DOI: 10.24996/ijs.2026.67.5.42

ISSN: 0067-2904

Land Use Decision Using Soil Indices and Fuzzy Inference System in AL-Khamisiyah

Amal J. Hatem[1], Ahmed Asaad Zaeen[2], Heba Kh. Abbas[3], Mustafa A. Raheem[4]

[1]Dept. of Physics, College of Education for Pure Science (Ibn Al-Haitham), University of Baghdad, Baghdad, Iraq

[2]Remote Sensing Unit, College of Science, University of Baghdad, Baghdad, Iraq

[3]Department of Physics, College of Science for Women, University of Baghdad, Baghdad, Iraq

[4]Department of Physics, College of Science, University of Wasit, Wasit, Iraq

Received: 3/12/2024 Accepted: 6/5/2025 Published: 30/5/2026

Abstract

The selection of the most suitable land for cultivating a particular crop is one of the major problems facing the Ministry of Agriculture in general and farmers in particular, and this suitability for cultivation depends on many factors (natural and human), including soil type. This research used indicators, remote sensing, and spatial modeling to solve this problem. The method of band rationing was applied to calculate the salinity index (SI) and the Normalized Multi-Drought Index (NMDI) as a pre-processing for agricultural decision-making in specific areas in southern Iraq (Dhi Qar, Al-Khamisiyah), using the Landsat-8 satellite image of this area. Maximum likelihood classification was used to classify the study area into multiple classes. The soil was classified in a study area using a fuzzy inference system (FIS) to determine suitability for growing different types of crops according to the values of the salinity index and the multiple drought index measured for each crop. The results of the study showed that Al-Khamisiyah land is valid and suitable for the cultivation of specific crops (onions, lettuce, cabbage, cucumbers, celery, guava, and cowpeas) with an area of 946,541,700 m^2 of the studied area, while it is not suitable for the cultivation of other crops namely pepper and beets.

Keywords: Remote sensing, land decision, salinity Indices, normalized multi-drought index, fuzzy inference system.

قرار استخدامات الأراضي باستخدام مؤشرات التربة ونظام الاستدلال الضبابي في منطقة الخميسية

آمال جبار حاتم[1] احمد اسعد زعين[2] هبة خضير عباس[3] مصطفى عبد الجليل رحيم[4]

[1]قسم الفيزياء، كلية التربية للعلوم الصرفة (ابن الهيثم)، جامعة بغداد، بغداد، العراق

[2]وحدة الاستشعار عن بعد، كلية العلوم، جامعة بغداد، بغداد، العراق

[3] قسم الفيزياء، كلية العلوم للبنات، جامعة بغداد، بغداد، العراق

[4] قسم الفيزياء، كلية العلوم، جامعة واسط، واسط، العراق

الخلاصه

يعد اختيار الأرض الأكثر ملائمة لزراعة محصول معين من المشاكل الكبيرة التي تواجه وزارة الزراعة بشكل عام والمزارعين بشكل خاص، وتعتمد هذه الصلاحية للزراعة على عوامل كثيرة (طبيعية وبشرية)، بما

* Email: ahmed.asaad@sc.uobaghdad.edu.iq

في ذلك نوع التربة. تمت المساهمة في هذا البحث باستخدام مؤشرات الاستشعار عن بعد والنمذجة المكانية لحل هذه المشكلة. تم تطبيق طريقة التقنين النطاقي لحساب مؤشر الملوحة (SI) ومؤشر الجفاف المتعدد المقاس (NMDI) كمعالجة مسبقة لاتخاذ القرار الزراعي في مناطق محددة في جنوب العراق (ذي قار، الخميسية)، باستخدام صورة القمر الصناعي لاندسات لهذه المنطقة. تم استخدام تصنيف الاحتمال الأقصى لتصنيف منطقة الدراسة إلى فئات متعددة. ومن ثم تم تصنيف التربة في منطقة الدراسة باستخدام نظام الاستدلال الضبابي (FIS) لتحديد مدى صلاحيتها لزراعة أنواع مختلفة من المحاصيل وفق قيم مؤشر الملوحة ومؤشر الجفاف المتعدد المقاس لكل محصول. وأظهرت نتائج الدراسة أن منطقة الخميسية أرض صالحة وصالحة لزراعة محاصيل محددة (البصل، الخس، الكرنب، الخيار، الكرفس، الجوافة، اللوبيا) بمساحة 946,541,700 م2 منطقة الدراسة، بينما لا تصلح لزراعة محاصيل أخرى مثل الفلفل والبنجر.

