Cellular Automata and Markov Chain Model (CA-Markov), Based Forecasts of Future Land Use and Land Cover Scenarios During (2002-2043) in the Batha District Southern Iraq using GIS.

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Abstract:

This study focused on forecasting future changes in land cover and land use in the southwest of Thi Qar Governorate for the years 2033 and 2043. The research utilized Landsat-7 and Landsat-9 satellite imagery, following the necessary digital processing of these images using ArcGIS 10.5 and ENVI software. Classification was performed using supervised classification techniques in Erdas Imagine 2014 and ArcGIS 10.5, adhering to Anderson's land use and land cover classification system.

The accuracy of the classification was evaluated using an error matrix based on field verification. The study aimed to predict land cover and land use categories for 2033 and 2043 using the hybrid Markov model and to quantify spatial changes in the area of different land cover types. Additionally, it sought to identify the categories experiencing the most significant changes, whether increasing or decreasing.

The research employed the IDRISI TerrSet software to simulate future changes in land cover and land use within the study area. This software enables the application of the CA-Markov model, which integrates cellular automata and Markov chain analysis. The model produced high-quality predictive maps illustrating differences in land cover areas across past, present, and future timeframes.

Keywords: *Classification, future change simulation, CA-Markov.*

Introduction:

Prediction is a topic of significant importance in contemporary geographical studies, as it plays a fundamental role in shaping future policies for planning and development. Decision-making based on data and information related to the phenomenon under investigation and analysis forms an integral part of this process. A model utilizing independent cellular automata has been developed to incorporate spatial dimensions into such studies and to understand the spatial distribution of changes in geographical phenomena. This model serves as a tool to estimate spatial and temporal changes concurrently, leveraging geographic information systems (GIS) technologies.

Prediction, though essential, is a complex topic. It represents a branch of inferential statistics that aims to estimate the future magnitude of a phenomenon by analyzing data collected over previous, consecutive time periods. In the late 20th century, advanced predictive techniques emerged, introducing sophisticated models that revolutionized time-series analysis. These methods have become widely adopted by researchers, particularly in developed countries, due to their numerous advantages, providing reliable modeling and forecasting systems for various time-series datasets. Among these models is the Markov chain, introduced by the Russian scientist Andrei A. Markov in the early 20th century. Originally applied to describe the movement of gas particles within a closed container, the Markov chain was later adapted to predict their future behavior.

1.1 Research Problem

1. What are the dominant land cover and land use categories in the study area?
2. What changes in land cover and land use are anticipated in the projected maps for 2033 and 2043?

1.2. Research Hypothesis

The study hypothesizes significant changes in the area of land cover and land use categories in the study area due to various geographical factors. It also highlights the potential of remote sensing and GIS technologies in monitoring, analyzing, and classifying land cover in the region. These technologies enable the detection, monitoring, and prediction of spatial changes in geographical phenomena and the creation of accurate thematic maps for these phenomena based on satellite imagery.

1.3 Research Objectives

1. To identify and analyze land cover and land use categories using multi-temporal Landsat imagery for the years 2002, 2013, and 2023.
2. To predict future land cover and land use changes in the study area for 2033 and 2043 using the CA-Markov model.

1.4 Research Significance

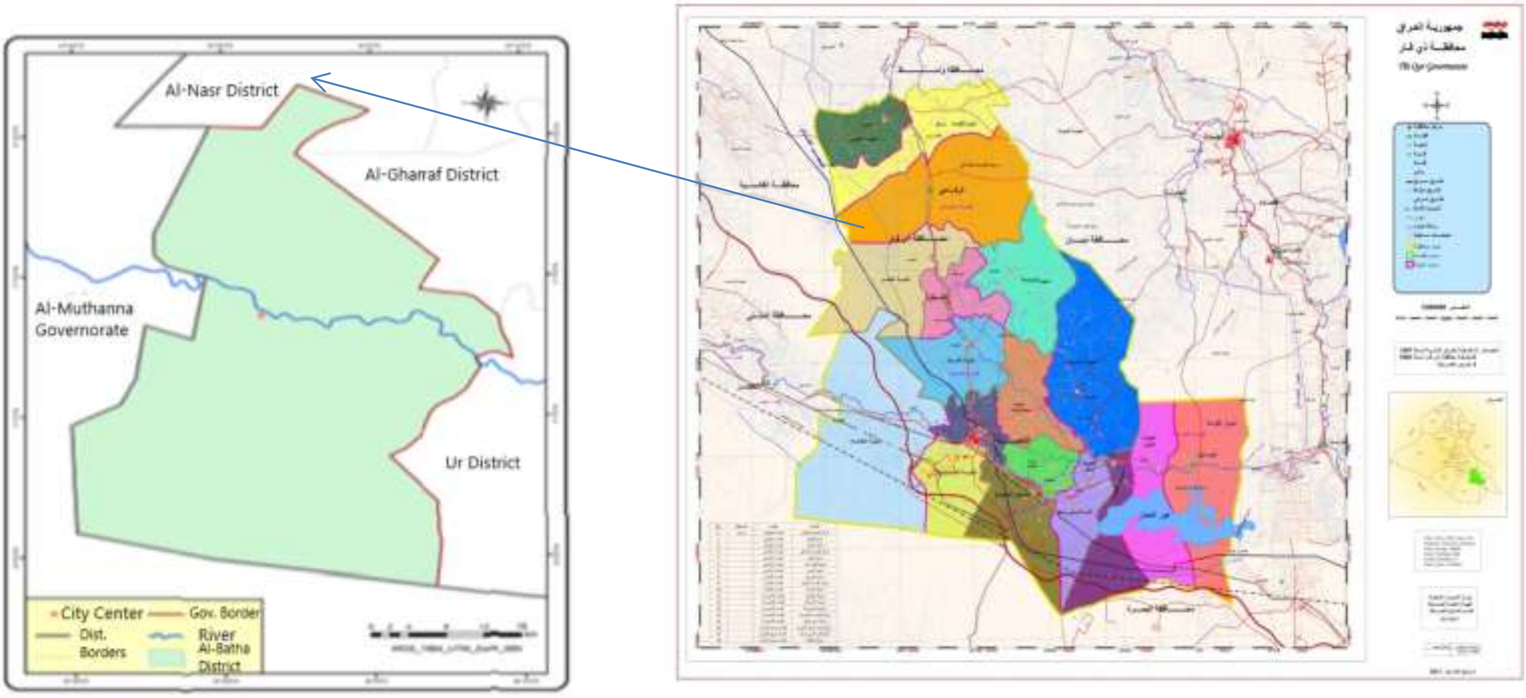
The significance of this study lies in detecting land cover changes in the study area to predict future changes for 2033 and 2043. The research aims to produce accurate thematic maps based on Anderson's classification system for satellite imagery and fieldwork within the study area. Furthermore, it emphasizes the role of remote sensing and GIS technologies in monitoring and analyzing these changes.

