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The Detection of Agricultural Land Changes Using Deep Learning and Open-Source Images

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ABSTRACT

Land cover assessment is a significant research area in GIS and remote sensing, aiding decision-makers in understanding the underlying forces of land use changes and enabling effective actions. In general, Iraqi cities are experiencing severe degradation of agricultural lands due to population growth and residential development, which impacts both socio-economic conditions and environmental quality. Additionally, the driving forces behind the transformation of agricultural lands to other land cover types are not well understood. Therefore, research is needed to map and assess agricultural lands for better economic and environmental solutions.
This study employs ANN-CA integration to predict agricultural land changes in Babil province, central Iraq. The CNN model achieved the highest accuracy, with a total land cover transformation of 2,143.1 square kilometers between 2000 and 2020. The overall accuracy was 0.95, 0.93, and 0.90 based on images captured in 2020, 2010, and 2000, respectively. This methodology is considered an efficient tool for monitoring agricultural lands and developing sustainable development plans in Iraq.

1. Introduction

Land cover mapping and thematic change assessment are crucial research areas in GIS and remote sensing. They help urban planners understand changes' forces, make better decisions, and minimize malicious effects. Accurate maps are essential for socioeconomic, urban, and environmental applications. Remote sensing is the basic source of information to produce land-cover maps. For instance, Landsat imagery provides new perspectives in remote sensing data analysis and it can solve the data availability issues in developing countries as they are

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free. However, in developing countries like Iraq, most of the changes occur almost randomly or the changes deriving forces are not well understood or predictable.

Population growth in Iraqi cities since 1990 has led to severe degradation of agricultural lands, which affecting socio-economic and environmental conditions, and affecting quality of life. In addition, the deriving forces of transforming the lands from agricultural to other land cover types are not well understood. As a result, research is needed to map and assess the agricultural lands in the Iraqi cities to provide solutions for a better economic and clean environment. Technically, several methods can be used to classify satellite images and extract land cover maps of the study areas and use the obtained maps to assess agricultural land changes and also project the change into the near future for better planning ahead of the potential crises.

Traditional land cover mapping classification models, based on probability and statistical theory, use satellite imagery spectral bands. Advanced models, developed using machine learning, are now the trending tool for land cover mapping. Jamali (2020) used advanced machine learning models, including ANNs, SVM, and GAMLP, to extract land cover in Shiraz, Iran between 1990 and 2018, with GAMLP outperforming others. Additional data, like elevation and environmental data, can be integrated with satellite imagery for classification. On the other hand, Sturari, Frontoni, Pierdicca, Mancini, Malinverni, Tassetti, and Zingaretti (2017) utilized elevation data and satellite imagery for land cover mapping, enhancing classification in mountainous farmlands and urban areas like Ancona, Italy. In another study, Talukdar et al.'s 2020 study compared three indices for land cover mapping: normalized differentiation water index, normalized difference vegetation index, and normalized difference built-up index, based on the random forest classifier, they showed that these indices perform well at 0.96, 0.99 and 1, respectively. The Cellular Automata (CA) is an efficient tool for characterizing land cover types via preliminary conditions, the engagement with neighborhoods, and transition (Walsh, Entwisle, Rindfuss, & Page, 2006). However, the standard CA model takes only historical Landsat images to make predictions on future land changes. The additional model should be integrated with CA to allow the inclusion of derived forces for the land changes. Models like regression ANN can be used to predict land transformation transition metrics, and CA can use the results to make more accurate predictions of future land cover.

Numerous studies were conducted at the level of Iraq to assess land cover changes. There is a dearth of studies that specifically focus on agricultural lands. For instance, Al Hillah district is considered one of the most important agricultural areas in Iraq; it has recently been subjected to significant transformation of lands from agriculture to other types of lands. The novelty of this study is the evaluation of agricultural changes in a novel area of interest in Hillah (Babil, central Iraq) during the last two decades (2000–2020) using multitemporal Landsat images. Our main contributions are comparing two machine learning models, SVM and ANN, for classification and a deep learning model (CNN). We did this by using Landsat images to make a land cover map for the study area and doing a change detection analysis to figure out how things changed between years, like from 2000 to 2020.

2. Literature review

Cellular Automata (CA) was combined with machine learning algorithms (e.g., SVM and ANN) to optimize the precision and the reliability of land cover change rule derivation. Qiang and Lam (2015) used an ANN algorithm to assess land cover transformation depending on 15 social and natural variables, which they then employed in a CA model to simulate future land cover scenarios at a regional level in the United States. They demonstrated that ANNs can accurately derive land cover change rules and precisely simulate land cover scenarios (above 92 percent on average). In North Sumatra, Indonesia, a combined ANN-CA was used to predict the transformation of land cover/land use (Saputra & Lee, 2019). They predicted based on five variables: elevation, aspect, slope, soil type, and the proximity to roads. They discovered that the elevation and the proximity to roads had significant effects when compared to other variables. ANN was used to prepare land cover transition rules (2004, 2006, and 2018), and the outputs were used by a CA model to predict future land cover scenarios for Warangal city, India (Aneesha Satya, Shashi, & Deva, 2020). Kafy's team recently combined CA and SVM to provide future scenarios of land cover transformation in Dhaka, Bangladesh (Kafy, Naim, Subramanyam, Ahmed, Al Rakib, Kona, & Sattar, 2021).