1. Introduction

The land use and cover are significant for the frugality planning of the area where the land used is linked to human effectiveness, such as residence, foundation, merchanting, recuperation, etc., while the land cover is related to the different types of lineaments present on the surface of the earth. For suitable planning exercises, information on both aspects should be obtainable separately [1&2]. The data from the satellite is processed and explicated in various forms using digital or optical techniques. Although the visual interpretation of the image is being used in many applications, it does not explicate the image pixel by pixel. Instead, it supplies synoptic information related to image lineaments of known targets. As a result, the information conclusion for land use and covered supply by the human interpreter is less precise and overlapping in many places [1&4]. Fuzzy logic has been used in a broad range of problem domains. The application areas are vast: process control, administration, decision-making, procedure research, and frugality [5]. Dealing with simple (black and white) responses is no longer satisfying enough; a degree of membership is a new mode of solving the problem. A fuzzy combination is a set whose elements have degrees of the complete member (100 membership) or fractional member (0 and 100 membership). The membership value assigned to a component is no taller finite than just two values but can be any value between them. A mathematical arithmetical function defines an element's membership degree in a fuzzy combination called a membership function [6 & 7].

The ground cover change was studied using foggy logic. The source of information on the region was obtained using the Landsat TM satellite, and the result showed that the accuracy of the ambiguous classification is better than the fragile classification [8]. A study determined soil moisture using a neuro-fuzzy logic model; the experimental results indicated that the system is sensitive to water content and ion concentration, and this model is capable of predicting the water content of the tested soils [9, 10], where satellite images used an approved methodology. They used the foggy estimation system in the classification. They concluded that classification accuracy is closely related to identifying the functions used [11, 12]. A study classified satellite images using different techniques. However, the fuzzy logic method mainly focused on a satellite image in which water will be detected using a Fuzzy Logic System (FLS) and membership function editor. Similarly, classification can be done in different areas for the various regions [13, 14]. Using the fuzzy logic approach, researchers studied land cover classification using Landsat-8 satellite data. They found that the fuzzy system approach is practical and can be explored and implemented for other areas of Landsat data [14]. The researchers studied the classification of the southwestern Iraq region using a fuzzy inference system to estimate the degree of its desertification using the satellite Landsat-5 and Landsat-8 data [15]. Improving quality image fusion was suggested by manipulating contemporary algorithms in auto-focus image fusion. The first algorithm is based on selecting the standard deviation to combine two images. The second algorithm focuses on the contrast at edge points and the correlation procedure as the measures parameter for the resultant image quality. This algorithm assumes three blocks with various sizes at the homogenous area and moves 10 pixels within the exact location. These blocks investigate the block's statistical properties and automatically decide the next step. The resulting combined image is adequate in contrast due to the added edge points from the two combined images that rely on the proposed algorithms [16].

The major aim of this research is to decide on using proper agricultural land for economic crops by employing remote sensing data in the region of the South of Iraq (Al-Khamisiyah area of Dhi Qar). The research is significant in exploiting agricultural land and determining which cultivable soils are unsuitable for agriculture in southern Iraq. It helps to know the quality of the crops that can be grown in this area by applying FIS and to give opinions to the decision-makers in this regard.

2. Methodology

2.1 Study area

The study area was in south Iraq (Figure 1.a), 946 km^2. The Landsat 8 satellite image data was picked by an Operational Land Imager (OLI) and Thermal Infrared Sensors (TIRS) on (12/11/2017) and located within Landsat coordinates (path=166) and (row=39) that cover the study area with 11 spectral bands that were used in this study (Figure 1.b). This region is situated between (30° 55' 53.11" - 30° 39' 28.99") latitude and (46° 33' 56.92"-46°53'30.02") longitude (Figure1.c), downloaded from the International Scientific Data Mirror, the site of the computer network information center directed by the Chinese Academy of Sciences [17].