2. Study Area Location:

The study area is located in the southwest of Thi Qar Governorate, specifically in the Al-Batha sub-district, which is administratively part of Al-Nasiriya District in Thi Qar Governorate. It is bordered to the north by the Al-Nasr sub-district, to the east by the Al-Ur and Al-Gharraf sub-districts, and to the south and west by Al-Muthanna Governorate.

Geographically, the area extends between latitudes 30°48' and 31°25' N and longitudes 45°38' and 46°10' E. The total area of the region is 1,759.80 km², making it the largest sub-district in Thi Qar Governorate in terms of area. It serves as the southwestern gateway to Thi Qar Governorate, bordering Al-Muthanna Governorate. Refer to Map (1) for the location of the study area within Thi Qar Governorate.

Map (1): Location of the Study Area in Thi Qar Governorate.



Source: *Map of Thi Qar Governorate, Scale 1:250,000, Cartography Production Department, General Directorate of Surveying, Ministry of Water Resources, Baghdad, Iraq, 2011.*

Tools and Materials Used in the Study

1. **Satellite Imagery Used in the Study**

	Date Taken	Path	Raw	Satellite	Sensor
1	2002/1/18	38	167	Landsat-7	ETM+
2	2013/1/16	38	167	Landsat-7	ETM+
3	2023/1/12	38	167	Landsat-9	OIL

Source: EarthExplorer

2. **Maps Used**:
    1. Administrative maps
    2. Geological maps
    3. Topographic maps

4. Hydrological maps

3. **Field Visits**: Conducted for validation and data collection.

1.7 Software Used in the Study

1. **ArcGIS 10.5**: A comprehensive geographic information system (GIS) comprising various tools for performing spatial and logical operations, as well as building geographic databases.
2. **Erdas Imagine 2014**: A software specialized in handling satellite imagery for processing, analysis, and classification. It was used to process and classify satellite images in this study.
3. **ENVI 5.3**: A specialized software for processing, interpreting, and analyzing satellite imagery, including extracting information and detecting changes.
4. **TerrSet**: An integrated geographic software system developed by Clark Labs for analyzing and visualizing spatial data. It is also used to evaluate classification accuracy.
5. **Excel 2010**: A program for statistical data analysis and for creating charts and graphs.

3. **Methodology**

1. **Satellite Images**: Landsat images were downloaded from the USGS website, covering a 21-year period between 2002 and 2023.
2. **Image Processing**: Satellite images were processed using ENVI and ArcGIS 10.5 to enhance their spectral and spatial quality for easier classification, interpretation, and analysis.
3. **Supervised Classification**: Conducted using Erdas Imagine 2014 with the maximum likelihood method. Training samples were collected based on prior knowledge of the study area to assess classification accuracy.
4. **Change Detection**: Changes during the period 2002–2023 were analyzed using TerrSet software.
5. **Future Projections**: Accurate thematic maps for 2033 and 2043 were produced, showing land cover and land use areas using the CA-Markov model in TerrSet.
6. **Prediction Accuracy Assessment**: Accuracy was evaluated using the Kappa coefficient. Predicted maps were compared with the original land cover and land use maps to identify similarities and differences, ensuring the reliability of the analysis.

CA-Markov Model

The CA-Markov model is a key component of this study, as it integrates various modeling elements and is one of the most effective methods for modeling spatiotemporal changes in land cover and land use within GIS frameworks.

The **Markov model** is based on the first law of geography, using a proximity rule that posits that pixels near a specified land cover category are more likely to transition to that category. The model not only accounts for quantitative changes but also calculates the rate of transition between different land cover and land use types.

Markov Transition Matrix

The Markov transition matrix is a square matrix (N x N) that represents the probabilities of transitions between categories. The following conditions apply:

- Each element of the matrix must be positive and non-negative.
- The sum of each row in the matrix equals one.
  A specific user-defined filter, such as a 5 x 5 filter, is applied to perform this process.

