlights the risks of unchecked sprawl, including habitat fragmentation, loss of biodiversity, and increased infrastructure costs. The gradual but persistent decline in agricultural and barren lands demands urgent policy interventions focused on sustainable land management, including the protection of agricultural zones, promotion of urban densification, and incorporation of green infrastructure in urban planning. Figure 5 comprehensive LULC maps vividly illustrate this progressive transformation, serving as a critical visual tool for policymakers to understand spatial trends and prioritize areas for conservation and controlled development. Overall, these projections call for a balanced approach that supports Amman’s growth while safeguarding essential natural resources for future resilience.

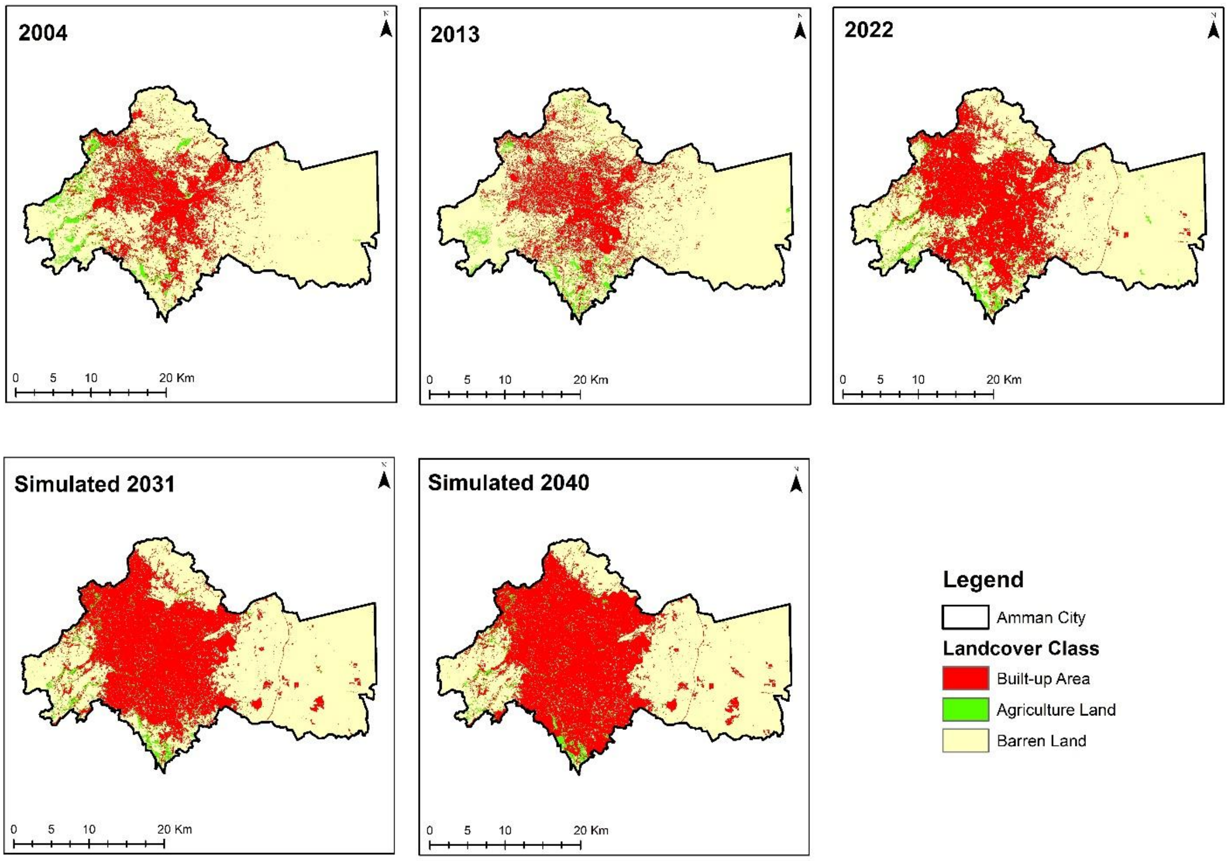


Figure 5. Overview of 2004, 2013, 2022, 2031 and 2040 LULC map.

Between 2022 and 2031, the built-up area in Amman is projected to increase significantly by 6.53%, reflecting continued urban expansion driven by socio-economic growth and infrastructure development. This expansion comes at the expense of other land-cover classes, with agricultural land and barren land decreasing by 0.78% and 5.75%, respectively. The substantial loss of barren land during this period highlights its role as the primary land source accommodating urban growth, while the moderate reduction in agricultural land signals ongoing pressure on these productive areas, which could have implications for local food security and environmental sustainability.

The subsequent period between 2031 and 2040 shows a similar pattern but with some variation in the rates of change. The built-up area is expected to gain an additional 5.03%, indicating a sustained, though slightly slower, pace of urban growth compared to the earlier period. Agricultural land continues to decline, albeit at a reduced rate of 0.15%, suggesting a potential stabilization or mitigation of agricultural land loss possibly due to emerging land-use policies or conservation efforts. Barren land, however, experiences a continued and notable decrease of 4.88%, reaffirming its critical role as the remaining buffer for urban expansion. These projections underscore the intensifying competition for land resources in Amman and highlight the urgent need for integrated planning strategies that balance urban development with the preservation of agricultural and open lands. Overall, the changing dynamics of land-cover classes over these two forecast periods emphasize the complex interplay between development pressures and environmental constraints. The results also reinforce the importance of adopting adaptive urban growth models and policy interventions that account for both spatial and temporal variability to promote sustainable urbanization in Amman.