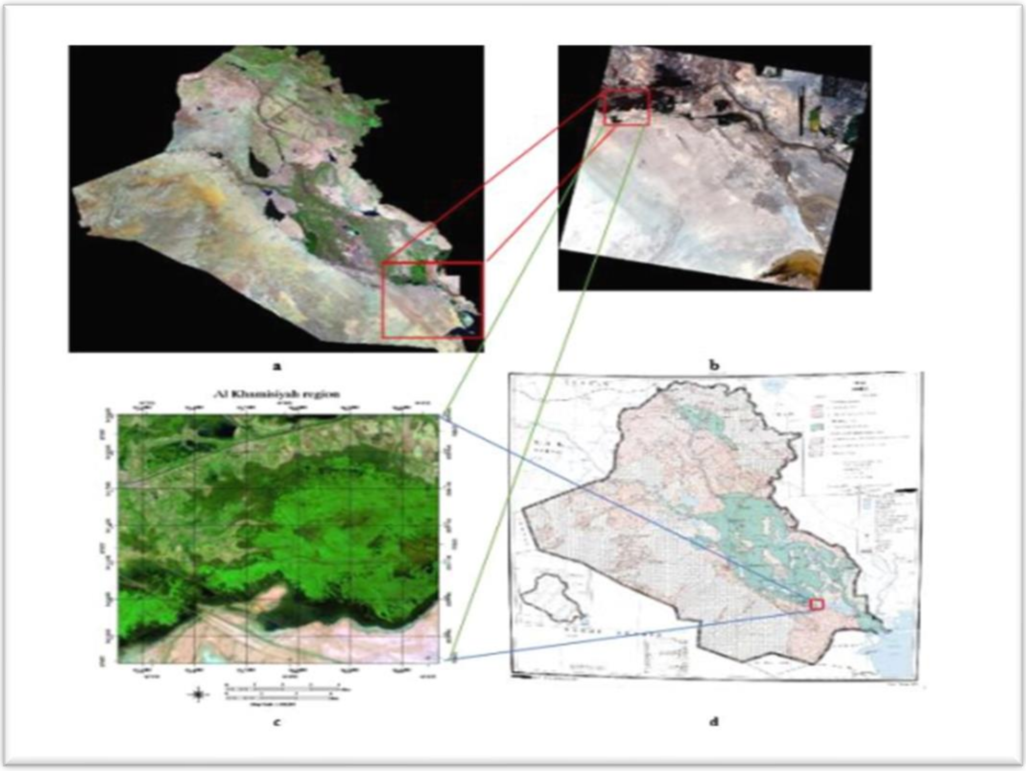


Figure 1: a) Map of Iraq location, (b) Landsat_8 satellite image for the region of interest [14]. (c) Photomap of the Al Khamisiyah study area, and (d) Iraq soil map (1961).

2.2. Data Used

In this study, ENVI 5.3 and Matlab2016a were used. The fuzzy model was built in the MATLAB program, and land use was added to the applicable model to obtain the desired decision. The proposed indices utilized the salinity index (SI) and the Normalized Multi-Band Drought Index (NMDI), as given by Eq. (1) and Eq. (2).