Several studies in Iraq have utilized CA and Markov models to estimate land cover over cities. For example, Hameed (2016) used the CA to examine changes in LULC in Baqubah, Iraq, from 2004 to 2010. The results of their simulations were checked using a multi-resolution method based on an 81.5 percent fuzzy similarity index, and they showed good fit with historical reference data. Usually, the Markov chain framework is used in conjunction with the CA model to estimate the change of LULC in the future. In another study, Deep and Saklani (2014) demonstrated how such integration can aid in the effective study of urban dynamics in rapidly expanding cities. the integration of CA and Markov models was also employed for the evaluation of urban sprawl in Karbala, Iraq. As presented by Aal-shamkhi, Mojaddadi, Pradhan, and Abdullahi (2017). They began by extracting land cover data using an object-based classification method. CA-Markov framework was then used to forecast the future scenarios for the changes in urban lands. They demonstrated that such forecasts can facilitate the determining of the spatial growth of urban areas. Land cover transformations in Tikrit, Iraq (2000–2010), were assessed, and the data was used to predict the 2030 scenario using the CA-Markov framework (Hadi, Shafri, & Mahir, 2014). Also, the CA-Markov framework was used with IDRISI software to model how Al-Najaf, Iraq, will grow in the future (Ali, Amany, & Jalil, 2020); they used data from 1986 to 2016 to guess what the land cover would be in 2036. They demonstrated that such models can aid in the evaluation of the rapid land use transformation and its consequences on the social economy and the environment.

Baghdad, Iraq's capital city, suffers from urban sprawl and has extremely congested roads. Hence, the forecasting of the future transformation in the land cover is a critical task for better planning urban developments and reducing the environmental impacts on humans in the area. Mohamedmeki and Al-Mumaiz (2020) provide a multi-land use framework for developing areas for domestic and commercial purposes while limiting consumption and increasing the city's greener coverage.

According to research concerning Iraq, few studies considered agricultural lands. Such areas require an advanced method for the assessment of transformation in agricultural lands. To evaluate how agricultural land has changed over the next 20 years (2020–2020), this study combined a deep learning algorithm with cellular automata and used open-source remote sensing data (Landsat).

3. Methodology and data

3.1. The overall methodology

This study aims to assess agricultural land changes over the center of Babylon Province in the middle of Iraq by using a framework that integrates cellular automata and machine learning. It aims to analyze time-series satellite images over the last two decades (2000–2020) to determine the transformation of agricultural lands. The proposed framework is depicted in Figure 1. The methodology includes several steps; the first step is conducted to prepare multitemporal Landsat satellite images (2000, 2010, and 2020) for the study area. In the second step, classification models based on SVM, ANN, and CNN algorithms are used to make land cover maps of the study area using Landsat imagery data. In the last step, change detection analysis is used to make an assessment map showing how the different types of land cover have changed in the area of interest.

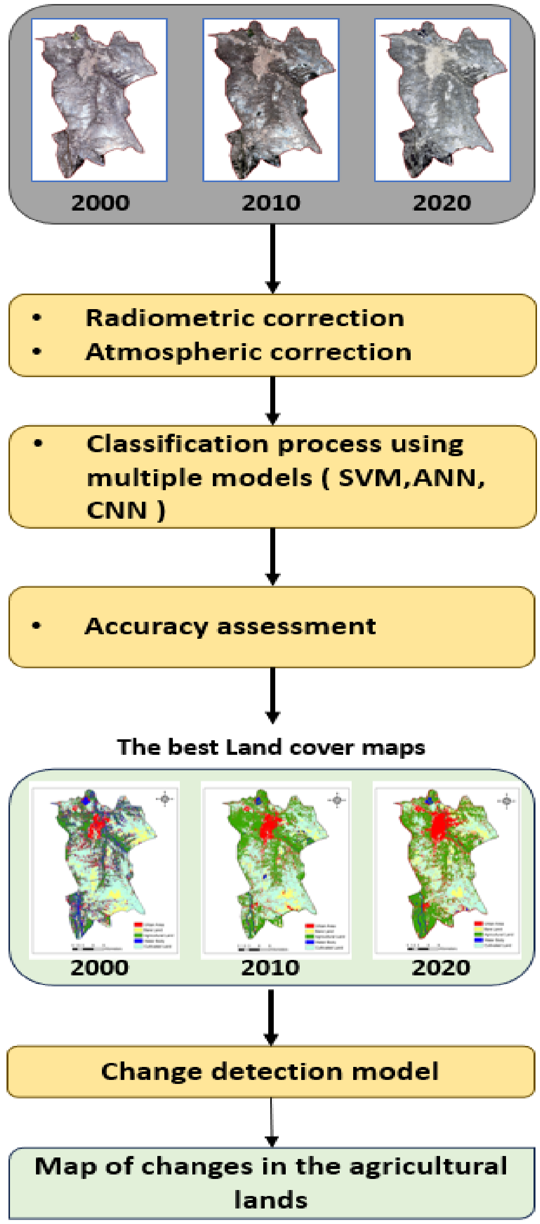

Fig. 1 the proposed methodology

3.2. Case Study

This research takes the area of Babil, central Iraq, as a case study to assess and project agricultural land changes using the proposed models. The study area is geographically bounded by (44˚15′0″ E, 32˚30′0″N) and (44˚35′0″ E, 32˚10′0″ N). Al-Hillah city is the capital of Babil province, established at the eastern side of the Euphrates, south of Baghdad (Figure 2). In general, Babil governorate is known for its agricultural activities due to the availability of fertile soil and irrigation water. As a result, there is a huge area of farmlands distributed alongside the Euphrates. On the other hand, it includes several activities such as trading, education, and tourism. It contains the famous historical city (Babylon). It's also characterized by a warm, dry climate during the summer and a moderate climate during winter. The population in the city as estimated in 2020 was about 643,328 (Nasser & Ibrahim, 2022).

