Int. J. Hum. Capital Urban Manage., 11(1): 191-212, Winter 2026

International Journal of Human Capital in Urban Management
(IJHCUM)

Homepage: http://www.ijhcum.net/

CASE STUDY

Urban growth prediction and development pattern using CA-MARKOV and SLEUTH models

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ARTICLE INFO

Article History:
Received 20 February 2025
Revised 24 April 2025
Accepted 15 July 2025

Keywords:
CA-MARKOV
Kirkuk
Master plan
SLEUTH
Urban growth

DOI: 10.22034/IJHCUM.2026.01.12

ABSTRACT

BACKGROUND AND OBJECTIVES: Urbanization and rapid population growth are significant global challenges, especially in cities with outdated planning systems. Effective urban growth models, which utilize historical data, land use patterns, and population dynamics, are essential for predicting future expansion. In Kirkuk, Iraq, urban growth has occurred unregulated due to an outdated master plan, and a new plan has been introduced. However, no local studies have assessed the effectiveness of urban growth models against this plan. This study aims to fill this gap by evaluating urban development in Kirkuk from 1993 to 2023 and forecasting growth to 2037 using remote sensing and Geo-spatial Information System-based models.

METHODS: This research applied two urban growth models: Cellular Automata Markov chain modeling (CA-MARCOV) and SLEUTH, to analyze urban expansion in Kirkuk. Satellite imagery from 1993, 2003, 2013, and 2023 was used for land use classification. The Cellular Automata Markov chain model used transition probability matrices derived from land use data, while the SLEUTH model incorporated urban density, road networks, and slope data for simulations. Both models were tested for accuracy by comparing predicted urban growth for 2023 with actual land use data. The study also used these models to forecast urban expansion for 2037, comparing their predictions with the city's new master plan.

FINDINGS: The land use classification indicated significant urban growth in Kirkuk, from 41.57 km² in 1993 to 155.5 km² in 2023. The accuracy of the predictions for 202F3 showed that the SLEUTH model achieved 87% accuracy, outperforming the Cellular Automata Markov chain model, which had 76% accuracy. For 2037, the Cellular Automata Markov chain model projected urban growth to 201.43 km², while the SLEUTH model predicted a larger expansion of 219.78 km². The SLEUTH model also excluded water bodies and restricted zones (such as oil fields and airports), which were manually identified, while the Cellular Automata Markov chain model did not account for these exclusions.

CONCLUSION: The SLEUTH model provided more accurate predictions of urban growth and was selected for comparison with the new master plan. The results indicated discrepancies between the SLEUTH model's predictions and the master plan, particularly in areas experiencing rapid growth, suggesting the need for adjustments. The southeastern and southwestern regions showed alignment with the plan. These findings highlight the importance of using accurate urban growth models for sustainable planning in Kirkuk, offering valuable insights for urban development through 2037.

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
35	20	9

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Note: Discussion period for this manuscript open until April 1, 2026 on IJHCUM website at the "Show Article.

INTRODUCTION

In recent decades, developing countries have been grappling with the phenomenon of urbanization and rapid population growth, leading to increased population density in urban areas (Angel *et al., 2021*; Asghar Pilehvar, 2021). Urbanization is a process that results in the expansion of cities and is primarily driven by population growth, rural-to-urban migration, and lifestyle changes (Badri Gari, 2020). An urban area is defined as a region that is more densely populated than its surrounding areas and experiences more intense human activities. In recent years, the importance of urban areas has increased, and urbanization has expanded at a faster pace than before (Barman *et al.,* 2024). Urban structures are dynamic, making cities complex systems. A city consists of several fixed elements and their interaction with social and human dynamics. According to a recent United Nations report, about 55% of the world's population lives in urban areas, and this figure is expected to reach 68% by 2050 (Badri Gari, 2020). This population growth, in addition to increasing urban density, has led to the uncontrolled expansion of urban land in the suburbs; a phenomenon often referred to as "urban sprawl" that typically occurs on the fringes of urban areas or along highways (Barman *et al.,* 2024). This sprawl has resulted in significant changes in land use, with agricultural land being the most affected by this rapid urban development (Dutta & Das, 2019; Ghasemi *et al.,* 2025). Land use changes and urban expansion have widespread negative impacts on natural resources and the environment (Njiru, 2016; Ghobadiha & Motieyan, 2023). Unplanned and uncontrolled urban development not only affects the environment and natural resources but can also directly impact access to urban infrastructure and services such as transportation networks and public services (Mihun *et al.,* 2022). This also has significant impacts on the quality of life and social welfare of individuals (Pavithra, 2020). Unplanned urban growth and its widespread dispersion can create serious challenges for urban planners, policymakers, and development agencies, which ultimately can lead to unsustainable development and significant economic and social damages (Mihun *et al.,* 2022). In the face of these challenges, researchers and urban planners have turned to the use of various Remote Sensing (RS) and Geo-spatial Information Systems (GIS) models and techniques to assess and analyze changes in land cover and land use (Barman *et al.,* 2024; Thamaga *et al.,* 2022). These tools have been widely used to analyze urban growth patterns, examine land cover changes, and provide the possibility of simulating the dynamics of urban growth (Ongsomwang & Saravisutra, 2011). Urban growth models are among the important tools in understanding and analyzing the driving forces of urban development, which can predict potential future scenarios in the field of urbanization (Lec & Mahmut, 2018). Given the importance of accurate prediction and planning for urban development, CA-MARKOV and SLEUTH models have been recognized as effective tools for simulating land use changes and predicting urban growth. The CA-MARKOV model is based on cellular automata and is often used to simulate land use changes and predict urban development (Al-Aali and AL-Khakani, 2022). On the other hand, the SLEUTH model, which includes various factors such as slope, transportation networks, and shadow maps, is more effective in analyzing land changes in a more detailed and comprehensive manner (Ongsomwang & Saravisutra, 2011). These models enable urban planners and policymakers to analyze various urban dynamics and development patterns. However, there are limited studies in Kirkuk that have compared the performance of these models and the accuracy of their predictions. Urban growth prediction and Land Use/Cover Change (LUCC) analysis have become essential components of urban planning and sustainable development. Numerous studies have employed various models and techniques, including Cellular Automata (CA), Markov chains, logistic regression, and remote sensing data, to forecast urban expansion and evaluate its impacts. Aziz *et al.,* (2022) analyzed LUCC dynamics and urban growth in the Tabriz Metropolitan Area, Iran, using four modeling methods: CA, Markov chains, logistic regression, and weighted linear combination analysis. Their results identified key factors such as proximity to large cities and access to roads as major drivers of urban expansion. They also simulated three development scenarios to predict LUCC until 2050, offering critical insights for policymakers on sustainable urban development strategies. Similarly, Shikari and Rudra (2022) applied the CA-Markov model to predict urban growth in Purulia Municipality, India, highlighting the rapid spread of built-up areas and the encroachment of agricultural land, underscoring the need for strategic land use planning. Remote sensing and GIS-based studies, such as Mohammad *et al.,* (2021), utilized satellite imagery to classify land use in Potiskum, Nigeria, and assess urban expansion from 1999 to 2018. By analyzing the accuracy of classified maps, this study provided vital data for urban management and infrastructure planning in rapidly urbanizing regions. Mataraj *et al.,* (2021) employed the CA-Markov model in Sri Lanka, demonstrating its effectiveness in predicting land use and urban expansion between 2000 and 2020, with significant projections for 2030. In addition to traditional models, the SLEUTH model has gained traction for urban growth prediction due to its ability to incorporate various spatial factors such as road networks, elevation, and land density. Gomez *et al.,* (2021) further explored the uncertainties in urban growth predictions, noting that the SLEUTH model can enhance accuracy by reducing spatial uncertainties in land use change predictions. Studies also highlight the need to account for environmental and social factors in urban growth modeling. Kharram *et al.,* (2021) applied the CA-Markov model in Duhok, Iraq, demonstrating significant shifts in land use and the importance of monitoring LUCC for sustainable urban planning. In Najaf, Iraq, Al-Basri *et al.,* (2022) used the Markov chain method to predict urban expansion patterns between 2005 and 2015, emphasizing random growth in residential areas and the model's utility in guiding urban management. Jayasinghe *et al.,* (2021) conducted a comparative evaluation of three open-source urban growth models: SLEUTH, FUTURES, and MOLUSCE, to determine the most suitable model for simulating urban growth in Colombo, Sri Lanka. Using Landsat satellite images from different time periods (1997, 2005, 2008, 2014, and 2019) for model calibration and validation, the study applied minimal datasets to ensure fair comparison. The results revealed that SLEUTH provided the most accurate spatial predictions, with a Figure of Merit (FoM) score of 0.26, outperforming FUTURES and MOLUSCE, which both scored 0.20. While FUTURES gave better overall estimates of urban area, SLEUTH excelled in spatial accuracy and flexibility in representing multiple urban growth scenarios, such as sprawl and infill growth, which were not available in MOLUSCE. The study recommended incorporating exclusion layers in SLEUTH to improve model accuracy and mitigate overestimations in urban growth predictions. SLEUTH was concluded to be a highly effective tool for simulating urban growth, particularly in cities undergoing significant transformations, offering valuable insights for sustainable urban planning. Kumar and Agrawal (2023) applied the SLEUTH model to simulate and predict future land use and urban growth in the rapidly developing smart city of Prayagraj, India. Using historical LULC data from 1990 to 2020, road networks, and elevation data, the study forecasted significant urban expansion, projecting an increase in built-up area from 85.89 km^2 in 2020 to approximately 118.66 km^2 by 2040. The model calibration process emphasized the critical influence of slope and road gravity coefficients, identifying them as primary drivers of land use change. Despite the model's rigorous calibration complexity, it yielded satisfactory results that align with observed LULC trends and were validated using satellite imagery and topographic maps. The study highlighted both the capabilities and limitations of SLEUTH, particularly the exclusion of socioeconomic factors, and stressed its potential as a tool for urban planners and policymakers to anticipate and manage urban sprawl more sustainably. Dhanaraj and Angadi (2022) applied the calibrated SLEUTH model to study urban growth in Mangaluru, India, from 2000 to 2020, with future projections until 2031. The study identified significant urban growth, from 3,798 ha in 2000 to 11,984 ha in 2020, with a predicted increase to 18,880 ha by 2031. Key drivers of growth were identified as slope resistance, spread, and road gravity. The study also emphasized the importance of combining spatial metrics with urban modeling to support sustainable urban planning in rapidly urbanizing small and medium-sized cities in developing countries. These studies collectively underscore the importance of predictive modeling in urban planning, with various approaches offering valuable tools to anticipate and manage urban growth in different geographical and socio-economic contexts. Furthermore, many previous studies have not compared the results of simulation models with actual urban master plans. Kirkuk, as one of the developing cities in Iraq, has faced random urban growth and the pressure of unplanned development; especially since the previous master plan also failed to address these needs. With the adoption of the "Kirkuk Basic Plan

2037", the goal is to manage the rapid growth of this city and address the problems caused by uncontrolled development and encroachment on government lands. This research, focusing on the city of Kirkuk, evaluates the results of the CA-MARKOV and SLEUTH models and compares these results with the city's master plan until 2037, which has been developed by the government. In this way, the advantages and disadvantages of each model and urban master plan can be examined in terms of sustainable development and controlling urban growth.