$$SI = \frac{(Red*NIR)}{(Green)} \quad (1)\ [17]$$

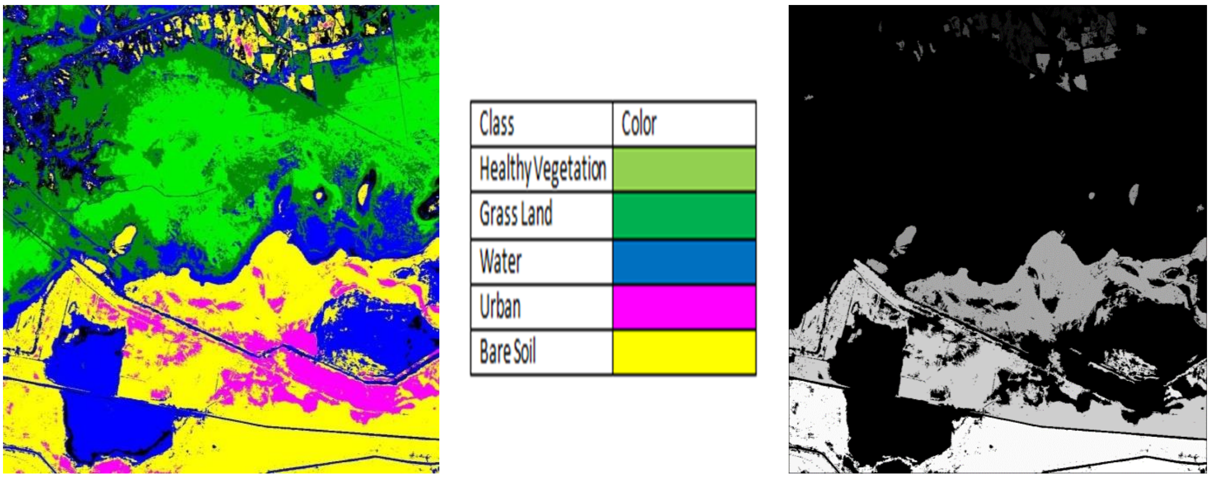
This spectral index effectively detects the degree of soil salinity that contains the dual salts. These salts need the band NIR to detect the presence of salts in the soil, so this indicator was used.

$$NMDI = \frac{((NIR)-(SWIR1-SWIR2))}{((NIR)+(SWIR1-SWIR2))} \quad (2)\ [19]$$

The Normalized Multi-Band Drought Index (NMDI) was proposed for remote sensing of soil water content from space by using three channels: NIR, SWIR1, and SWIR2. This index depends on the slope variation, and this characteristic is used to extract information about soil water status [20-22].

2.3 The following step is performed to obtain the land use decision.

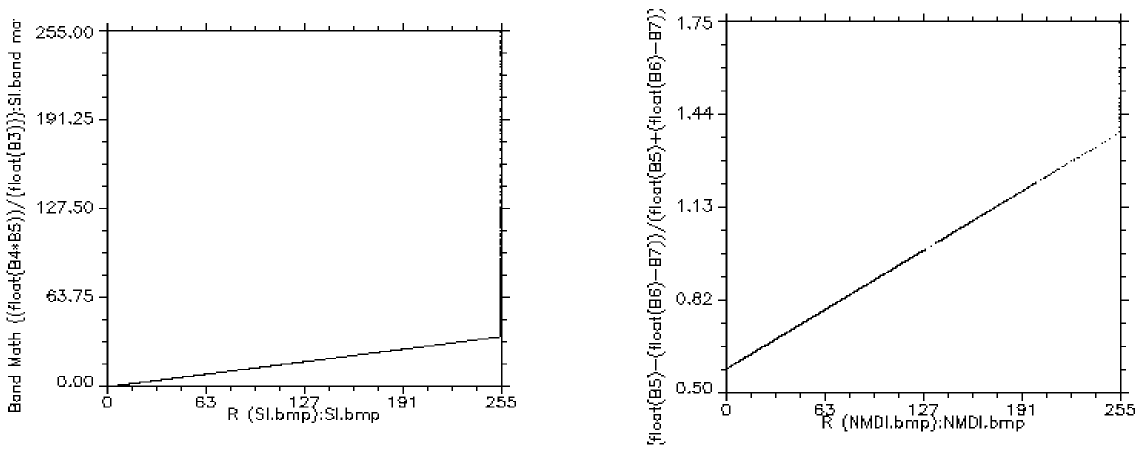
The study area contains many land features (soil, water, vegetation, etc.). Therefore, the study image was classified using the maximum likelihood method (Figure 2-a). With the help of MATLAB, the bare soils were separated (Figure 2-b) to calculate their salinity index and the Normalized Multi-Band Drought Index, where the resultant images for both features were saved as bitmap images.



(a) (b)

Figure 2: (a) The classified image, (b) The segment image of the bare soil class.

The saved feature images for both SI and NMDI were recalibrated to the values of the SI and NMDI instead of the intensity values by calculating empirical fitting equations by comparing the pixel's intensity values with the SI and NMDI indexes (Figure 3).



(a) (b)

Figure 3: Comparing the intensity values of the bare soil image with the SI and NMDI indexes.