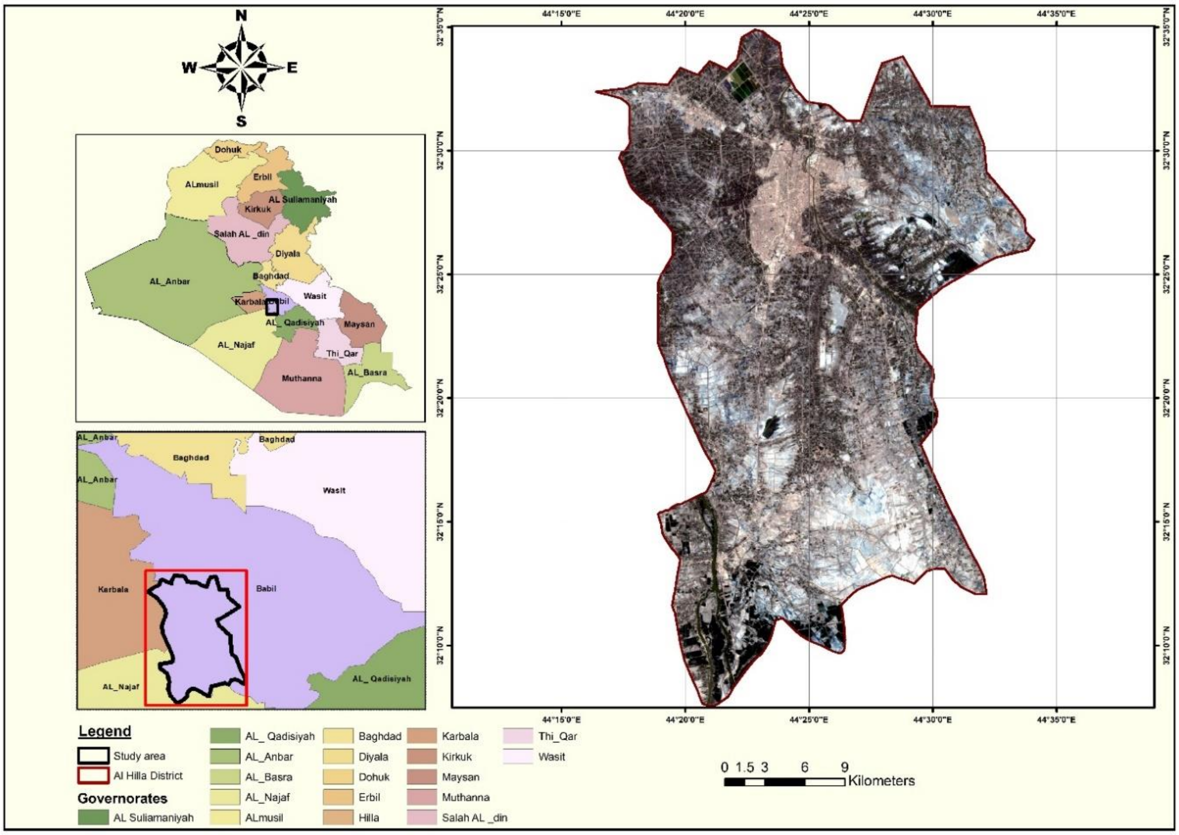

Fig. 2 Al- Hillah district map

3.3. The Image Acquisition

Three Landsat images were acquired and employed in the proposed method. In general, Landsat images are suitable for multidate image analysis, especially for studies that depend on data from old archives. Therefore, even though the higher-resolution data, like Sentinel-2, is considered more suitable for image classification, it is not suitable for our case. We utilized imagery data prior to the launch of the Sentinel-2 satellite. Two different Landsat sensors were used (Landsat7 (ETM+)) and Landsat8 (OLI)), Table 1 describes Landsat7 and 8 specifications.

Table 1 – Details of the Landsat7 (ETM+) and Landsat8 (OLI).

Sensors	Landsat7 (ETM+)	Landsat8 (OLI)
Launch date	15 April 1999	11 February 2013
No. of spectral bands	10	11
Spatial resolution	15 m	15m
Temporal resolution	16 days	16 days

The images covered the study area in the years (i.e., 2000, 2010, and 2020), which were downloaded from the USGS website. Table 2 describes the collected Landsat image details. The dataset was organized in ENVI software and preprocessed in a custom tool programmed in the Python programming language. The classification was performed using the popular Sklearn library in Python. The change assessment and prediction were conducted in Python using open-source libraries, including Scikit-learn, Keras, and NumPy.

Table 2 – Details of the Landsat dataset.