MATERIALS AND METHODS

Survey design and data collection

Kirkuk, a city in northern Iraq and the capital of Kirkuk Governorate, located at 35.4571° North and 44.3832° East, is one of the most important and strategic regions of the country (Fig. 1). Due to its connection between the Kurdistan Region and the capital and southern cities of Iraq, it holds significant importance. Kirkuk covers an area of approximately 9,679 square kilometers and, due to its geographical location, borders areas such as Erbil in the north, Sulaymaniyah in the east, Salah al-Din in the west, and Diyala in the south. The city is located 233 kilometers north of Baghdad, the country's capital. The Zab River passes through part of the governorate, and the Khasa River runs through the city center, dividing it into two parts. Fig. 1 shows the geographical location of Kirkuk in Iraq.

In the data preprocessing phase for Land Use/ Land Cover (LULC) analysis using ENVI and GIS software, several steps are involved to enhance the accuracy and quality of the results. Initially, primary data, including satellite imagery and other relevant layers, is collected from reliable sources such as the USGS (United States Geological Survey) website and OpenStreetMap. Subsequently, the preprocessing of satellite imagery commences, which involves radiometric correction to eliminate errors caused by atmospheric conditions and sensor issues. Furthermore, various image bands are combined to generate multi-band images that contain more information about the study area. Additionally, other spatial layers are prepared for analysis. These layers include urban and transportation layers to depict human infrastructure, elevation layers to identify topographic changes, exclusion layers to define unclassified areas, and shaded relief layers for visual analysis. After the completion of the preprocessing steps, the data is input into ENVI and GIS software to prepare for advanced analyses such as supervised classification, change analysis, and accuracy assessment. Table 1 presents the details of the input datasets required for each of the SLEUTH and CA-Markov models.

In remote sensing, image classification plays a pivotal role in identifying and mapping various land cover types, such as urban areas, vegetation, and water bodies. This process involves categorizing

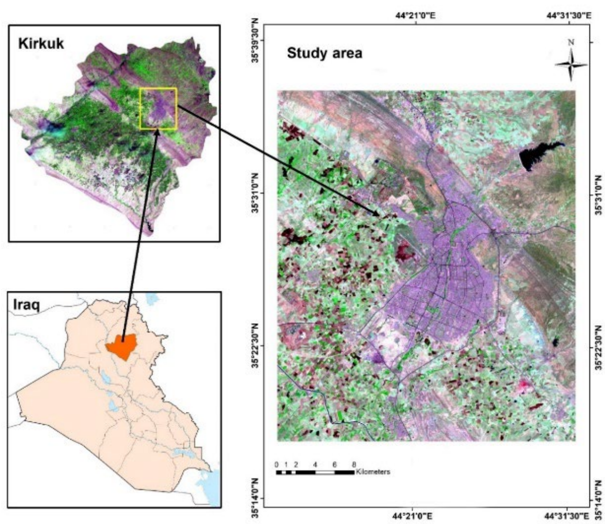


Fig. 1: Location of Kirkuk City

individual pixels within satellite images into distinct classes based on their spectral characteristics. ENVI software, a widely used tool for image processing, employs a variety of methods, including supervised and unsupervised classification, to accomplish this task. In this study, Landsat satellite imagery with a spatial resolution of 30 meters was acquired from the USGS website for the years 1993, 2003, 2013, 2017, and 2023. Subsequently, these images were processed and classified using ENVI 5.3 software to analyze land cover changes over this period. By examining the spectral signatures of different land cover types, we can identify trends in urban expansion, deforestation, and other land use changes. Table 2 shows the characteristics of the images used in this study.

In the process of preparing satellite images, existing errors, including radiometric errors and data gaps, are initially removed to improve image quality. This step involves correcting any noise or errors present in the image, such as those caused by the satellite sensor or atmospheric conditions, to produce a clearer and more analyzable image. Subsequently, the different bands of the images are merged using a layer stack operation to create a multi-band image for each year, providing a more comprehensive analysis of land cover. In satellite imagery, each band represents information about a specific wavelength of light. By combining these bands, more information can be extracted from each pixel, leading to a more detailed analysis of land cover. To focus on the study area, extraneous portions of the images are cropped using the Subset via the ROI tool. This means that only the desired portion of the image is selected for analysis, increasing processing speed and allowing for a more focused analysis of the area of interest. Finally, sampling of various land cover types, such as urban areas, vegetation, and water bodies, is conducted to train classification models accurately and assign pixels to the correct classes. This step is crucial as it teaches the model the spectral characteristics of each land cover type. Using these samples, the model can correctly classify

Table 1: Data collection

Input Layer	Data Source	Format	Data Years	Input Format and Data for CA-MARKOV Model	Input Format and Data for SLEUTH Model	Software Used
Slope	DEM	Raster		Raster	Raster (GIF)	ArcMap 10.8
In percent %						
Land Use Land Cover	USGS (Landsat images)	Vector	1993, 2003, 2013, 2017, 2023	Raster	Raster (GIF) 1993-2017	ENVI 5.3
Urban	Shapefile from land use	Vector	1993, 2003, 2013, 2017		Raster (GIF) 1993, 2003, 2013, 2017	ArcMap 10.8
Transportation	OpenStreetMap	Vector	2023		Raster (GIF) 1993, 2003, 2013, 2017	ArcMap 10.8
Exclusion	On-screen (master plan)	Vector			Raster (GIF)	ArcMap 10.8
Hill Shade	DEM	Raster			Raster (GIF)	ArcMap 10.8

Table 2: Satellite data for classification

Satellite Images	Dates	Sensor	Path/Row	Cloud cover	Scale (Resolution)	Data source
Landsat 5	20/6/1993	Thematic mapper (TM)	169/35	0 %	30 m	Earth Explorer, USGS
Landsat 7	11/5/2003	Enhanced Thematic mapper Plus (ETM+)	169/35	0 %	30 m	Earth Explorer, USGS
Landsat 7	6/5/2013	Enhanced Thematic mapper Plus (ETM+)	169/35	0 %	30 m	Earth Explorer, USGS
Landsat 8	10/6/2017	Operational Landsat Imager (OLI)	169/35	0.01 %	30 m	Earth Explorer, USGS
Landsat 8	16/4/2023	Operational Landsat Imager (OLI)	169/35	0.05 %	30 m	Earth Explorer, USGS

unknown pixels in the image into different classes (e.g., urban, forest, water). These samples represent pixels that belong unequivocally to one of the defined classes. This means that the samples must be carefully selected to be representative of each class Therefore, the classification models are trained more accurately and can assign image pixels to the correct classes. Once the model is trained, it can be used to classify the entire image and create a land cover map. As shown in Table 3, different areas are represented by different colors, allowing for easy identification of different land cover types on the map.

In the final stage, image classification was performed using a supervised classification method and the Maximum Likelihood algorithm. Based on the selected samples, this method assigns the image pixels to one of the defined classes. This process was repeated for each image corresponding to different years to obtain classification results. This method enables a detailed analysis of land cover and land use changes over different years and contributes to a better understanding of urban dynamics and environmental changes in the region. The SLEUTH model requires six grayscale GIF images for its operation. These images should depict urban areas, transportation networks, areas excluded from urbanization, slope, and shaded relief. A sixth layer for land use is optional. The selection of these six input layers was based on the established structure of the SLEUTH model, which is specifically designed to simulate urban growth using these spatial parameters. These layers represent key physical and infrastructural factors that directly influence the spatial dynamics of urban expansion (Jantz *et al.,* 2004, Rafiee *et al.,* 2009). Their selection was driven by both their methodological relevance and the availability of consistent, high-quality data over the study period (1993–2023). Data preparation increasingly relies on GIS and remote sensing techniques, such as data conversion and reclassification (Tobgye, 2019).

Slope layer

Slope is a key element in urban development, as the cost of converting non-urban land to urban use is significantly influenced by the land slope. The steeper the land, the higher the construction costs. In this study, the slope layer was derived from a Digital Elevation Model (DEM) as a percentage (Fig. 2), and points with a slope greater than 25% were identified as CRITICAL-SLOPE, a suitable criterion for mountainous or hilly areas. Pixels were classified into integer values from 0 to 100, and the output file was produced as an 8-bit GIF image.

Urban layer

For effective construction and calibration of the SLEUTH model, at least four urban layers from the study area are required as input data. In this study, urban areas corresponding to the years 1993, 2003, 2013, and 2023 were selected. These layers were prepared by extracting urban pixels from land cover classification in images of each period. Here, urban areas in Kirkuk were defined with a value of 0 for non-urban areas and 1 for urban areas. Each output file was extracted as an 8-bit GIF image (Fig. 3).