Formula for Simulating Land Use and Land Cover Changes

The formula used for simulating land use and land cover changes is as follows (references provided where applicable):

$S(t,t+1)=Pij \cdot S(t)$

Explanation of the Markov Process

Transition System

- **S(t, t+1)**: The state of the system at a specific time
- **Pij**: Transition probability matrix

The Markov transition probability is expressed as follows:

$P=p11p21\vdots pn1p12p22\vdots pn2\cdots\cdots\ddots\cdots p1np2n\vdots pnn$

Based on rule:

- **P**: Markov transition matrix
- **Pij**: Probability of transition from one state to another

If the transition probability is close to zero, it indicates a low likelihood of transition. Conversely, probabilities close to one signify a high likelihood of transition.

4. **Prediction Implementation Using TerrSet**

The prediction process was conducted using the **TerrSet** software, developed by Clark University Labs, utilizing the hybrid **CA-Markov model**. This model combines cellular automata with statistical Markov chains to predict land cover and land use changes over specific time periods. It is one of the most widely accepted methods for spatial modeling in land use and cover change studies.

Given the precision required in prediction processes, which depend on reliable and sufficient data over a defined period, remote sensing data is the most suitable source for achieving this goal. Historical spatiotemporal data, represented by thematic maps classified at level two of the adopted classification system, were used. The system categorizes land into seven classes:

1. Field crop lands
2. Orchard lands
3. Other agricultural lands
4. Water bodies
5. Dry saline lands
6. Sandy lands

7. Sand dune lands

These classes were identified using satellite imagery classified with a 30-meter resolution to determine land cover and use changes up to 2033 and 2043. The process involved the following steps:

Steps to Simulate Land Cover Changes

1. **Raster Conversion to ASCII Format**:
   Files were converted to text format (ASCII) using **ArcGIS**, as TerrSet requires maps in this format for analysis. This is a raster file extension.
2. **Reclassification**:
   The Resample tool in TerrSet was applied for each year to ensure consistent resolution and categorization.
3. **Markov Modeling**:

   The Markov model in TerrSet was used to create spatial suitability maps and transition probability matrices for the period 2002–2023. These served as the basis for predicting land cover changes for 2033 and 2043. An error margin of 0.15% was set as a default in the software.
4. **Prediction of Future Changes**:

   The **CA-Markov model** was employed to predict land cover changes starting from 2023. Transition probability matrices and a starting year of 2023 were used, with the following parameters:

   - 10 iterations for projections to 2033
   - 21 iterations for projections to 2043
     A 5×5 filter, predefined by the software, was applied during these iterations.

Processing Time:

This stage requires significant computational time, ranging from 10 to 24 hours per operation, depending on the data and accuracy refinement needed.

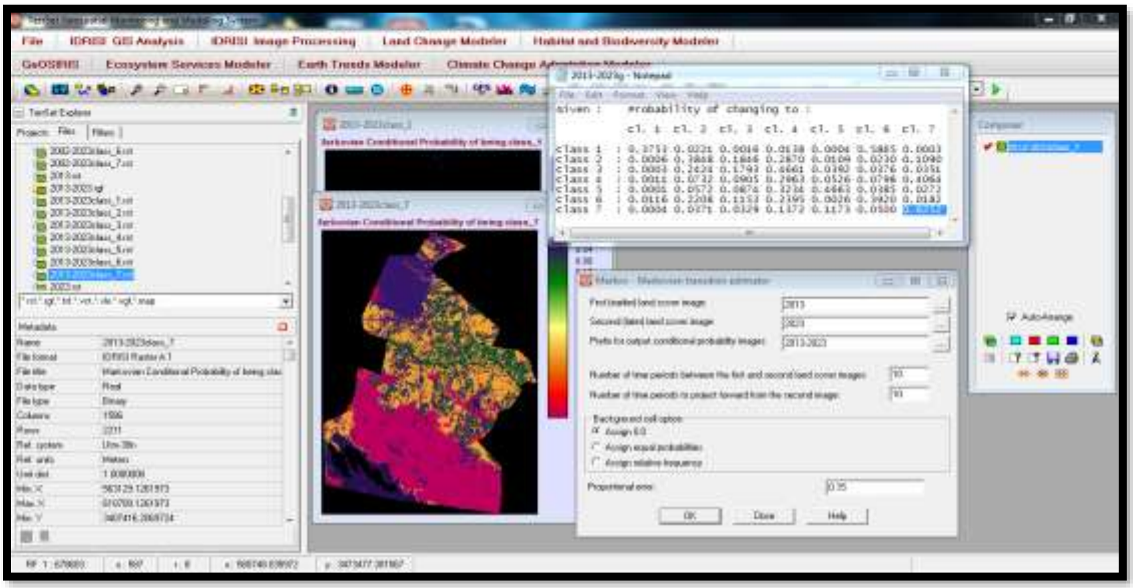
Table (1): Markov Transition Matrix for Land Cover Changes in 2033.