Year	2000	2010	2020
Path	168, 169	168, 169	168, 169
Raw	37, 38	37, 38	37, 38
Date of acquisition	10/9/2000	22/9/2010	24/9/2020
Cloud cover	0	0	0.04

3.4. The scientific background of used models

3.4.1. Convolutional Neural Network (CNN)

The standard CNN architecture employed for the classification process is shown in Figure 3, which comprises seven layers, including the input and output layers. The imagery data converted to array data, then the array data were exported to CNN model, the first process in CNN model is the application of convolutional analysis to derive several information and produce the feature map. The second process is known as the pooling layer (i.e. 2D max-pooling), which implemented to generalize the information resulted from the feature map to decrease the computations. The third step is called the flattening process that includes the transformation of generalized feature map to isolated feature vector. The fourth step is the application of a deep fully connected neural network model to learn numerous contextual information from the input features and provide the classification layer to the next process. The final step involves the final prediction of image classes depending on the softmax layer (Schmidhuber, 2015).

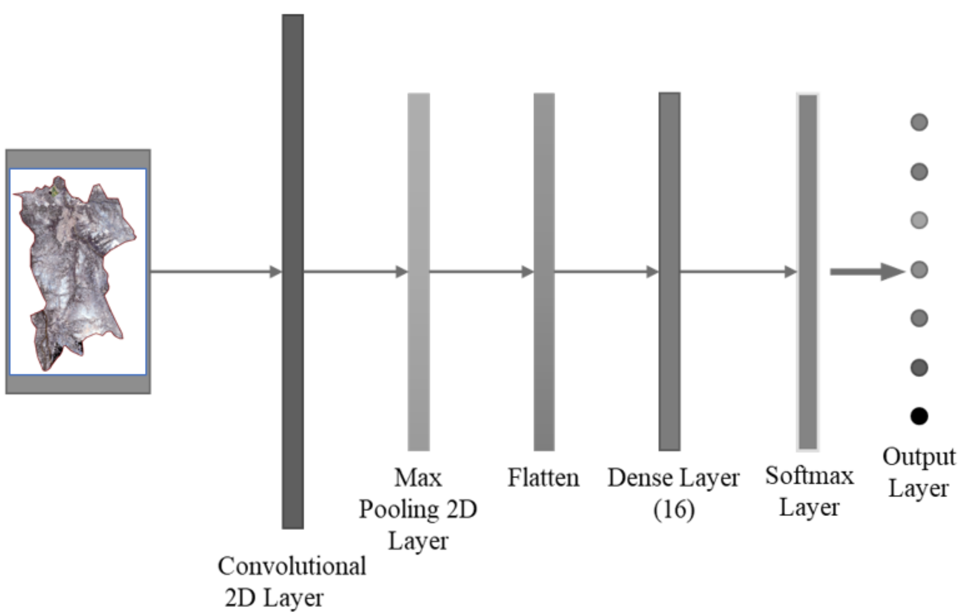

Fig. 3 CNN architecture

3.4.2. Support Vector Machine (SVM)

SVM models are the most popular supervised classifiers, they considered a shallow learning models, which work depending on the reduction of structural risk (Yao et al. 2008). SVM models generate a hyperplane or group of hyperplanes the original space between the points belonged to different classes (Marjanovic et al. 2011), then the classification decision conducted based on the proximity of point to the nearest hyperplane. On the other hand, the hyperplane requires the adjustment of the kernel to perform the classification process. The most basic kernels used for SVM model (i.e. Radial Basis Function kernel, Linear Kernel, Sigmoid Kernel, and Polynomial Kernel).

3.4.3. Artificial Neural Network (ANN)

ANN algorithms are particularly organized in layers. The simple layer comprises a set of processing elements (i.e., neurons). Each neuron receives and analyze and transmit information to another connected neuron. In this study, Multilayer Perceptron neural network (MLP) is used for the classification. The basic architecture of MLP is shown in Figure 4, which includes three elements (input layer, hidden layers, and output layer). The input layer receives and transmit the input data as a weighted signals to the hidden layers. Which in turns processed the signals using an activation function (i.e. sigmoid) and transmit the output signals to the subsequent neurons. The learning process depends on the loss function that mainly depends on the difference between the actual and predicted values. The network propagates information until it generates the final decision (i.e. Output).

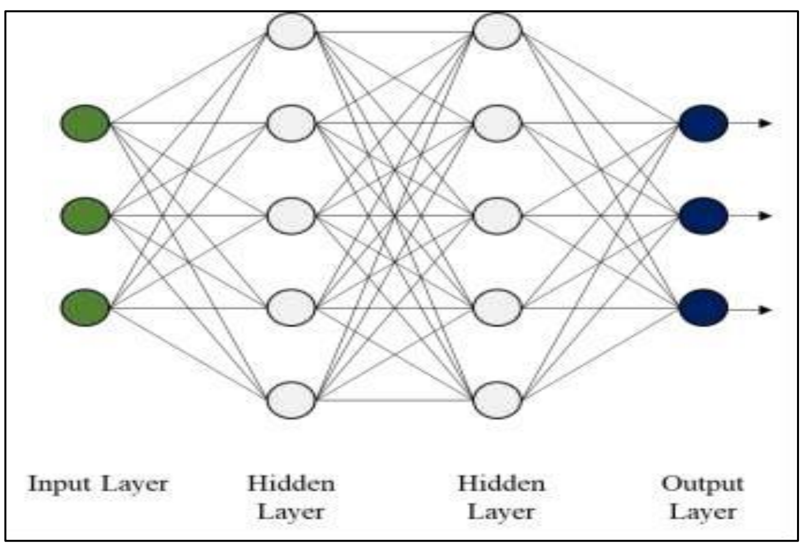

Fig. 4 A typical ANN with two hidden layers

3.4.4. Hybrid ANN-CA

Cellular automata (CA) is a nonlinear dynamic mathematical algorithm with discrete time and space dimensions.CA evolves in discrete time steps by updating its states (i.e., cell values) in accordance with a universal and synchronous transition rule that applies to each cell at every time step. Each cell's value is determined by a geometric configuration of adjacent cells described in the transition rules. Individually changed cell values become inputs for the following iteration. Based on the rules defined, an initial cellular adjustment, which is a type of cellular map including a primary state of each cell, develops as iteration proceeds. One distinguishing feature of CA is the ability of simple local rules to produce complex global behavior across the entire cellular space. The fundamental principle that extracts the system via time is relied on the idea of the change of cells and their impacts on other cells in their immediate vicinity.