Transportation Layer

The transportation network plays a crucial role in urban expansion, as cities typically develop along these networks. Therefore, the SLEUTH model requires two or more datasets of road and transportation networks from different years to simulate urban dynamics more effectively. In this study, four datasets of Kirkuk's transportation networks for the years 1993, 2003, 2013, and 2017 were collected using the OSM website and satellite imagery. These data were processed using ARMCAP software and converted into GIF format (Fig. 4). Values were set between 0

Table 3: Satellite data for classification

Class Number	Class	Color	Description
1	Urban/Built-up Areas	Red	Buildings, infrastructure, and roads (residential, industrial, commercial areas, street networks)
2	Vegetation Area	Green	Agricultural lands, natural and artificial forests, grasslands, pastures, and natural trees
3	Barren Land/Others	Yellow	All vacant spaces, sandy areas, and rocky regions
4	Water Bodies	Blue	Includes bodies of water like lakes and rivers

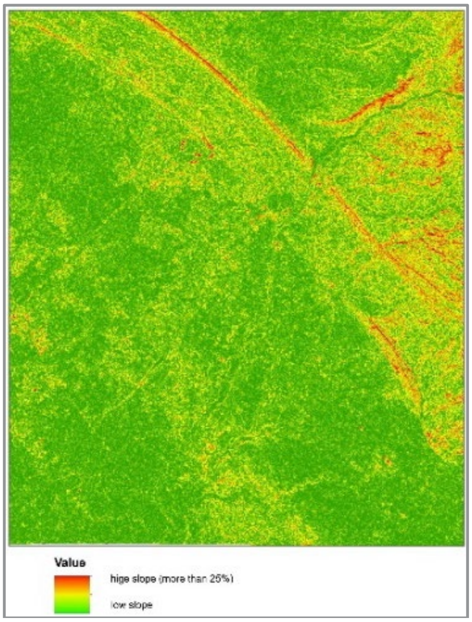


Fig. 2: Slope map of Kirkuk City

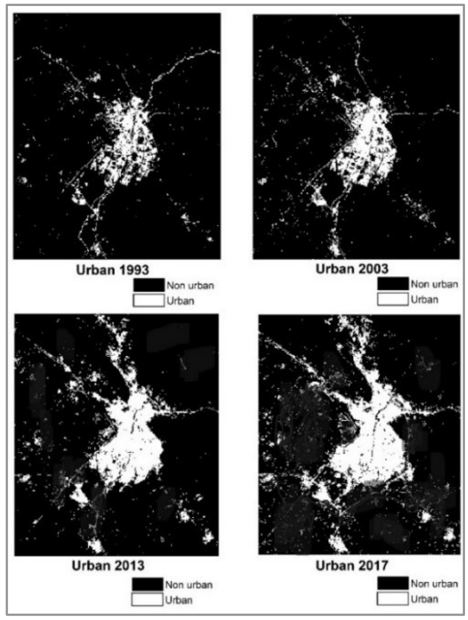


Fig. 3: Map of urban layers of Kirkuk

and 255, where 0 indicates the absence of a route and other values represent the relative accessibility to transportation networks. Additionally, this layer can also be defined as binary (0 or 1).

Exclusion layer

Exclusion layers consist of cells representing areas that are protected from future urbanization. In this study, the excluded classes include water bodies such as rivers and dams, as well as areas prohibited from urban development, including oil production areas owned by the National Oil Company. All data related to these layers were prepared as vector data, then merged and converted to raster format (Fig. 5). These layers have pixel values ranging from 0 to 100, where a value of 0 indicates the highest probability for urban development and no restrictions on urbanization, while values equal to or greater than 100 means that the area should be excluded from urban expansion.

Hill shade layer

The hill shade layer is used as a background image for the SLEUTH model's spatial data and does not directly affect the model simulation, but it helps to improve the visualization of the model results. This layer can be useful in visually analyzing the model output, and to enhance visual effects, a pixel value of 0 is used to represent water bodies such as rivers and lakes. This layer was created using DEM data and the "hill-shade" function in ArcGIS software and stored as an 8-bit grayscale GIF file. Fig. 6 shows an image of this layer.

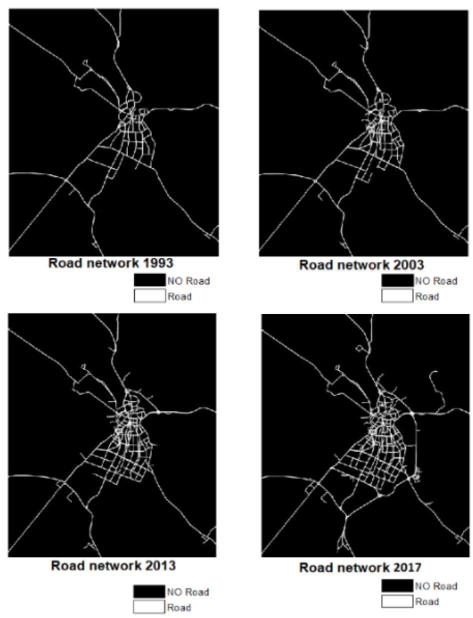


Fig. 4: Kirkuk city transportation layer map

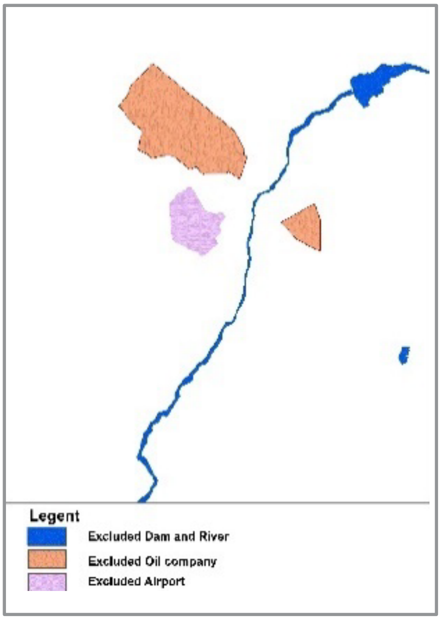


Fig. 5: Exclusion map of Kirkuk city

Fig. 6: hill shade map of Kirkuk City

Land use Layer

Land use data provides information about the land use of an area. Although this information is not essential for simulating urban growth, at least two classified land use categories at two different times are required to assess changes in land use (Mahamud *et al.,* 2019). Pixel values for input vary from 0 to 255

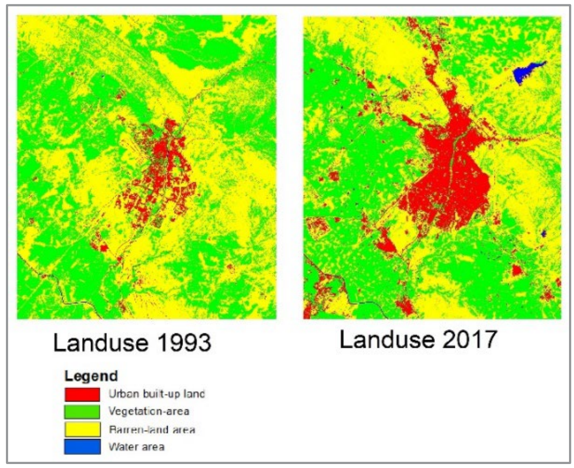


Fig. 7: The change of use layer of the city of Kirkuk

and images are stored as 8-bit grayscale GIF files. Fig. 7 shows the land use map of Kirkuk city.

Analytical framework

After collecting data from the study area and preparing and extracting classified images and the necessary factors for the model, the next step involves executing the workflow according to the flowchart shown in Fig. 8.

Dynamic models, such as SLEUTH and CA-MARKOV, are designed to simulate urban expansion and analyze land use changes (Das & Jain 2022; Zhang *et al.,* 2023). By considering time, these models help analyze the evolution of cities over time and space, and they utilize techniques like cellular automata to reduce uncertainty in understanding urban systems (Badri Gari, 2022). These models are widely used in urban research and planning and can provide accurate predictions for policymakers and planners (Yadav & Ghosh, 2019). The CA-Markov model is a powerful tool for analyzing land use changes and predicting urban growth, combining Markov Chain and Cellular Automata models. The Markov Chain component calculates the probability of land use change from one class to another based on historical data, while the Cellular Automata component examines spatial relationships and the influence of neighboring cells on one another (Li *et al.,* 2025; Tahir *et al.,* 2025). To run the 'TerrSet' program, satellite images from 1993 and 2017 are first classified using 'ENVI 5.3 software to generate land use maps. The