Category	Field Crop Lands	Orchards Lands	Other Agricultural Land	Water	Saline dry lands	Sandy lands	Sand Dunes
Field Crop Lands	0.3848	0.1846	0.287	0.0006	0.023	0.109	0.0109
Orchards Lands	0.2424	0.1793	0.4661	0.0003	0.0376	0.0351	0.0392
Other Agricultural Land	0.0732	0.0905	0.2963	0.0011	0.0798	0.4064	0.0526
Water	0.0221	0.0016	0.0138	0.3753	0.5865	0.0003	0.0004

Saline dry lands	0.0371	0.0329	0.1372	0.0004	0.05	0.6252	0.1173
Sandy lands	0.2208	0.1153	0.2395	0.0116	0.392	0.0182	0.0026
Sand Dunes	0.0572	0.0874	0.3234	0.0001	0.0385	0.0272	0.4663

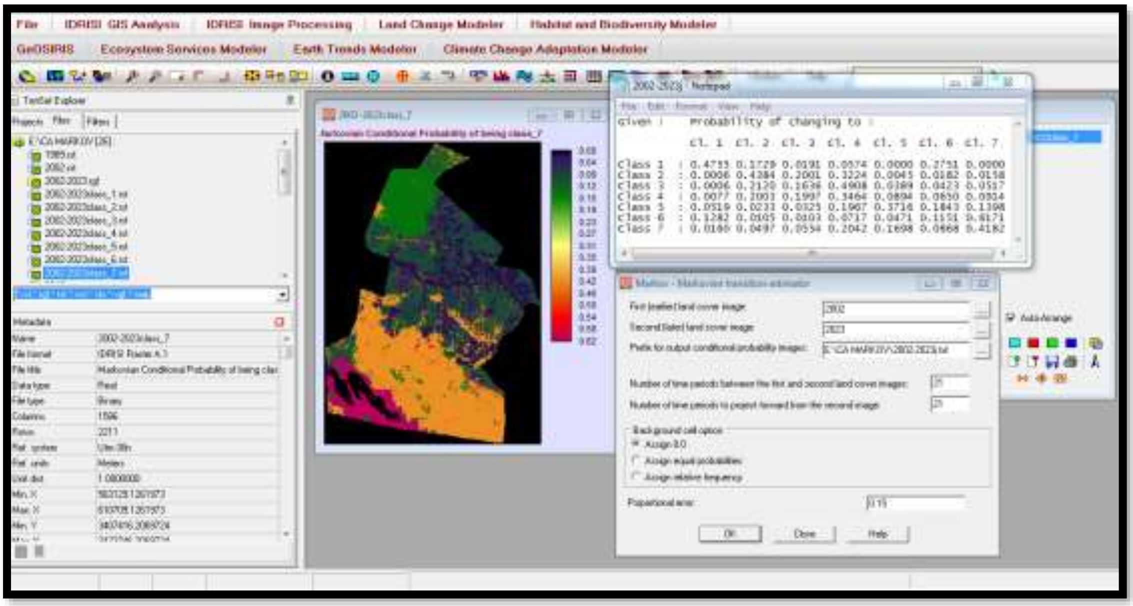
Source: *Researcher's work based on the TerrSer program, the Markov model and classified maps (2013-2023).*

Figure (1): Markov matrix for predicting the future of land cover types for the year 2033



Source: Researcher's work based on TerrSet program

Figure (2): Markov matrix for predicting the future of land cover types for the year 2043.



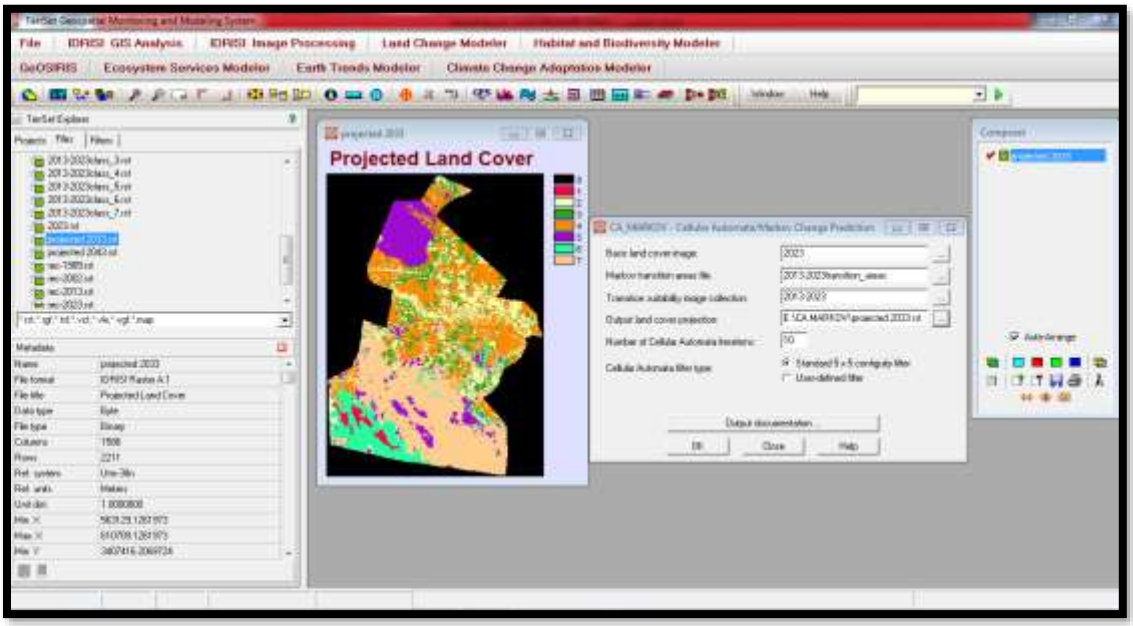
Source: *Researcher's work based on TerrSet program*

Table (2): Markov transition probability matrix for land cover changes for the year 2043.