3.5. The models implementation

The methodology comprises several steps; the first step includes the data pre-processing step where the dataset (Landsat 7 and Landsat 8) for dates (2000, 2010, 2020) was organized and pre-processed in ENVI software, including the radiometric calibration and atmospheric correction to convert the pixel values to reflectance value. The ground truth data were collected manually. The classification was performed using the popular Sklearn library in Python. The change assessment and prediction were conducted in Python using open-source libraries, including Scikit-learn, Keras, and NumPy. CNN's modeling is performed using the Python libraries Keras and Scikit-learn. Basically, the CNN model requires fine-tuning to adjust hyperparameters. Therefore, in this study, empirical experiments were conducted on a subset of data to adjust the training parameters. The analyses reported that CNNs reached the ideal state with the learning rate, learning rate decay, and epoch number (0.001, 0.001/100, 500), respectively.

The SVM model was performed using the Python language based on the scikit-learn library and the non-linear kernel, which is suitable for image classification tasks. And the ANN model was also implemented using Python with a library (TensorFlow and Theano) with Nesterov momentum. The learning rate and learning rate decay were set at 0.001 and 0.001/100, respectively. The ANN model was trained for 500 epochs with early stopping criteria set to the patience of 15 epochs, monitoring the validation loss. The data visualization was implemented using the Matplotlib library. The accuracy assessment was conducted using the Python library. On the other hand, the cellular automata model was implemented using the Python library (CellPyLib).

4. Results and discussion

The first data obtained from the proposed method is the land cover maps that created based on three years (2000, 2010, and 2020) and by applying three classifiers (SVM, ANN, and CNN), the classification performance was assessed based on three methods, the Overall accuracy, F1-score, Kappa coefficient. The result of the overall accuracy indicated that CNN classifier was reached the highest value of 0.95, 0.93, and 0.90 for images (2020, 2000, 2010) respectively. While other classifiers achieved lower accuracy than CNN model. On the other hand, CNN classifier achieved F-score values (0.95, 0.94, and 0.93) based on images captured during (2020, 2010, and 2020). Moreover, kappa coefficient recorded the highest value (0.95) based on CNN model based on the image captured in 2020, and its achieved 0.94 and 0.93 based on images that dated in 2000 and 2010 respectively. Table 2 illustrates the result of the accuracy assessment of the classification of three images that dated in (2000, 2010, and 2020). According to the classification result, CNN have achieved the highest accuracy (OA, F1-score, and Kappa). Therefore, we conducted the change detection assessment based on the result of CNN classifier. Figure 4 shows land cover maps.

Table 3 – The accuracy results of the image classification.

Dataset	2000			2010			2020		
Model	**OA**	**F1-score**	**Kappa**	**OA**	**F1-score**	**Kappa**	**OA**	**F1-score**	**Kappa**
SVM	0.82	0.82	0.80	0.77	0.90	0.88	0.93	0.93	0.91
ANN	0.78	0.78	0.75	0.72	0.87	0.85	0.88	0.88	0.85
CNN	0.93	0.93	0.94	0.90	0.94	0.93	0.95	0.95	0.94

According to the change detection results, the transformation between land cover types is calculated from (2000-2010), (2010-2020), (2000-2020). The total transformation from different land cover (Cultivated Land, Urban Areas, Water Body, and Bare Land) to agricultural lands during the period between 2000 and 2010 is 6,41 square kilometers. On the other hand, the transformation from agricultural lands to other types of land cover such as (cultivated land, urban Areas, waterbody, and bare land) is 734.3 square kilometers. While the total transformation to agricultural lands during 2010-2020 is 3455.2 square kilometers and the transformation from agricultural lands to other types of land cover is 10031 square kilometers. During the period from 2000 to 2020, the total transformation to agriculture lands is 2143.1 square kilometers. And the total transformation from agricultural lands to other types of land cover is 2071.1 square kilometers. Figure 5 illustrates the map of the land cover changes that included the changed and the non-changed areas. The map shows a significant change in the land cover of the area of interest during the period (2000-2020). While, Figure 6 explains the transformation statistics of the land cover to agricultural lands and from agricultural lands to other land cover.

According to the final findings, the agricultural lands were subjected to a huge transformation in urban areas due to several reasons, such as the low cost of lands in the rural areas, the shortage of irrigation water that forced farmers to leave their lands, and the absence of specified laws that organized the land use in the rural areas. Therefore, the government should tackle some solution to preserve the agricultural lands because this type of lands is considered a national wealth.