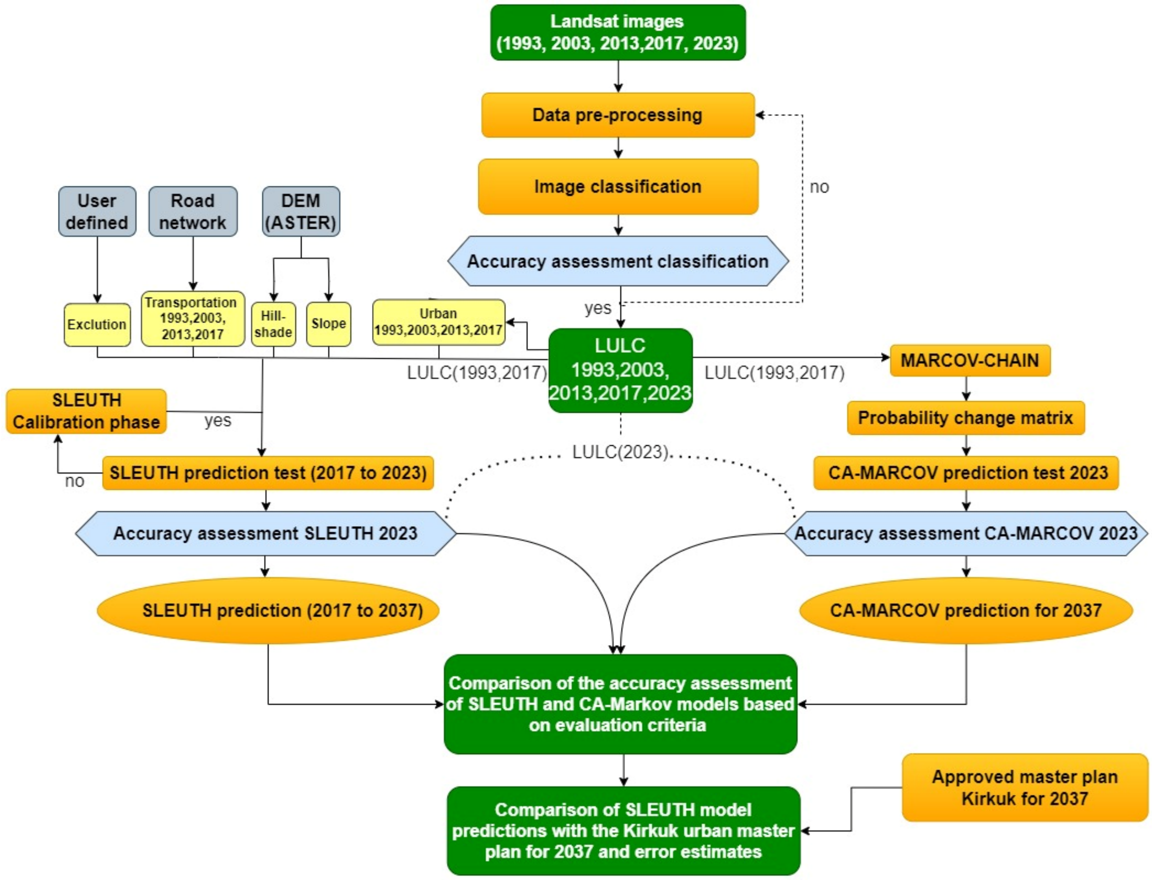


Fig. 8: Flowchart of the procedure steps

images are then imported individually, and the Markov Chain is used to select and compare the two images. This process generates a land use transition probability matrix. Using the CA-Markov model, the second image used in the Markov Chain analysis and the land use transition probability matrix are then applied to simulate and predict future land use maps. The SLEUTH model, based on cellular automata and written in C, simulates urban changes using various layers of information such as slope, land use, and transportation. This model involves experimental testing and calibration phases to achieve higher accuracy by adjusting its parameters (Lec & Mahmut, 2018; Parvar *et al.*, 2025). The SLEUTH model requires a set of key input data for simulating and predicting land use changes and urban growth, which must be prepared with high accuracy and quality. These data include slope maps that show the slope at different points in the study area, historical land use maps that display the land use status in the past and are used for comparison and prediction of changes, and urban density maps that show the extent of urban expansion at different times and help simulate urban growth. In addition, road network maps, including roads, highways, railways, and other transportation routes, play an important role in modeling accessibility and its effects on urban expansion. Furthermore, restriction maps identify areas that are excluded from development and land use change for various reasons. This comprehensive and accurate data forms the basis of the SLEUTH model to provide reliable results in predicting land use changes and urban growth. As shown in Fig. 9 for the input data of the SLEUTH model. In this study, classified images for the years 1993, 2003, 2013, 2017, and 2023 are compared to analyze land use changes over the study

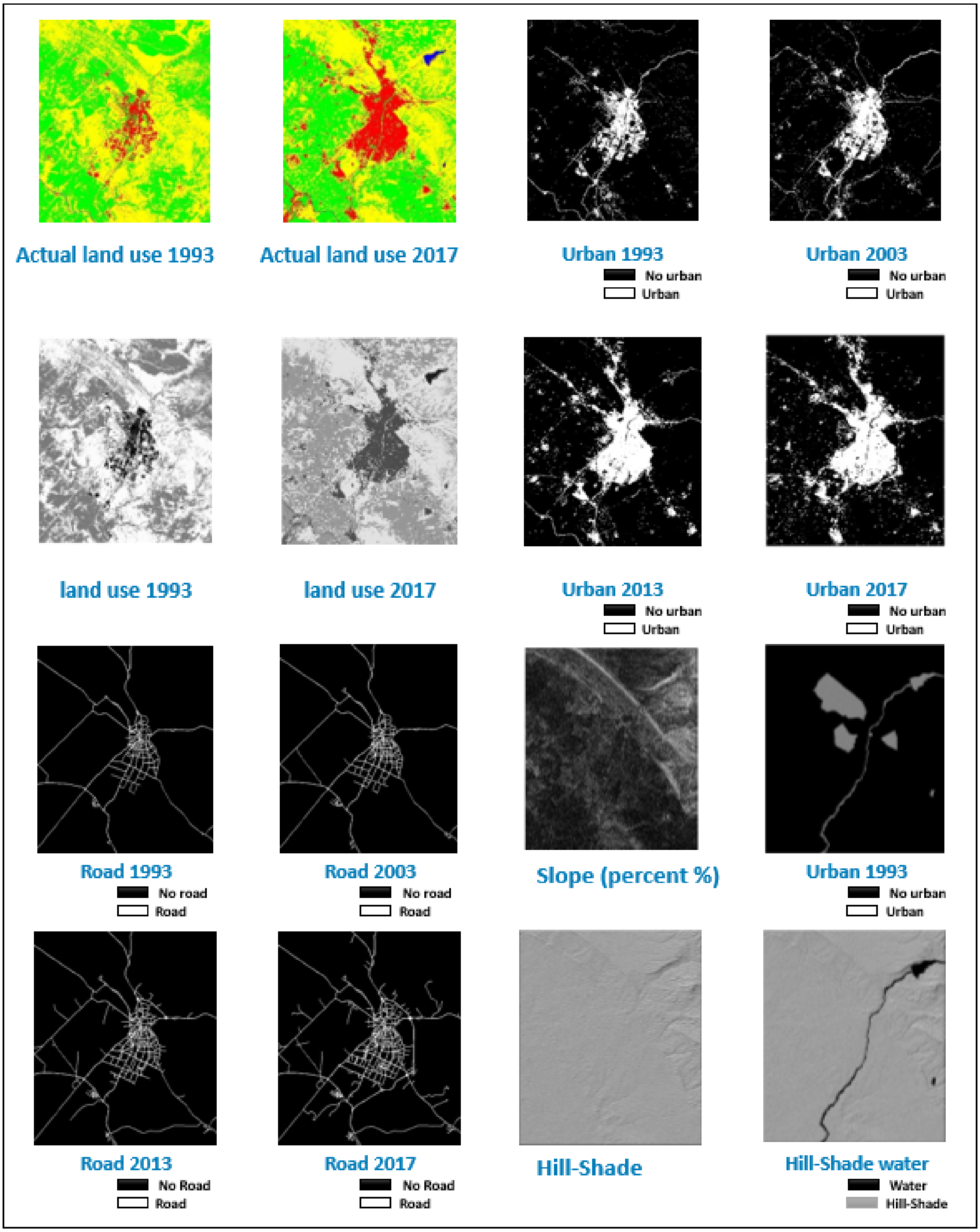


Fig. 9: SLEUTH model input data

period. The accuracy of the classified images for the years 1993, 2003, 2013, 2017, and 2023 is assessed using the Kappa coefficient and overall accuracy. After data preparation, the CA-MARKOV model is used to predict land use changes for 2023 using data from 1993 and 2017. The SLEUTH model, as one of the leading models in simulating and predicting urban growth, requires careful calibration to ensure that its results align with historical realities.

SLEUTH model calibration

The SLEUTH model, as one of the prominent tools for simulating and predicting urban growth, requires precise calibration to align its results with historical realities (Satari *et al.*, 2024; Saulawa, 2024). During the calibration process, various components of the model are tested by altering growth rates to determine a set of suitable values that can interpret historical land-use changes in the study area, covering the period from 1993 to 2017. The SLEUTH model incorporates five growth rates (Dispersion, Breed, Spread, Slope Resistance, and Road Gravity), The model applies several growth rules, including new spreading center growth, edge growth, spontaneous growth, and road-influenced growth. A unique feature of the SLEUTH model is its ability to assign relative importance to each parameter during the calibration process, measured on a scale of 0 (least important) to 100 (most important). This reflects the relative influence of each rate during the calibration phase. The calibration process aims to identify the optimal range for each parameter based on historical data. Afterward, the coefficients are adjusted to suit the specific characteristics of the study area. The Optimal SLEUTH Metric is used to evaluate the calibration and ensure the model's effectiveness. Through this meticulous process, the calibrated model provides reliable insights for simulating and predicting urban growth patterns.

As can be seen in Table 4, this table outlines the calibration results for the SLEUTH model, presenting the Optimal Growth Coefficients for five key urban growth parameters: Diffusion, Seed, Spread, Slope, and Road Gravity. The calibration process is conducted in three progressive stages (Coarse, Fine, and Final) to refine parameter values and achieve the highest accuracy based on the Optimal SLEUTH Metric (OSM). Key Insights:

- The Final Calibration provides the most precise parameter values, reflecting the dynamics of urban growth in the study area.

- Parameters such as Road Gravity (90), Seed (74), and Spread (67) emphasize the significant role of transportation networks and urban expansion from the city center.

- Minimal influence is observed from Diffusion (1) and Slope (9), indicating limited spontaneous growth and low topographical resistance.

- The progressive refinement of ranges and step sizes across calibration stages results in improved OSM values, ensuring a highly accurate model to simulate urban growth patterns effectively.

RESULTS AND DISCUSSION

CA-Markov model prediction

Classified images from 1993 and 2017 were used to predict the 2023 urbanization map. It is then compared with the actual image of the same year, and the accuracy of the predicted image is obtained. The classified images are then reused to obtain the

Table 4: SLEUTH model calibration results

Coefficient	Calibration Coefficient						Optimal growth coefficient
	Coarse		Fine		Final		
	OSM = 0.52		OSM = 0.55		OSM =0.57		
	Range	Step	Range	Step	Range	Step	
Diffusion	0-100	25	0-25	5	0-20	4	1
Seed	0-100	25	50-75	5	70-75	1	74
Spread	0-100	25	0-100	25	25-100	10	67
Slope	0-100	25	0-20	5	5-1	1	9
Road Gravity	0-100	25	25-100	15	20-30	2	90

2037 m. Fig. 10 shows a comparison between the CA-Markov model prediction results and the actual land use map in 2023; in this comparison, the left image shows the urban growth prediction by 2023 using the CA-Markov model, which includes urban areas (in red), vegetation (in green), Barren land (in yellow), and water areas (in blue), while the right image shows the actual land use situation in 2023.