Category	Field crop lands	Orchards lands	Other Agricultural land	Water	Dry saline lands	Sandy lands	Sand dunes
Field crop lands	0.4384	0.2001	0.3224	0.0006	0.0182	0.0158	0.0045
Orchard lands	0.212	0.1636	0.4908	0.0006	0.0423	0.0517	0.0389
Other agricultural lands	0.2003	0.1997	0.3464	0.0077	0.065	0.0914	0.0894
Water	0.1729	0.0191	0.0574	0.4755	0.2751	0	0
Dry saline lands	0.0105	0.0103	0.0717	0.1282	0.1151	0.6171	0.0471
Sandy lands	0.0497	0.0554	0.2042	0.016	0.0868	0.4182	0.1698
Sand dunes	0.0233	0.0325	0.1967	0.0519	0.1843	0.1398	0.3716

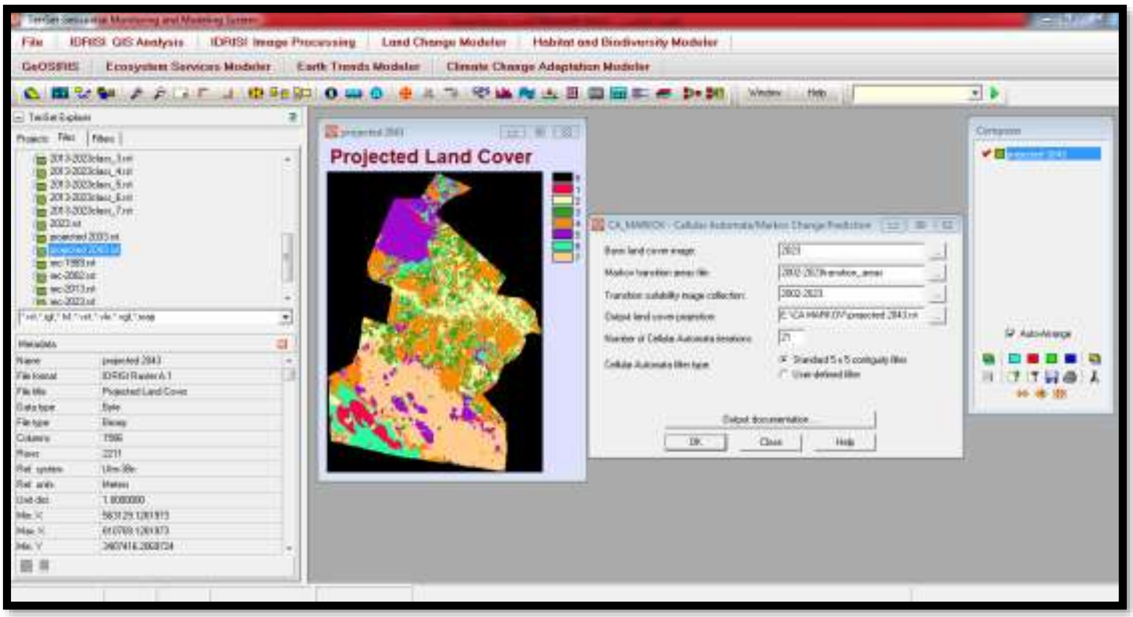
Source: *Researcher's work based on the TerrSer program, the (Markov) model and classified maps (2002-2023).*

Figure (3): How to apply the (CA-Markov) model in the TerrSet program for the year 2033



Source: *Researcher's work based on TerrSet program and (CA-Markov) model*

Figure (4): How to apply (CA-Markov) model in TerrSet program for the year 2043



Source: Researcher's work based on TerrSet program and CA-Markov model

5. **Statistical Accuracy Assessment Using the Kappa Coefficient for Predicting 2033 and 2043**

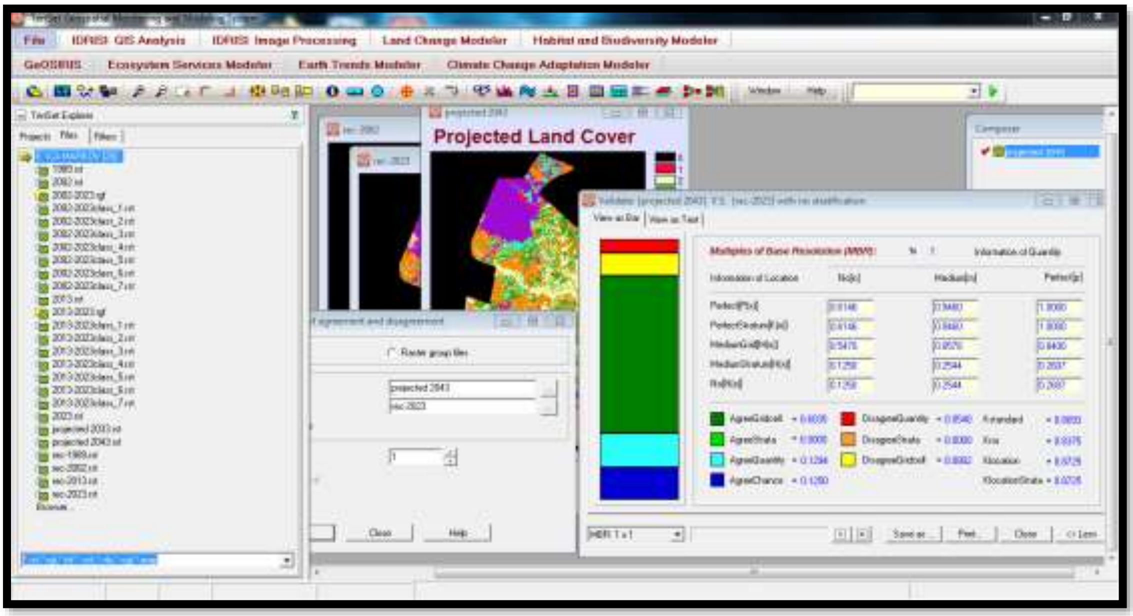
The significance of the prediction process in this study lies in the accuracy of the prediction results, which fundamentally depend on the correct application of the model used to obtain the final outcomes. One of the most important methods for evaluating the accuracy of this model is by comparing the simulation results with the reference map or by using the Kappa coefficient of agreement (kappa) (5). Based on this, the accuracy of the predicted future change maps was assessed by visually comparing them with the 2023 map, as well as calculating the Kappa coefficient in **TerrSet**, which is considered one of the main indicators used in many studies focused on land cover prediction using the **CA-Markov model**. It provides a reliable summary of agreement based on the total number of pixels, making it a useful tool for evaluating the accuracy of prediction results as used by many researchers (6).