The FIS model is built using the MATLAB fuzzy toolbox using the Mamdani inference system (Figure 4). The SI and NMDI are input parameters with Gaussian membership, and each is split into three ranges (low, mid, and high). The output comprised nine membership functions (pepper, onion, lettuce, cabbage, cucumber, celery, Gao, lob, and beet) using a non-overlap triangle member function (Figure 5).

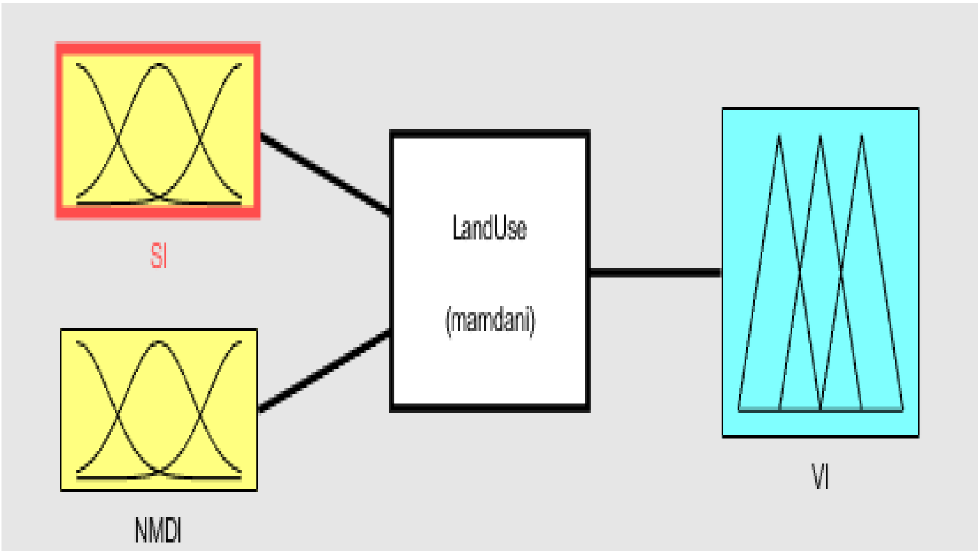
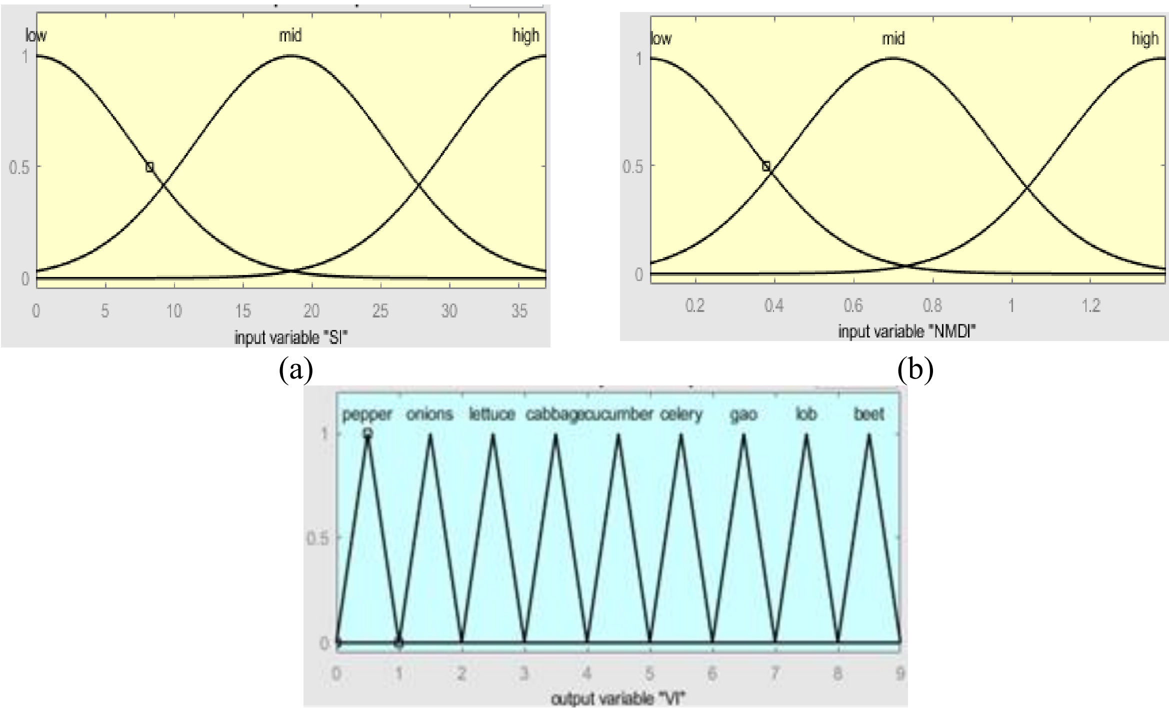