Table 5 presents the results of urban growth forecasting using the CA-Markov model for the year 2023 compared to the actual values. The table shows that the CA-Markov model predicted 5.49 km² less than the actual value for urban areas, which necessitates the need to improve the accuracy and model adjustments for future predictions. Urban growth prediction using the CA-Markov model for the year 2037, showing changes in land use and the expansion of urban areas, is presented in Fig. 11. According to this map, urban areas (marked in red) have expanded in the center and other scattered points, indicating significant urban development and an increase in population density by 2037. Additionally, green areas representing vegetation can be widely observed around urban areas, while yellow areas indicating barren land are scattered throughout the map. Table 6 shows the land use changes from 2023 to 2037 using the CA-Markov model. The area of urban land has increased from 155.5 square kilometers to 201.43 square kilometers, indicating a significant growth of 46.36 square kilometers. These changes depict a significant expansion of urban and agricultural areas and a decrease in barren land, emphasizing the need for improved land management and sustainable development.

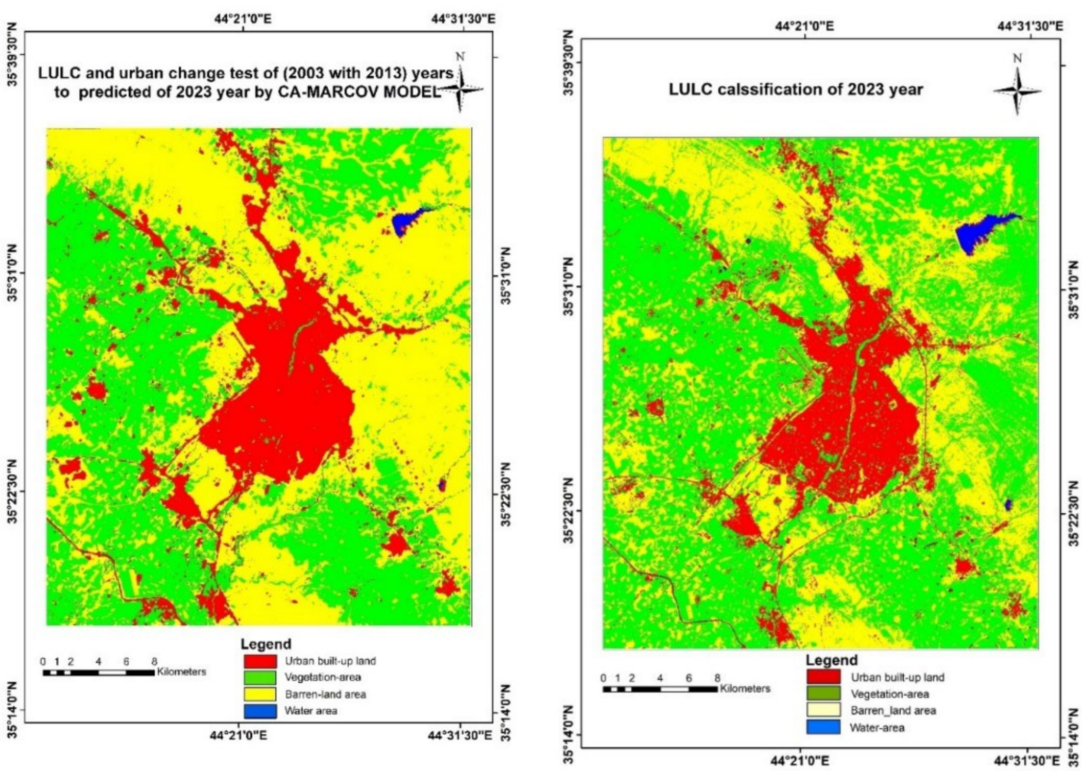


Fig. 10: Comparison of urban growth prediction using the CA-Markov model in 2023 with actual land use

Table 5: Urban growth prediction using the CA-Markov model in 2023

LULC Classes	Actual Value (Area, km²) 2023	Predicted Value (Area, km²) 2023	Difference (Area, km²)
Urban	155.5	150.01	-5.49

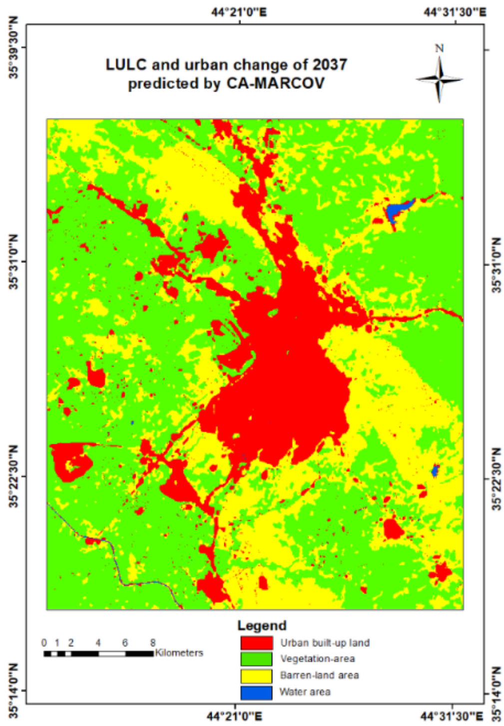


Fig. 11: Prediction with the CA-Markov model in 2037

Table 6: Comparison of Urban Growth Using the CA-Markov Model from 2023 to 2037

LULC Classes	Land Use (Area, km²) 2023	Projected Land Use (Area, km²) 2037	Growth (Area, km²)
Urban	155.5	201.43	46.36

SLEUTH model prediction

Various maps from 1993 to 2017, along with other input data, were used to forecast the state of land use in 2023, obtaining a similar urban growth forecast to the previous model in the same year, and then comparing them. The same map and data are then used to predict the 2037 map. Fig. 12 contains two maps that analyze and compare the accuracy of urban growth predictions using the SLEUTH model in 2023. The map on the left shows the urban growth predicted for 2023 using the SLEUTH model, with urban areas shown (in yellow/orange) and water areas in blue. The map on the right shows the actual land use classification in 2023, with urban areas (in red), vegetation (in green), Barren land (in yellow), and water areas (in blue). A comparison of these two maps shows the relative accuracy of the SLEUTH model in predicting urban growth; while the model can predict the main areas of urban development well, there are differences in detail and smaller areas. Table 7 compares urban growth forecasting using the SLEUTH model in 2023. The results show that the model has a difference of +3.89 km2 for urban areas with an actual value of 155.5 km2 and a predicted value of 159.39 km2. This analysis shows that the SLEUTH model has generally provided accurate forecasts, although there is room for improvement in some cases. The urban growth prediction for 2037 based on the SLEUTH model is shown in Fig. 13. In this image, existing urban areas and areas with high potential for urban growth (between 70% and 100%) are marked in yellow/orange. Areas with a medium probability of expansion (between 40% and 70%) are shown in red, and areas with a low probability (between 0% and 40%) are shown in

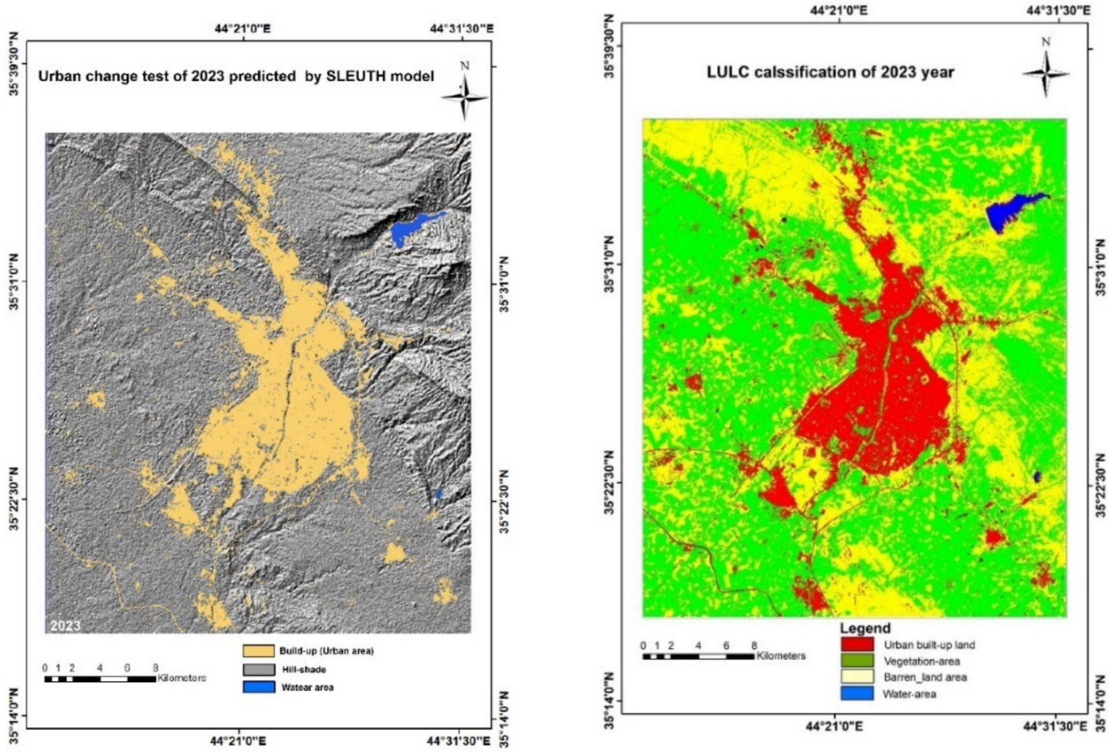


Fig. 12: Comparison of urban growth prediction using the SLEUTH model in 2023 with actual land use

Table 7: Urban growth prediction using the SLEUTH model in 2023

LULC Classes	Actual Value (Area, km²) 2023	Predicted Value (Area, km²) 2023	Difference (Area, km²)
Urban	155.5	159.39	+3.89

green. Additionally, water bodies are marked in blue. This image indicates a significant expansion of urban areas and an increase in their population density by 2037. This prediction indicates rapid and widespread growth of urban areas and an increase in population in these areas by 2037.

Table 8 indicates that, according to the SLEUTH model, the area of urban land has increased from 155.5 square kilometers in 2023 to 219.78 square kilometers in 2037, representing an increase of 64.28 square kilometers. These changes demonstrate the trend of urban development and shifts in land use patterns during this time period.