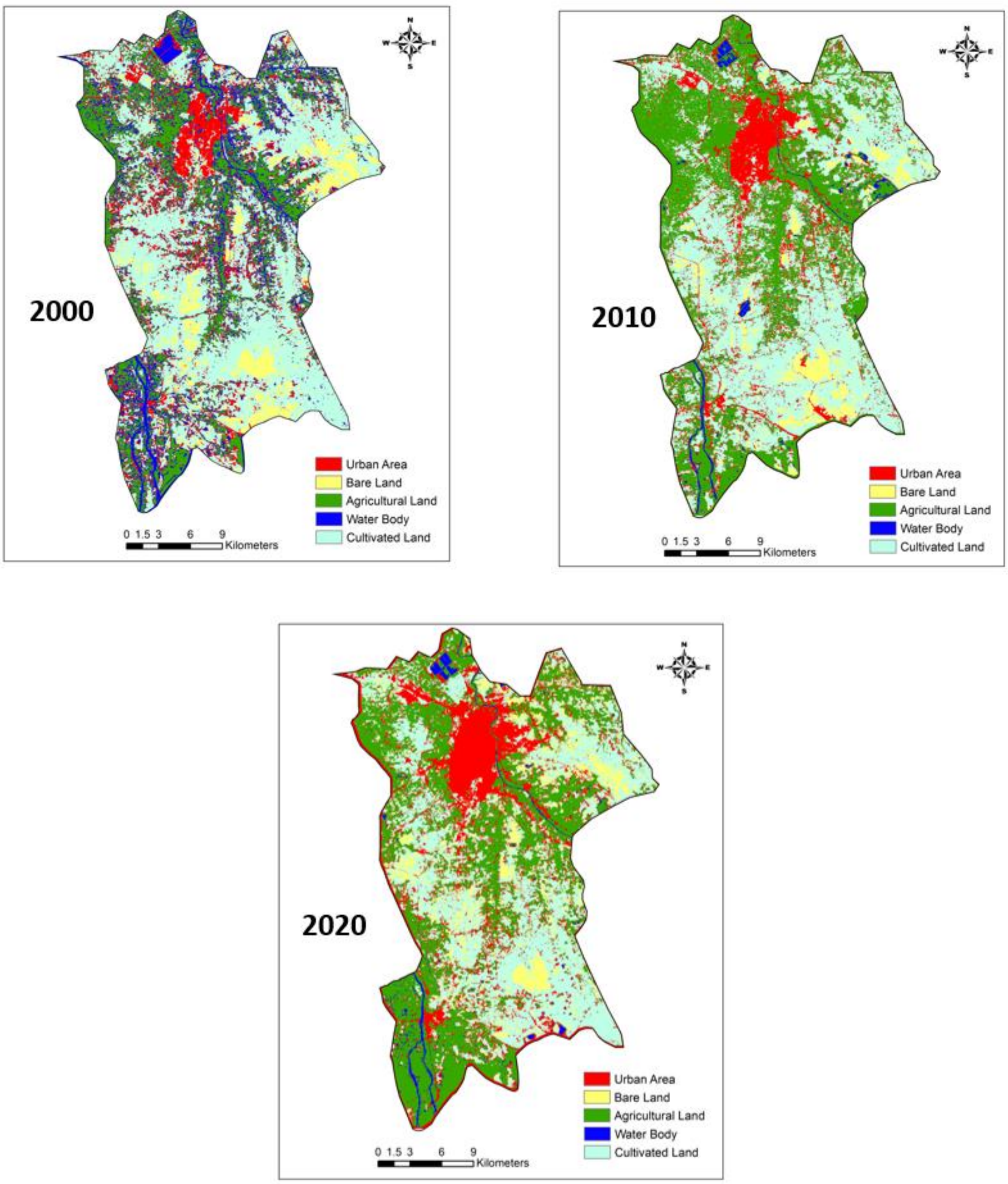

Fig.5 Land cover map for three years (2000, 2010, and 2020)