Figure 4: The inference system structure



(a) (b)

(c)

Figure 5: The input and the output of the fuzzy inference system are (a) the SI index, (b) the NMDI index, and (c) the output vegetation kind (index).

These crops were used based on their need for different salinity index conditions and different drought indices. Therefore, the decision rules were built depending on their needs for each SI and NMDI value (Figure 6).

1. If (SI is low) and (NMDI is low) then (VI is pepper) (1)
2. If (SI is low) and (NMDI is mid) then (VI is onions) (1)
3. If (SI is low) and (NMDI is high) then (VI is lettuce) (1)
4. If (SI is mid) and (NMDI is low) then (VI is cabbage) (1)
5. If (SI is mid) and (NMDI is mid) then (VI is cucumber) (1)
6. If (SI is mid) and (NMDI is high) then (VI is celery) (1)
7. If (SI is high) and (NMDI is low) then (VI is gao) (1)
8. If (SI is high) and (NMDI is mid) then (VI is lob) (1)
9. If (SI is high) and (NMDI is high) then (VI is beet) (1)

Figure 6: The inference decision rule.

Based on the previous structure and decision rule, the fuzzy inference model is built to map the two input indexes to one output variable of nine indexes; each index represents one kind of the selected crops, Figures 7 and 8.

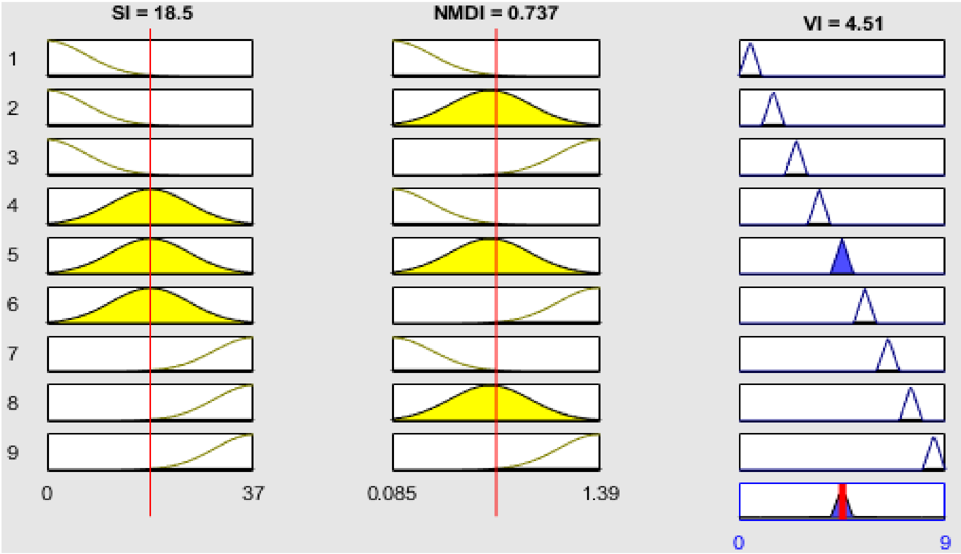


Figure 7: The infrastructure of the fuzzy inference model.