Accuracy assessment Comparison between CA-Markov Model and SLEUTH Model

Accuracy assessment is a process used to verify the accuracy of image classification by comparing the classified image with reference data. The accuracy of classified images is calculated using ground truth points randomly selected and distributed in the study area (Njiru, 2016). This study employs a pixel-based accuracy assessment method to evaluate classification accuracy in remotely sensed data using an error matrix. The assessment results include overall accuracy, with the Kappa coefficient being a widely recognized measure. The Kappa coefficient evaluates the agreement between actual and chance classifications. A Kappa value above 0.80 indicates good classification, values between 0.40 and 0.80 represent moderate classification, and values below 0.40 indicate poor classification. Fig. 14 shows a detailed comparison of urban growth forecasts in 2023 using both CA-Markov and SLEUTH models for urban

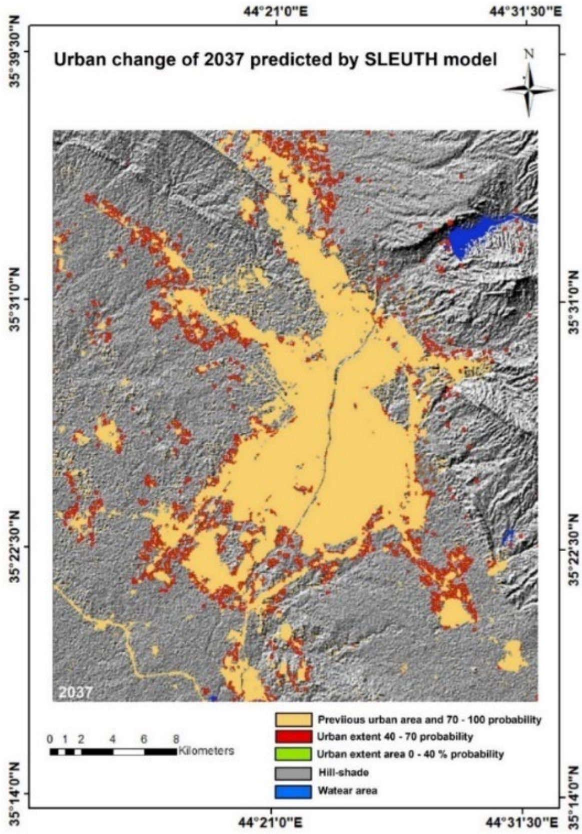


Fig. 13: Prediction with the SLEUTH model in 2037

Table 8: Comparison of Urban Growth Using the SLEUTH Model from 2023 to 2037

LULC Classes	Land Use (Area, km²) 2023	Projected Land Use (Area, km²) 2037	Growth (Area, km²)
Urban	155.5	219.78	+64.28

areas obtained in Figs. 7 & 8. The obtained results show that the CA-Markov model performed less than the true value in predicting the area of urban areas. In contrast, the SLEUTH model is closer to the true value in predicting the area of urban areas. According to Table 9, the kappa coefficient was 87.42 for the SLEUTH model, while this value was only 77.44 for the CA-Markov model. The overall accuracy rate for the SLEUTH model was also 80.26%, while this rate was only 69% for the CA-Markov model. These results show that the SLEUTH model had better performance than the CA-Markov model in predicting urban areas and overall accuracy.

The comparison of urban growth from 1993 to

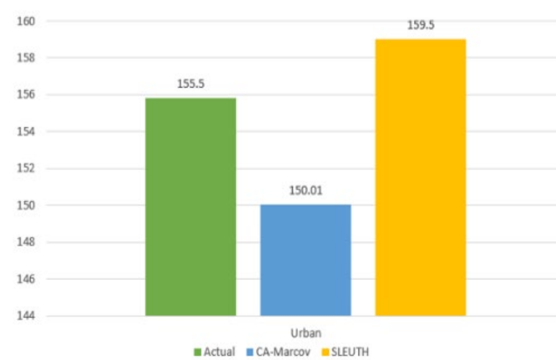


Fig. 14: Comparison of urban growth forecasting of CA-Markov model with SLEUTH in 2023

Table 9: Comparison of the accuracy of urban growth of the CA-Markov model with SLEUTH model in 2023

Accuracy Assessment	Land Use (Area, km²) 2023	Projected Land Use (Area, km²) 2037
Overall accuracy	87%,42	77٪,44
Kappa coefficient	80,26	0,69

2037 using two CA-Markov and SLEUTH models is shown in Figure 15. The chart allows you to see the actual changes in the area of urban areas between 1993 and 2023, followed by the forecast of both models for 2037 in square kilometers. The comparison of urban growth prediction for the year 2037 between the SLEUTH and CA-Markov models is analyzed and compared in Figure 16. The left-hand map shows the predicted urban growth for 2037 using the SLEUTH model, where urban areas are depicted in yellow/orange and water bodies are shown in blue. In contrast, the right-hand map illustrates the predicted urban growth until 2037 based on the CA-Markov model; in this map, urban areas are represented in red, vegetation in green, barren land in yellow, and water bodies in blue.

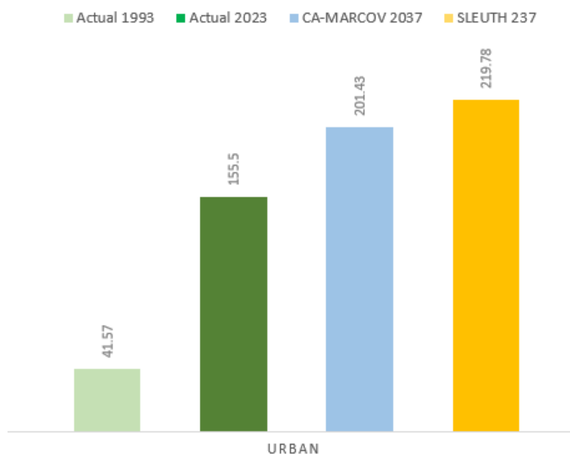


Fig. 15. The comparison of urban growth from 1993 to 2037

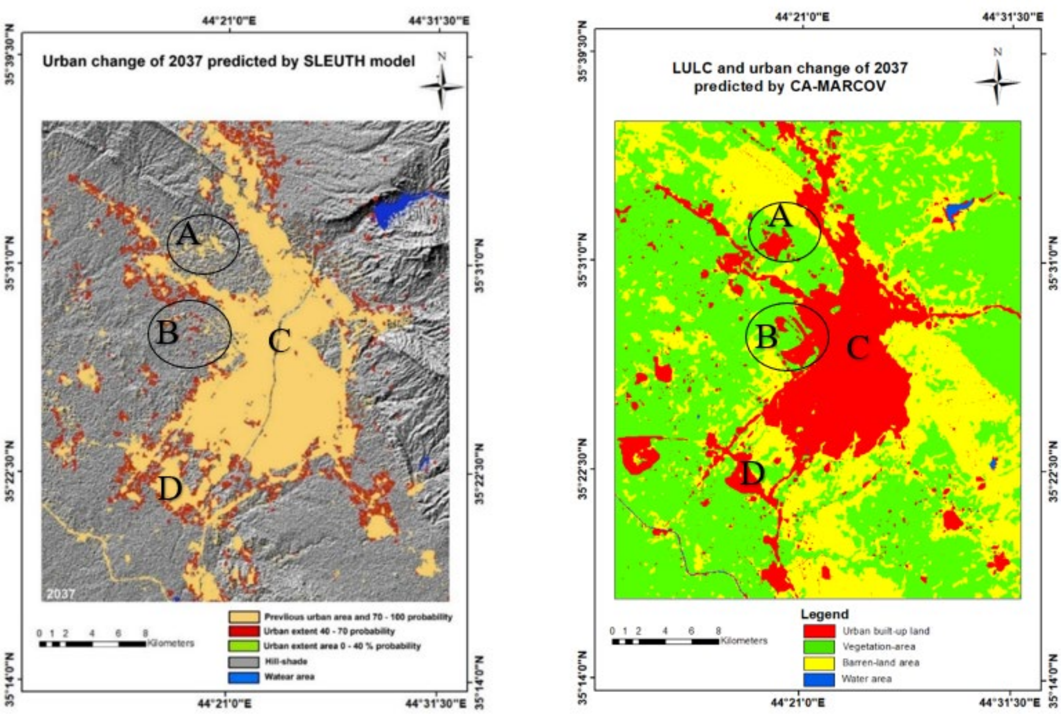


Fig. 16: Comparison of urban growth forecasting of the CA-Markov model with SLEUTH in 2037

When comparing the images, several observations can be made, including the areas marked with (A, B, C) that were removed from the SLEUTH model and excluded from urbanization, which are the areas of: (National Oil Company, airport, and rivers). However, with the CA-MARCOV model, these areas had become largely urbanized, indicating the superiority of the SLEUTH model compared to the CA-MARCOV model. On the other hand, as is known, roads are the main pillar of urban development, as more development of urban areas can be observed in the images marked with (D) along the roads in the SLEUTH model compared to the CA-MARCOV model. Due to the higher accuracy of the SLEUTH model urban forecasts compared to the actual city image in 2023, and the high level of determination of urban expansion patterns and the removal of restricted urban areas seen in the 2037 model forecast, SLEUTH for further analysis is selected.

Reclassification of the Kirkuk City Master Plan and Comparison of SLEUTH Model Results with Kirkuk's Comprehensive Plan

This research reclassified the Kirkuk Comprehensive Plan map (Fig. 17) to facilitate comparison with the SLEUTH model results. In this map, urban areas are colored red, vegetation green, and water bodies blue, while oil company boundaries and airports are gray, and the 2037 comprehensive plan boundaries are black. According to the 2037 Comprehensive Plan, the area of urban and residential areas, including the no-go zone for oil and airports, will reach 315 square kilometers. However, excluding oil fields and airports, which cover 75 square kilometers, the net urban area reduces to 240 square kilometers. Additionally, some villages and residential areas outside the comprehensive plan are added to this area, bringing the total urban area to 275 square kilometers.