This research is highly relevant in today's context, where rapid urbanization, increasing land scarcity, and growing food security challenges necessitate the development of advanced predictive spatial tools to support sustainable urban planning. This is especially critical in rapidly expanding, data-limited cities like Amman, where unplanned growth can strain natural resources and undermine agricultural productivity. Integrating historical land-use patterns with key urban growth drivers through the Cellular Automata–Markov (CA–Markov) model and the Analytical Hierarchy Process (AHP), this study provides a nuanced understanding of how urban expansion unfolds spatially and temporally, enabling more informed decision-making. Urban growth in Amman is projected to continue primarily through the infilling of pocket spaces adjacent to existing built-up areas, rather than sprawling indiscriminately into new territories. This pattern of consolidation intensifies development pressure on surrounding agricultural and barren lands, which show corresponding decreases in spatial extent. The encroachment on agricultural land raises particular concerns due to its vital role in local food production and ecological balance, while the reduction of barren land previously a buffer zone signals diminishing land availability for future expansion. These dynamics underscore the pressing need for proactive, spatially explicit planning strategies that prioritize efficient land use, protect agricultural zones, and mitigate the environmental impacts of urban growth. Ultimately, the research offers valuable insights and tools that can help planners and policymakers in Amman and similar rapidly urbanizing cities to manage growth sustainably despite data limitations and competing land demands.

The simulated land-use and land-cover (LULC) maps for 2031 and 2040 indicate that urban expansion in Amman will intensify, leading to a continued reduction in both agricultural and barren lands. This growth is expected to be most prominent in districts characterized by the high-weight factors identified in the AHP analysis: high population density, higher GDP per capita, gentle slopes, low elevation, and strong access to road networks. Notably, by 2031 and 2040, significant urban growth is projected in Amman's northern districts such as Tariq, Shafa Badran, Al-Jubeibah, Abu Nuseir, and Sweileh. Expansion is also anticipated in the eastern districts of An-Nasir, Uhud, and Al-Qwaismah, as well as the southern districts, including Ras Al-Ain, Khraibet As-Souq, and Marj Al-Hamam. This ongoing expansion will place increasing pressure on the city's existing infrastructure, which may struggle to keep pace with the needs of a growing population. By 2040, Amman will require significant investment in commercial centers, educational institutions, transportation networks, and other public facilities to accommodate this urban growth. In addition, the steady decline in agricultural land raises concerns about food security and agricultural productivity, underscoring the need for effective protective measures and sustainable urban planning.

The spatial distribution of urban growth in Amman between 2022 and 2040, highlighting the concentrated expansion along key transportation corridors and adjacent to existing built-up areas. This spatial pattern reflects the critical influence of road networks as primary drivers of urban development, facilitating accessibility and attracting new construction. These findings align closely with prior research, such as Abdeljawad et al. [1], who emphasized the pivotal role of road infrastructure in shaping urban growth patterns in Amman and surrounding regions. Additionally, the observed expansion dynamics resonate with the work of Jawarneh et al. [3], who highlighted the challenges of achieving sustainable urban development in Jordan's arid environments, where water scarcity and fragile ecosystems heighten the stakes of unplanned growth. Together, these spatial and temporal analyses not only corroborate existing literature but also provide actionable insights for urban planners and policymakers aiming to balance infrastructural development with environmental sustainability. By integrating these patterns into planning frameworks, stakeholders can better anticipate growth hotspots, design targeted interventions, and promote resilient urban environments in the face of rapid urbanization and climatic constraints.

4. Conclusions

The analysis emphasizes the critical role of socio-economic and geographic factors namely GDP per capita, population density, slope, elevation, and road accessibility in directing Amman's urban growth trajectory. Aligned with the priority weights from the AHP analysis, areas with concentrated economic activity, high population density, and favorable terrain are projected to experience the most significant expansion. While the CA–Markov model effectively captures historical trends and projects likely future changes, its predictive power is constrained by limited capacity to incorporate sudden policy shifts, economic fluctuations, or unexpected socio-environmental events. These findings provide important policy-oriented implications for Amman's spatial development. Without strategic intervention, there is a heightened risk of informal settlement proliferation, uneven access to resources and services, increased strain on existing infrastructure, and accelerated loss of valuable natural and agricultural lands. To mitigate these risks, urban planning policies must prioritize the preservation of agricultural zones, enhance land-use monitoring through higher-resolution spatial data, and explicitly integrate policy-driven scenarios into growth simulations. Such an approach will enable more adaptive, evidence-based decision-making that balances development needs with environmental sustainability. Ultimately, this study underscores the urgent necessity for proactive, coordinated urban management in Amman and provides a foundation for future research aimed at embedding advanced simulation tools within comprehensive socio-economic and policy frameworks to guide sustainable urban growth.

Author Contribution

All Authors (Nour Abdeljawad, Ahmad Awajan, Victor Adedokun) contributed to the conceptualization and writing of the manuscript. The methodology was developed by Nour Abdeljawad and Victor Adedokun. Data collection was performed by Ahmad Awajan, and Nour Abdeljawad, while data analysis was carried out by Victor Adedokun.

Competing Interest

The authors declare that they have no financial, personal, or professional relationships that could influence or appear to influence the research conducted and presented in this study. There are no competing interests to disclose.

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