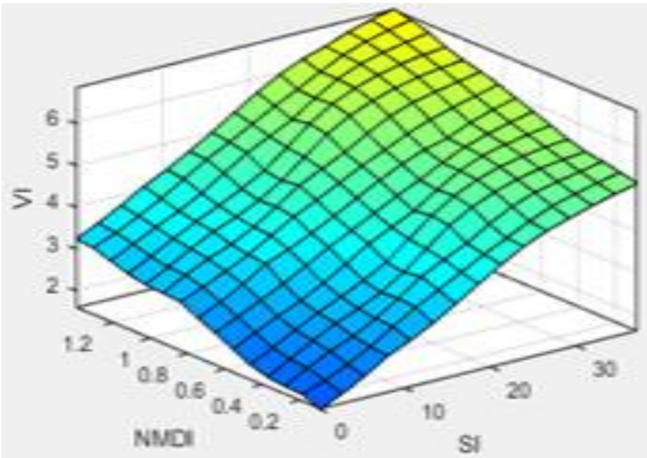
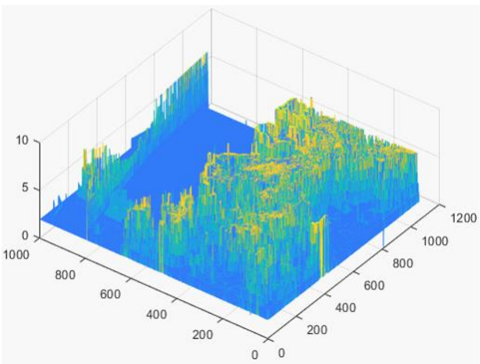
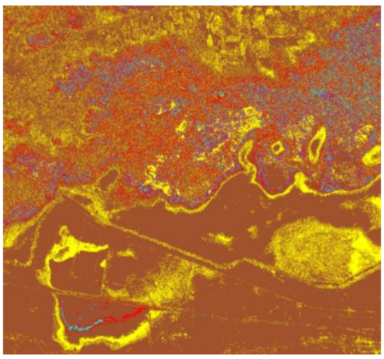


Figure 8: The decision surface based on the inference model.

The study area was classified based on the fuzzy decision surface. The decision surface was applied by writing a MATLAB model to remap the study area to specify crops according to the Si and NMDI values. The resultant crop map image is recolored to recognize each crop kind from the other (Figure 9).



(a)



Pepper	
Onions	
Lettuce	
Cabbage	
Cucumber	
Celery	
Gao	
Lob	
Beet	

(b)

Figure 9: The results of (a) mapping the study area and (b) coloring based on the fuzzy inference decision surface.

3. Results and Discussion

The minimum and maximum values for each of the SI and NMDI extracted in the methodology (2.3) Figure (3a and 3b) are shown in Table 1.

Table 1: The minimum and maximum values of SI and NMDI.

Value	SI	NMDI
Minimum	0	0.085
Maximum	37	1.39

In Land Use Design (2.3), the range of membership functions (MF) values for input 1 (SI) and input 2 (NMDI) is indicated in Table 2, where these range values were extracted from the minimum and maximum values.

Table 2: The Ranges of Membership Functions (SI, NMDI)

MF	Input 1(SI)	Input 2(NMDI)
low	7- 0	0.25- 0.085
Mid	7 -24.666	0.25- 0.947
High	7- 37	0.25- 1.378

The resultant crop after mapping (Figure 9-a), the number of pixels, area, and percentage compared with the total area were calculated in Table 3.

Table 3: The result of the land decision using the fuzzy inference

Crop	Index	Pixel	Area m^2	Percent
Pepper	1	0	0	0
Onion	2	753456	678,110,400	71.64084
Lettuce	3	168443	151,598,700	16.01606
Cabbage	4	59898	53,908,200	5.69528
Cucumber	5	29304	26,373,600	2.786311
Celery	6	13913	12,521,700	1.322889
Gao	7	24985	22,486,500	2.375648
Lob	8	1714	1,542,600	0.162972
Beet	9	0	0	0
total		1051713	946,541,700	100

According to Table 3, it can be noticed that the studied area can be grown with particular types of crops, which are onions, lettuce, cabbage, cucumber, celery, gao, and lob, where noticed that they are with varying degrees, forefronted by onion, followed by lettuce, then cabbage, cucumber, Gao, celery, and finally Lob crop, while other crops (pepper and beet) cannot be cultivated in the soil of this area.