After conducting the accuracy assessment, it was found that the level of agreement and disagreement between the base map of 2023 and the predicted map for 2033 yielded a Kappa coefficient of **0.8446** (84%), which is considered very high. Similarly, the agreement and disagreement between the base map of 2023 and the predicted map for 2043 resulted in a Kappa coefficient of **0.8725** (87%), which is also very high. This indicates that the prediction process was conducted with a high degree of accuracy.

Figure (5): Accuracy Assessment Method in TerrSet for 2033.

Source: *Researcher's work based on TerrSet program*

Figure (6): Method of evaluating accuracy in TerrSet program for the year 2043



Source: Researcher's work based on TerrSet program

After conducting the prediction process and obtaining the future change maps for 2033 and 2043, as shown in **Maps (2) and (3)**, **Table (3)** illustrates the percentages and areas of land cover classes and land use for the period from 2023 to 2033. The area of field crops is expected to reach **206.08 km²** in 2033, up from **186.16 km²** in 2023. The water class, however, saw a reduction in area, decreasing from **53.84 km²** in 2023 to **22.51 km²** in 2033. Other land cover classes, such as orchards, other agricultural lands, saline lands, sandy lands, and dunes, showed minimal change in their areas, which is a positive sign considering the expected population growth and the related urban, industrial, and suburban expansion. This is confirmed by the transition probability matrix (Markov) in **Table (1)**, where the horizontal values (rows) represent changes until 2023, and the vertical values represent future changes for the period 2013–2023. The table intersections indicate the probability of change by 2033, showing potential transitions of land cover classes. Most of the land cover classes exhibited relatively stable probabilities of transition, ranging from **0.3848** for field crops, **0.1793** for orchards, **0.2963** for other agricultural lands, and **0.3753** for water, of which a portion shifted to saline land with a transformation probability of **0.5865**. The probability of transition to saline land was **0.0500**, with a transformation rate of **0.6252** to sandy lands. The probability of transition for sandy lands was **0.0182**, and for dunes, it was **1.4663**, with a transformation rate of **0.1175** towards saline lands.

These results indicate a degradation of the water class, with most of its areas transitioning into saline lands, a portion of which then became sandy lands.

As shown in **Table (4)**, the percentages and areas of land cover and land use for the period from 2023 to 2043 are outlined. The area of field crops is expected to reach **242.62** km² in 2043, up from 186.16 km² in 2023. The water class has increased in area, from 53.84 km² in 2023 to 67.90 km² in 2043. However, the sandy land class is the only class that has decreased in area, shrinking from 583.55 km² in 2023 to 413.08 km² in 2043. Additionally, most of the land cover classes, such as orchards, other agricultural lands, saline lands, and dunes, have shown relative increases compared to 2023 and the expected 2033 values. This difference between the 2033 and 2043 projections may be due to the fact that the 2033 forecast was based on the past ten years, whereas the 2043 forecast was based on the past twenty years. This is also a positive sign, given the expected population growth and the related urban, industrial, and suburban expansion.

These findings are further supported by the transition probability matrix (Markov) in Table (2). The horizontal values (rows) indicate the changes up to 2023, while the vertical values represent future changes for the period from 2002 to 2023. The intersections of the table show the probability of change up to 2043, i.e., the likely transitions of land cover classes. Most classes exhibit relatively higher probabilities of transition, ranging from 0.4384 for field crops, 0.1636 for orchards, 0.3464 for other agricultural lands, and 0.4755 for water. The transition probability for saline lands was 0.1151, with a transformation rate of 0.6171, at the expense of sandy lands, while the transition probability for sandy lands was 0.4183, and for dunes, it was 0.3716, with a transformation rate of 0.1175.

These results show an overall increase in most land cover classes, particularly field crops and water, suggesting a positive trend driven by urbanization and population growth. However, the reduction in sandy lands indicates a shift in land use patterns, possibly due to changes in agricultural practices or land reclamation.