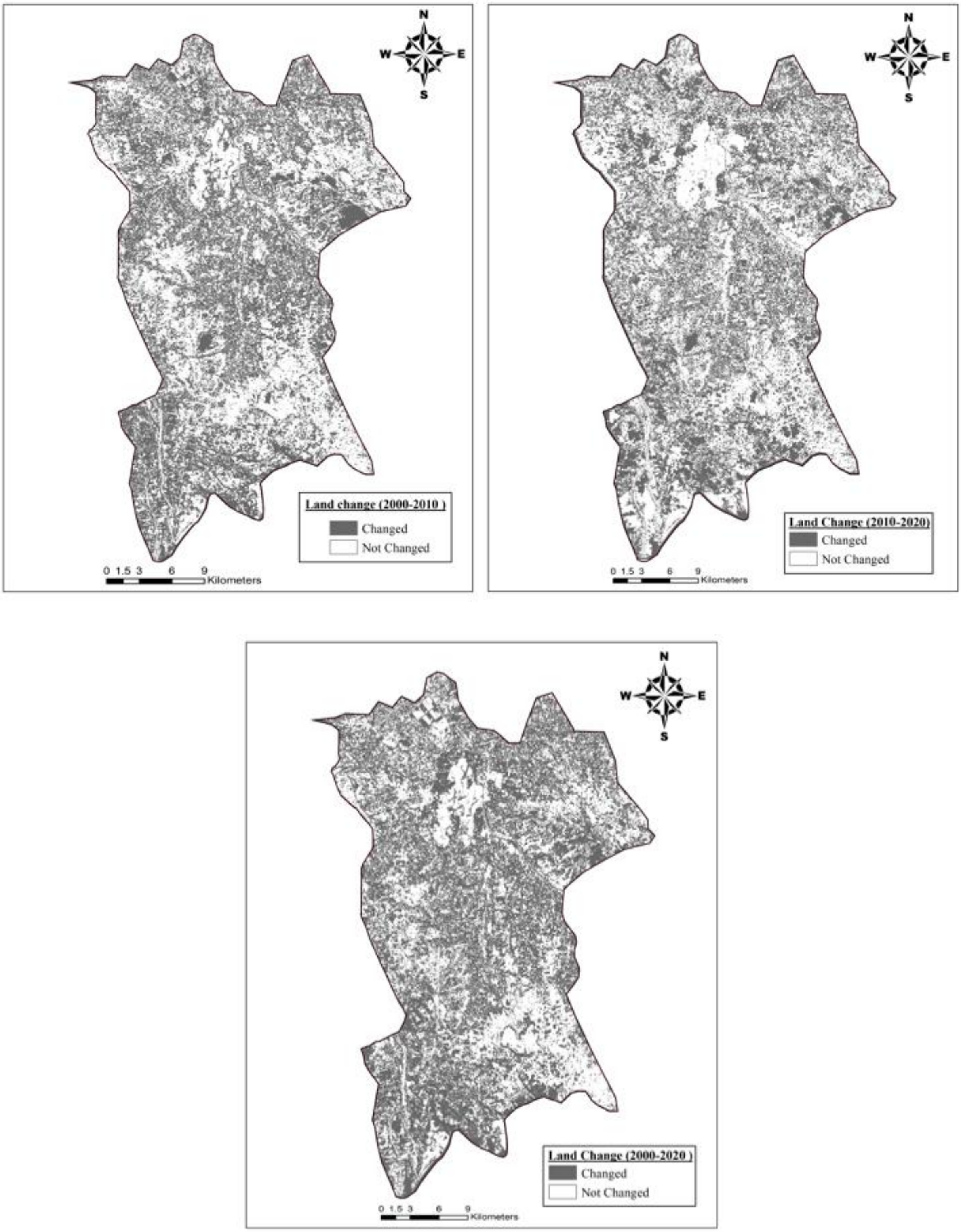

Fig. 6 The land cover changes map

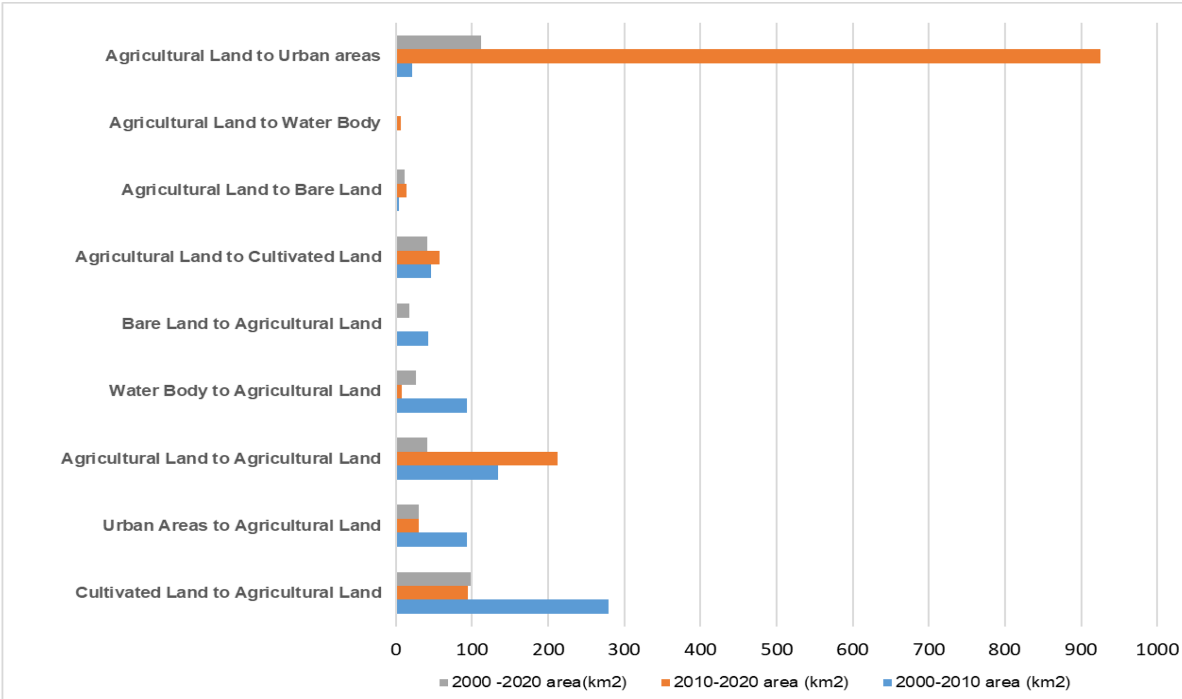

Fig. 7 The land cover transformation during (2000-2010), (2010-2020), and (2000-2020)