Fig. 18 presents two maps with different colors,

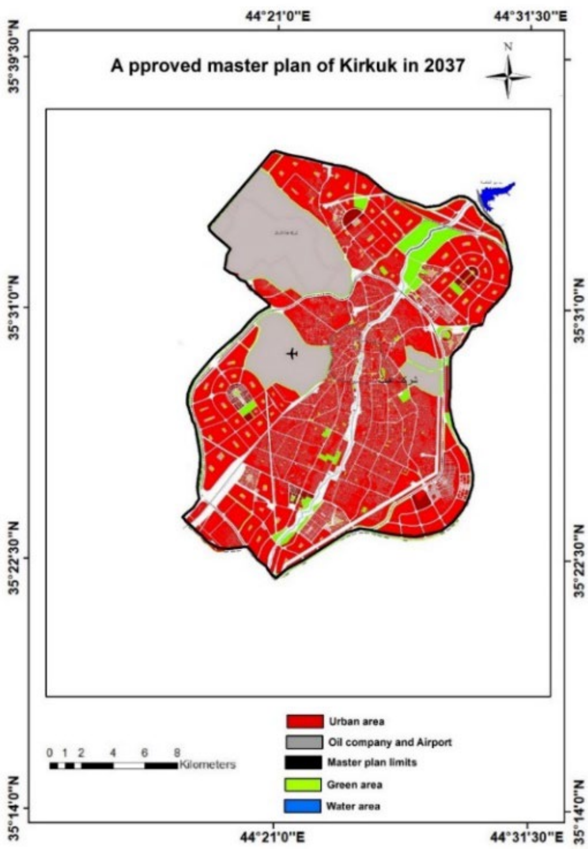


Fig. 17: Reclassification of the Urban Comprehensive Plan

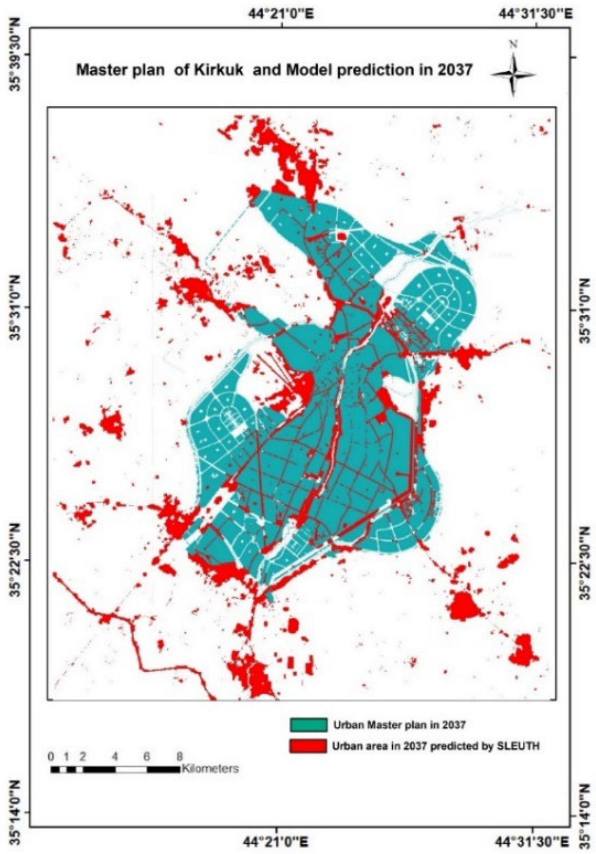
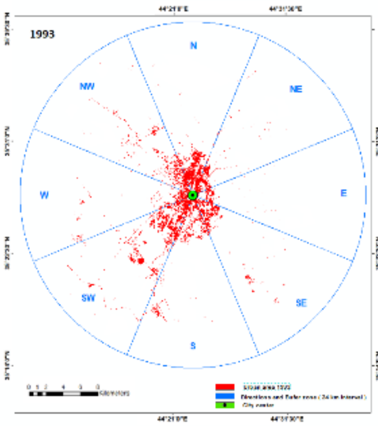


Fig. 18: Comparison of SLEUTH Model Classification Results with the Kirkuk Comprehensive Plan

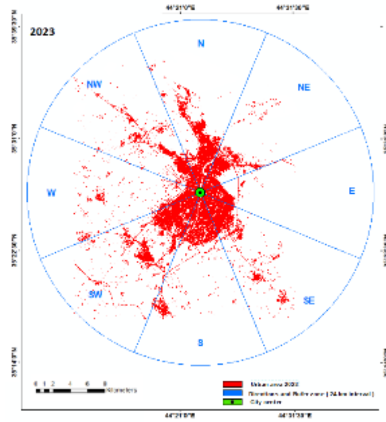
illustrating the predicted urban development for Kirkuk in 2037. The blue area represents the urban structures predicted by the Comprehensive Plan, while the red area indicates urban development predicted by the SLEUTH model. Comparing the Comprehensive Plan and the SLEUTH model's predictions for urban development in Kirkuk by 2037 reveals significant differences in the scope and approach to urban growth.

A comparison of the two models shows that the Comprehensive Plan, with an area of 275 square kilometers, is significantly more extensive than the SLEUTH model prediction of 219.78 square kilometers, indicating a more comprehensive and widespread development in the Comprehensive Plan compared to the SLEUTH model, which focuses more on specific and limited areas. The Comprehensive Plan addresses a wider range of land uses, including residential, commercial, and industrial, and assists decision-makers in more detailed planning. In contrast, the SLEUTH model emphasizes the overall trend of urban expansion and provides fewer details. Therefore, the Comprehensive Plan serves as an effective tool for detailed planning and urban development decision-making, while the SLEUTH model is more recognized as a tool for predicting overall urban growth trends and has limitations in the details and accuracy of specific predictions.

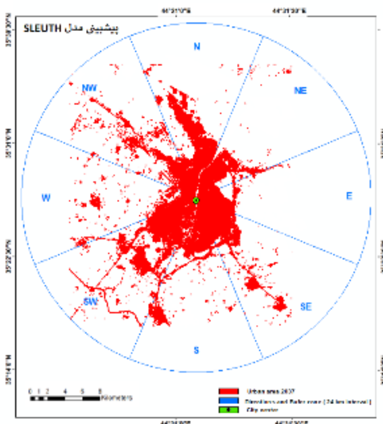
Based on Fig. 19 Analysis of urban growth in Kirkuk from 1993 to 2023 reveals a significant increase in various parts of the city. For instance, the eastern region experienced a 361% growth, expanding from 1.61 square kilometers to 7.29 square kilometers. The SLEUTH model predicts a further increase to 10.12 square kilometers by 2037, while the comprehensive plan projects a slightly smaller area of 8.21 square kilometers. Similarly, the northern region has grown from 6.55 square kilometers to 28.49



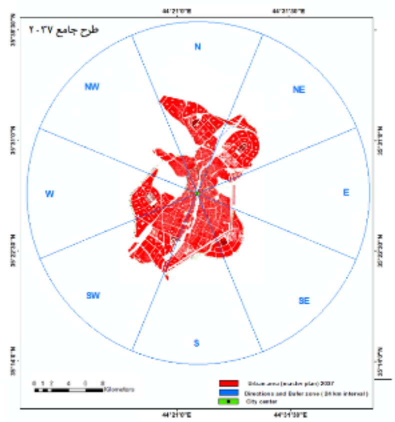
A- The direction of urban growth in 1993



B- The direction of urban growth in 2023



C- Direction of urban growth in 2037 (SLEUTH model)



D- The direction of urban growth in 2037 (master plan)

Fig. 19: Urban growth direction in 1993, 2023, and 2037

square kilometers and is projected to reach 43.24 square kilometers, although the comprehensive plan predicts an even larger growth of 54.11 square kilometers. However, significant discrepancies exist between the SLEUTH model and the comprehensive plan in other regions, such as the northeast, northwest, south, and southeast. For example, the comprehensive plan predicts a growth of 42.41 square kilometers in the northeast, which is double the SLEUTH model's prediction. Likewise, in the western region, the comprehensive plan shows double the growth compared to SLEUTH, possibly indicating an overestimation by the comprehensive plan. Therefore, it is recommended that the municipality carefully review the SLEUTH model's predictions and revise the comprehensive plan to align with actual and sustainable growth.

CONCLUSION

This study analyzed land use change and urban growth in the study area using satellite imagery from 1993, 2003, 2013, 2017, and 2023, remote sensing techniques, and ENVI 5.8 software. The results indicate that the area of urban land increased from 41.57 square kilometers in 1993 to 155.5 square kilometers in 2023, and the extent of green and water areas also experienced a significant increase. The overall accuracy of the maps was reported to be between 86% and 94%, and the predictions of both the SLEUTH and CA-Markov models for urban growth by 2037 indicate a substantial increase in urban areas. The SLEUTH model, with an accuracy of 87.42%, predicted that the urban area would reach 219.78 square kilometers, while the CA-Markov model predicted 201.43 square kilometers. A comparison of the SLEUTH model with the urban comprehensive plan revealed that the comprehensive plan forecasted a development of 275 square kilometers and served as a guideline for urban planning. This research emphasizes that the CA-Markov and SLEUTH models can be effective tools for predicting land use changes and sustainable resource management. Additionally, identifying environmentally sensitive areas and detailed planning for water resources and infrastructure are important applications of these results in urban planning. Ultimately, this study highlights the need to improve planning processes and integrate advanced techniques to manage the challenges of rapid urban growth and resource sustainability. In future research, it is recommended that input data for models be collected and pre-processed with greater accuracy, including the use of higher-resolution satellite imagery and regular data updates. Furthermore, developing hybrid models by integrating the results of CA-Markov and SLEUTH models with artificial intelligence and machine learning techniques can provide more accurate predictions. Community involvement in data collection and the use of ground-truth data to validate results are also highly important. Additionally, examining the impact of other environmental and socio-economic factors, such as soil type and land price, on urban development can contribute to a better understanding of development processes and lead to a more comprehensive approach, e.g., coupling SLEUTH with agent-based models, to analyze land use change.

AUTHOR CONTRIBUTIONS

Sh. R. Jabari conducted the literature review, data collection, and data analysis, outlined the research findings, and drafted the initial manuscript. H. Motieyan and A. Sam-Khaniani screened and analyzed the gathered data, synthesized the findings, discussed, and conclusion. All authors reviewed and approved the final version.