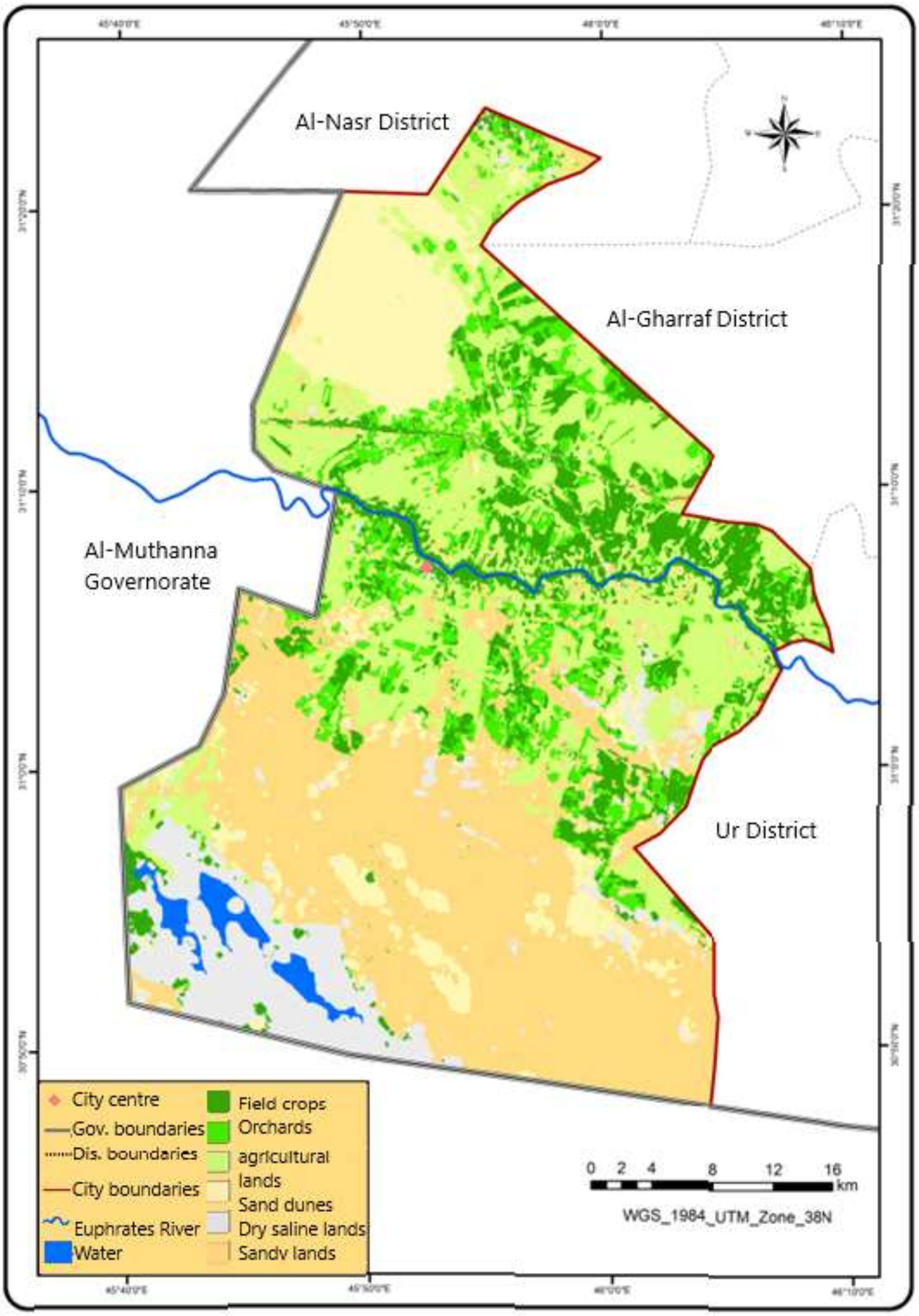
Table (3): Percentages and Areas of Land Cover and Land Use for the Period 2023–2043 in the Study Area

Category	**2023**		**2043**	
	Area km2	**Rate %**	**Area km2**	**Rate %**
Field crops	186.16	10.57	242.62	13.78

Orchards	150.3	8.54	187.78	10.67
Other agricultural lands	420.12	23.87	455.69	25.89
Water	53.84	3.05	67.9	3.85
Dry saline lands	143.56	8.15	160	9.09
Sandy lands	583.55	33.16	413.08	23.47
Sand dunes	222.22	12.62	232.7	13.22
Total	1759.8	100	1759.8	100