5. Conclusion

During the last two decades (1990-current), most of the Iraqi cities have witnessed a severe degradation of agricultural lands due to population growth and transforming agricultural lands into built-ups and residential areas. This has significantly affected the socio-conomic and environment of the areas and as a result the quality of life. In addition, the deriving forces of transforming the lands from agricultural to other land cover types are not well understood. As a result, research is needed to map and assess the agricultural lands in the Iraqi cities to provide solutions for a better economic and clean environment. This study is conducted based on integration of ANN-CA for the prediction of agricultural land changes in the study area (Babil, central Iraq). The novelty of this research is a novel assessment of the deriving forces of the agricultural land changes in Babylon Province, Iraq over the last two decades (2000-2020) using integrated cellular automata and artificial neural networks by using multitemporal Landsat images. The classification result showed that CNN model has achieved the highest accuracy in terms of (OA, F1-score, and Kappa). The overall accuracy was 0.95, 0.93, and 0.90 based on images captured in 2020, 2000, 2010) respectively. On the other hand, other models achieved lower accuracy than CNN model. Furthermore, CNN model achieved F-score values (0.95, 0.94, and 0.93) based on images captured during (2020, 2010, and 2020). kappa coefficient recorded the highest value (0.95) based on CNN model based on the image captured in 2020, and its achieved 0.94 and 0.93 based on images that dated in 2000 and 2010 respectively. Table 2 illustrates the result of the accuracy assessment of the classification of three images that dated in (2000, 2010, and 2020)

The map shows a significant change in the land cover within the study area during the period (2000-2020). During the period from 2000 to 2020, the total transformation to agriculture lands is 2143.1 square kilometers. And the total transformation from agricultural lands to other types of land cover is 2071.1 square kilometers. The proposed method can be used as an efficient tool for the agricultural agencies in terms of the agricultural lands monitoring as well as the conducting of the development plans to improve the agriculture sector in Iraq.

In general, the agricultural lands are subjected to a significant transformation to different type of land cover due to various factors such as the rapid population growth, low cost of agricultural lands compared to urban areas, the draught of agricultural lands due to the shortage of irrigation, and the laws that organize the land use in rural areas. As a result, the government should preserve the agricultural lands because this type of lands is considered a national wealth.

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References

Aal-shamkhi, A. D. S., Mojaddadi, H., Pradhan, B., & Abdullahi, S. (2017). Extraction and Modeling of Urban Sprawl Development in Karbala City Using VHR Satellite Imagery. In B. Pradhan, (Eds), *Spatial Modeling and Assessment of Urban Form* (pp. 281–296). Springer, Cham. https://doi.org/10.1007/978-3-319-54217-1_12

Ali, A. H. S., Amany, A. K., & Jalil, M. A. (2020). Predicting the future growth depending on GIS and IDRISI program, city of Najaf-Iraq. In *IOP Conference Series: Materials Science and Engineering* (Vol. 881, No. 1, p. 012031). IOP Publishing.

Aneesha Satya, B., Shashi, M., & Deva, P. (2020). Future land use land cover scenario simulation using open source GIS for the city of Warangal, Telangana, India. *Applied Geomatics*, *12*(3), 281-290.

Deep, S., & Saklani, A. (2014). Urban sprawl modeling using cellular automata. *The Egyptian Journal of Remote Sensing and Space Science*, *17*(2), 179-187.

Hadi, S. J., Shafri, H. Z., & Mahir, M. D. (2014). Modelling LULC for the period 2010-2030 using GIS and Remote sensing: a case study of Tikrit, Iraq. In *IOP conference series: earth and environmental science* (Vol. 20, No. 1, p. 012053). IOP Publishing.

Jamali, A. (2020). Land use land cover mapping using advanced machine learning classifiers: A case study of Shiraz city, Iran. *Earth Science Informatics*, *13*(4), 1015-1030.

Kafy, A. A., Naim, M. N. H., Subramanyam, G., Ahmed, N. U., Al Rakib, A., Kona, M. A., & Sattar, G. S. (2021). Cellular Automata approach in dynamic modelling of land cover changes using RapidEye images in Dhaka, Bangladesh. *Environmental Challenges*, *4*, 100084.

Mohamedmeki, M. Z., & Al-Mumaiz, M. (2020). Multi Land Use Approach towards Sustainable Baghdad City: Bab Al-Muatham Garage as a Case Study. In *IOP Conference Series: Materials Science and Engineering* (Vol. 870, No. 1, p. 012101). IOP Publishing.

Nasser, H. J., & Ibrahim, L. F. (2022). Analysis of the efficiency of the geographical distribution of secondary education services in the district of Hilla for the academic year (2020-2021). *Journal of The College of Education*, *1*(48).

Qiang, Y., & Lam, N. S. (2015). Modeling land use and land cover changes in a vulnerable coastal region using artificial neural networks and cellular automata. *Environmental monitoring and assessment*, *187*, 1-16.

Saputra, M. H., & Lee, H. S. (2019). Prediction of land use and land cover changes for North Sumatra, Indonesia, using an artificial-neural-network-based cellular automaton. *Sustainability*, *11*(11), 3024.

Schmidhuber, J. (2015). Deep learning in neural networks: An overview. *Neural networks*, *61*, 85-117.

Sturari, M., Frontoni, E., Pierdicca, R., Mancini, A., Malinverni, E. S., Tassetti, A. N., & Zingaretti, P. (2017). Integrating elevation data and multispectral high-resolution images for an improved hybrid Land Use/Land Cover mapping. *European Journal of Remote Sensing*, *50*(1), 1-17.

Walsh, S. J., Entwisle, B., Rindfuss, R. R., & Page, P. H. (2006). Spatial simulation modelling of land use/land cover change scenarios in northeastern Thailand: a cellular automata approach. *Journal of Land Use Science*, *1*(1), 5-28.