ACKNOWLEDGEMENT

The authors acknowledge the contributions of the editorial team and reviewers, which strengthened the quality of the presentation of this research manuscript.

CONFLICT OF INTEREST

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy, have been completely witnessed by the authors.

PUBLISHER NOTE

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ABBREVIATIONS (NOMENCLATURE)

CA	Cellular Automat
CA-MARCOV	Cellular Automata Markov chain modeling
DEM	Digital Elevation Model
ETM+	Enhanced Thematic mapper Plus
GIS	Geo-Spatial Information System
LUCC	Land Use/Cover Change
LULC	Land Use/Land Cover
OLI	Operational Landsat Imager
RS	Remote Sensing
USGS	United States Geological Survey
TM	Thematic Mapper

REFERENCES

Al-Aali, F.A.; T AL-Khakani, E., (2022) Simulating and Predicting Land Cover Changes in Al Najaf Province Utilizing a CA-Markov Model. Int. J. Mech. Eng. Educ., 2(7):1-10 (**10 pages**).

Albasri, N.A.H.; Al-Jawari, S.M.; Al-Mosherefawi, O.J., (2022). Prediction of urban spatial changes pattern using Markov chain. Civil Engineering Journal., 8(4): 710-722 (**13 pages**)

Angel, S.; Lamson-Hall, P.; Blei, A.; Shingade, S.; Kumar, S., (2021). Densify and expand: A global analysis of recent urban growth. *Sustainability.*, *13*(7): 3835 (**28 pages**).

Azizi, P.; Soltani, A.; Bagheri, F.; Sharifi, S.; Mikaeili, M., (2022). An integrated modelling approach to urban growth and land use/cover change. Land., 11(10): 1715 (**26 pages**)

Badri Gari, R., (2022). Urban growth modeling and assesment using agent-based model (Master's thesis, University of Twente) (**87 pages**).

Barman, S.; Roy, D.; Chandra Sarkar, B.; Almohamad, H.; Abdo, H. G., (2024). Assessment of urban growth in relation to urban sprawl using landscape metrics and Shannon's entropy model in Jalpaiguri urban agglomeration, West Bengal, India. Geocarto Int., 39(1): 2306258 (**31 pages**).

Das, S.; Jain, G.V., (2022). Assessment and prediction of urban expansion using CA-based SLEUTH urban growth model: A case study of Kolkata Metropolitan area (KMA), West Bengal, India. *J. Indian Soc. Remote Sens.*, *50*(12), 2277-2302 (**25 pages**).

Dhanaraj, K., & Jain, G. V. (2023). Urban growth simulations in a medium-sized city of Mangaluru, India, through CA-based SLEUTH urban growth model. *J. Indian Soc. Remote Sens.*, *51*(3): 497-517 (**20 pages**).

Dutta, I.; Das, A., (2019). Exploring the dynamics of urban sprawl using geo-spatial indices: a study of English Bazar Urban Agglomeration, West Bengal. *Appl. Geomatics.*, *11:* 259-276 (**17 pages**).

Ghasemi, K.; Al-Zubaidi, A.M.J.; Qelichi, M.M.; Dolatkhahi, K., (2025). Understanding urban sprawl in Baqubah, Iraq: A study of influential factors. *Journal of Urban Management* (**26 pages**).

Ghobadiha, Y.; Motieyan, H., (2023). Urban growth modelling in Qazvin, Iran: An investigation into the performance of three ANFIS methods. J. Spatial Sci., 68(4): 523-542 (**19 pages**)

Gómez, J.A.; Guan, C.; Tripathy, P.; Duque, J.C.; Passos, S.; Keith, M.; Liu, J., (2021). Analyzing the spatiotemporal uncertainty in urbanization predictions. Remote Sens., 13(3): 512 (**28 pages**)

Jantz, C.A.; Goetz, S.J.; Shelley, M.K., (2004). Using the SLEUTH urban growth model to simulate the impacts of future policy scenarios on urban land use in the Baltimore-Washington metropolitan area. *Environ. Plann. B: Urban Anal. City Sci.*, *31*(2): 251-271 (**21 pages**).

Jayasinghe, P.; Kantakumar, L.N.; Raghavan, V.; Yonezawa, G., (2021). Comparative Evaluation of Open Source Urban Simulation Models Applied to Colombo City and Environs in Sri Lanka. *International Journal of Geoinformatics*, *17*(3): 1-12 (**12 pages**)

Khwarahm, N.R.; Najmaddin, P.M.; Ararat, K.; Qader, S., (2021). Past and future prediction of land cover land use change based on earth observation data by the CA–Markov model: a case study from Duhok governorate, Iraq. Arabian J. Geosci., 14(15), 1-14. (**15 pages**)

Kim, D.; Batty, M., (2011). Calibrating cellular automata models for simulating urban growth: Comparative analysis of SLEUTH and Metronamica. Documento de trabajo. UCL WORKING PAPERS SERIES (176) (**39 pages**)

Kumar, V.; Agrawal, S., (2023). Urban modelling and forecasting of landuse using SLEUTH model. Int. J. Environ. Sci. Technol., 20(6): 6499-6518 (**20 pages**)

Li, X., Mao, D., Xue, J., Wang, S., Chang, J.; Liu, X., (2025). Integrative assessment and management implications on loss of ecosystem services value of desert-oasis ecotone due to artificial oasis expansion. *Global Ecol. Conserv.*, e03450 (**15 pages**).

Mahamud, M. A.; Samat, N.; Tan, M. L.; Chan, N. W.; Tew, Y. L., (2019). Prediction of future land use land cover changes of Kelantan, Malaysia. The International Archives of the Photogrammetry, ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci., 42: 379-384 (**6 pages**)

Mathanraj, S.; Rusli, N.; Ling, G. H. T., (2021). Applicability of the CA-Markov model in land-use/land cover change prediction for urban sprawling in Batticaloa Municipal Council, Sri Lanka. In IOP Conference Series: Earth and Environmental Science (Vol. 620, No. 1, p. 012015) (**13 pages**)

Mithun, S.; Sahana, M.; Chattopadhyay, S.; Chatterjee, S.; Islam, J.; Costache, R., (2022). Comparative framework for spatially explicit urban growth modeling for monitoring urban land-use efficiency and sustainable urban development (SDG 11.3. 1): a study on Kolkata metropolitan area, India. *Geocarto Int*., 37(27): 17933-17970 (**38 pages**)

Njiru, B.E., (2016). Evaluation of urban expansion and its implications on land use in Kiambu County, Kenya. Kenyatta University (**134 pages**).

Ongsomwang, S.; Saravisutra, A., (2011). Optimum predictive model for urban growth prediction. Suranaree J. Sci. Technol., 18(2): 141-152 (**12 pages**)

Rafiee, R.; Mahiny, A.S.; Khorasani, N., (2009). Assessment of changes in urban green spaces of Mashad city using satellite data. *Int. J. Appl. Earth Obs. Geoinf.*, *11*(6): 431-438 (**8 pages**).

Pavithra, P. J., (2021). Exploration of Spatiotemporal Expansion Pattern and Comparative Evaluation of Urban Growth Models: A Case Study of Colombo, Sri Lanka (Doctoral dissertation) (**135 pages**)

Parvar, Z.; Mohammadzadeh, M.; Saeidi, S., (2024). Enhancing decision-making for climate change mitigation and sustainable urban growth. *Urban Clim.*, *58*: 102223 **(? pages).**

Pilehvar, A., (2021). Spatial-geographical analysis of urbanization in Iran. *Humanities and Social Sciences Communications.*, *8*(1): 1-12 (**12 Pages**).

Satari, N., Erfani, M., & Jahanishakib, F., (2024). Modeling urban expansion in Zahedan's dry climate: insights from the SLEUTH model. *Front. Sustainable Cities.*, *6*: 1357350 (**18 pages**).

Saulawa, U.A.; Ibrahim, Y.; Bello, A., (2024). Assessing the suitability of the SLEUTH cellular automata model for capturing heterogeneous urban growth in developing cities: A case study in Northern Nigeria. *Heliyon*, *10*(17): 1-15 (**15 pages**).

Shikary, C.; Rudra, S., (2022). Urban growth prediction for sustainable urban management using Markov chain model: a study on Purulia Municipality, West Bengal, India. J. Indian Soc. Remote Sens., 50(11), 2229-2244 (**16 pages**)

Tahir, Z.; Haseeb, M.; Mahmood, S. A.; Batool, S.; Abdullah-Al-Wadud, M.; Ullah, S.; Tariq, A., (2025). Predicting land use and land cover changes for sustainable land management using CA-Markov modelling and GIS techniques. *Sci. Rep.*, *15*(1): 3271 (**23 pages**).

Thamaga, K.H.; Dube, T.; Shoko, C., (2022). Evaluating the impact of land use and land cover change on unprotected wetland ecosystems in the arid-tropical areas of South Africa using the Landsat dataset and support vector machine. *Geocarto Int.*, *37*(25): 10344–10365 (**22 pages**).

Tobgye, L.; Piyathamrongchai, K., (2019). Urban growth simulation using remote sensing, GIS, and SLEUTH urban model in Gelephu City, Bhutan (Doctoral dissertation, Naresuan University) (**138 pages**).

Tombuş, F.; Yüksel, M., (2018). Use of SLEUTH model in land cover/ land use change simulation. IOSR-JMCEpp., 7-15 (**9 pages**).

Yadav, V.; Ghosh, S.K., (2021). Assessment and prediction of urban growth for a mega-city using CA-Markov model. *Geocarto Int.*, 36(17): 1960-1992 (**33 pages**)

Zhang, Y.; Kwan, M.P.; Yang, J., (2023). A user-friendly assessment of six commonly used urban growth models. *Comput. Environ. Urban Syst.*, *104*: 102004 (**15 pages**).

HOW TO CITE THIS ARTICLE

Jabari, Sh. R.; Motieyan, H.; Sam-khaniani, A., (2026). Urban growth prediction and development pattern using CA-MARKOV and SLEUTH models. Int. J. Hum. Capital. Urban Manage., 11(1): 191-212.

DOI: 10.22034/IJHCUM.2026.01.12

URL: https://www.ijhcum.net/article_726419.html