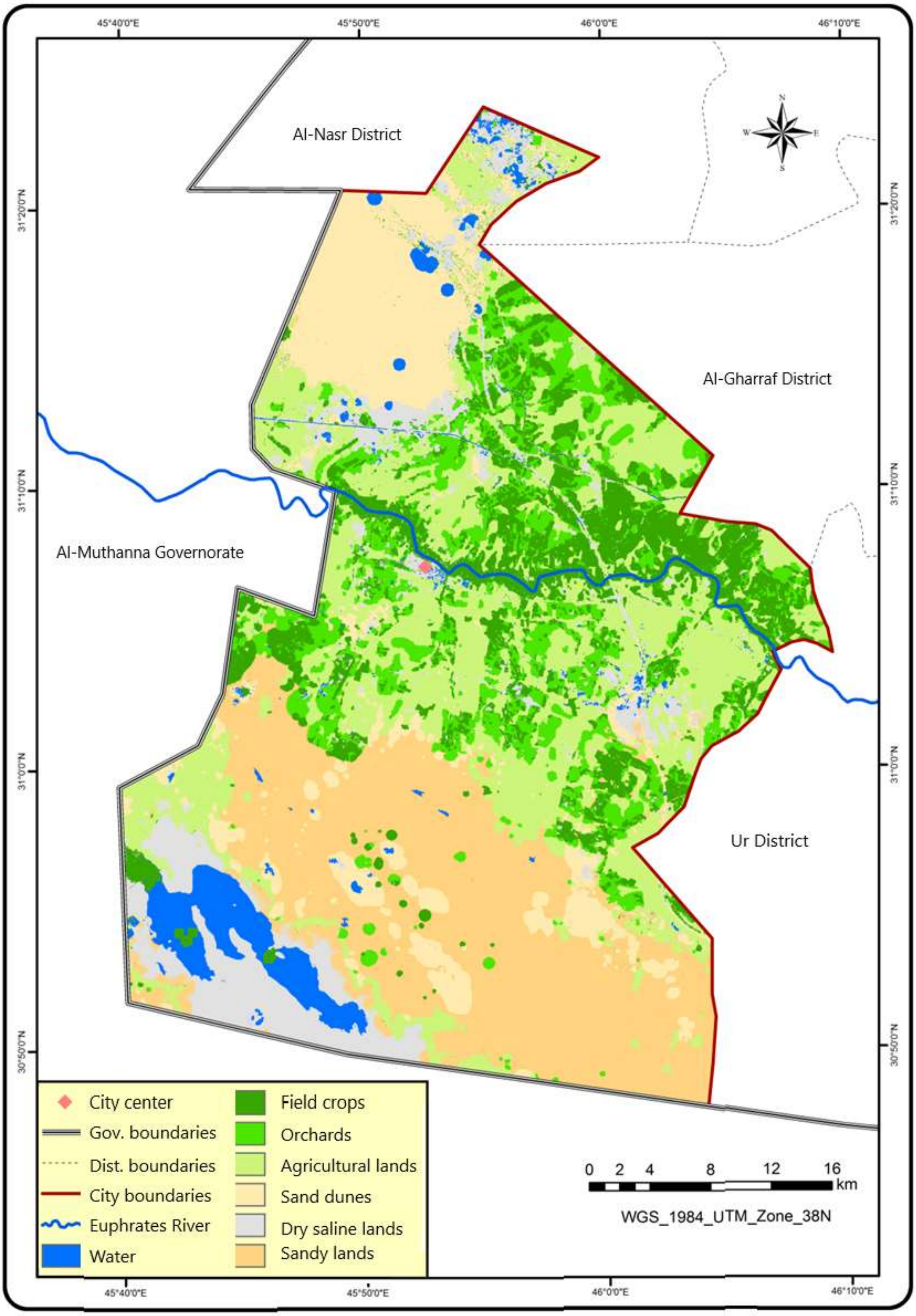
Source: *Researcher's work based on TerrSer program and classified maps 2023.*

Map (2): Future prediction of land cover and land use changes for the year 2033.



Source: *Researcher's work based on the change detection technique in the TerrSet program and the ArcGis program*

Map (3) Future prediction of land cover and land use changes for the year 2043



Source: *Based on the researcher's work utilizing change detection techniques in TerrSet and ArcGIS software.*

6. Conclusions:

1. The study concluded that, through the application of the future simulation model using LCM modeling and the CA-Markov model, future land cover and land use changes for the study area, located in the southwest of Dhi Qar Governorate, specifically in the Al-Bathaa district, were predicted for the years 2033 and 2043.

2. The results of applying LCM modeling and the CA-Markov model showed that the area of field crops will reach 206.08 km² in the projected year 2033, up from 186.16 km² in 2023. The water category, on the other hand, showed a decrease in area, from 53.84 km² in 2023 to 22.51 km² in 2033. Meanwhile, the area of other land categories, such as orchards, other agricultural lands, saline lands, sandy lands, and sand dunes, remained almost unchanged.

3. Furthermore, the predictive results showed that the area of field crops will reach 242.62 km² in 2043, up from 186.16 km² in 2023. The water category showed an increase in area, from 53.84 km² in 2023 to 67.90 km² in 2043. The only category that showed a decrease in area was sandy lands, which will reduce from 583.55 km² in 2023 to 413.08 km² in 2043. A relative increase was observed in most categories, such as orchards, other agricultural lands, saline lands, and sand dunes, compared to 2023 and the projected 2033. This difference between the predictions for 2033 and 2043 may stem from the fact that the 2033 prediction relied on the past ten years, while the 2043 prediction was based on the past twenty years.

4. The study demonstrated the ability to predict land cover and land use changes by leveraging past and present data to forecast future changes, using various prediction techniques and models, such as Markov Chains, particularly the **CA-Markov** model, which allowed us to predict land cover changes for 2033 and 2043.

Recommendations:

1. It is essential to emphasize the integration of remote sensing techniques with geographic information systems (GIS) to monitor, analyze, interpret, and predict future land cover changes, as well as to generate detailed maps for these changes.

2. It is recommended to conduct periodic ground surveys and continuously monitor and update land use changes, relying on high-resolution satellite imagery.

3. The **CA-Markov** model should be further emphasized for predicting future land cover and land use, as its results are highly accurate and closely aligned with reality.

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