4. Conclusion

1- The results of the salinity and moisture values showed the diversity of the soil, as the salinity index was considered greater compared to the range of the moisture index. Therefore, it can be concluded that the soil of the study area (Khamsi soil) is characterized by high

salinity and low moisture levels, so crops suitable for these conditions can be grown in this region, such as (onions, lettuce, cabbage, cucumber, celery, gao, and lob) crops.
2- The results validate using Fuzzy inference to decide which crops should be implanted in a manner close to humans. This land use decision was based on the soil characteristics of its salinity and moisture content indexes, where the saline content was (low-mid), compared with moisture content (low-mid-high). On this basis, crops that need these conditions have been cultivated.
3- To conclude, the Mamdani model of the fuzzy inference system (FIS) is very appropriate in making decisions compared to other models for the (FIS).
The research results conclude that the study area can be cultivated with certain types of crops, namely (onions, lettuce, cabbage, cucumbers, celery, jao, and lupine). It was noticed that, to varying degrees, onion crops are at the forefront, followed by lettuce, then cabbage, cucumbers, Jao, celery, and finally lupine. At the same time, other crops (peppers and beets) cannot be cultivated in the soil of this area. This helps those interested in agricultural crop trade to choose the best place to cultivate them and increase their production.

Acknowledgments
Thanks to the Univeristy of Baghdad, Iraq, and the researchers who supported this article with their ideas and writing.

Funding
There is no specific funding source; the authors have paid the total cost independently.

References
[1] F. F. Sabins Jr and J. M. Ellis, *Remote sensing: Principles, interpretation, and applications*. Waveland Press, 2020.
[2] M. A. Mohammed, and A. J. Hatem, “Change detection of the land cover for three decades using remote sensing data and geographic information system,” AIP Conference Proceedings **2307**, 020029 (2020).
[3] R. Zhang, Y. Yang, Z. Li, P. Li, and H. Wang, "Optical and SAR Image Fusion: A Review of Theories, Methods, and Applications," Remote Sensing, vol. 18, no. 1, p. 73.2025.
[4] A. Bazrafkan, C. Igathinathane, N. Bandillo, and P. Flores, "Optimizing integration techniques for UAS and satellite image data in precision agriculture — a review," (in English), Frontiers in Remote Sensing, Review vol. Volume 6 - 2025.2025-June-24 2025.
[5] E. Momeni, M. R. Sahebi, and A. Mohammadzadeh, "Classification of high-resolution satellite images using fuzzy logics into a decision tree," *Malaysian Journal of Geosciences,* vol. 4, no. 1, pp. 07-12.2020.
[6] B. Valipour Shokouhi and M. Eslami, "Fuzzy logic based burned severity classification and mapping with Landsat-8 data," *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences,* vol. 42, pp. 259-265.2019.
[7] I. Hadi and S. B. Semeein, "Fuzzy Distributive Modules," *Ibn AL-Haitham Journal For Pure and Applied Science,* vol. 24, no. 1. 2016.
[8] M. W. Naikoo, S. Talukdar, M. Ishtiaq, and A. Rahman, "Modelling built-up land expansion probability using the integrated fuzzy logic and coupling coordination degree model," *Journal of Environmental Management,* vol. 325, p. 116441.2023.
[9] L. Yu, X. Cai, and J. m. Li, "Hybrid neuro-fuzzy models for assessing the optimum moisture content of lime cement-treated soil," *Multiscale and Multidisciplinary Modeling, Experiments and* Design, pp. 1-18.2024.
[10] Z. J. Kamil, M. J. Zoory, and H. J. Mohamad, "LIBS technique for plant mineral ratio analysis and environmental and agricultural importance: a comprehensive review," The European Physical Journal D, vol. 78, no. 3, p. 27.2024.

[11] M. Alkhelaiwi, W. Boulila, J. Ahmad, A. Koubaa, and M. Driss, "An efficient approach based on privacy-preserving deep learning for satellite image classification," *Remote Sensing,* vol. 13, no. 11, p. 2221.2021.

[12] L. Sharma, S. Bali, A. Zaeen, P. Baldwin, and D. Franzen, "Use of rainfall data to improve ground-based active optical sensors yield estimates," Agronomy Journal, vol. 110, no. 4, pp. 1561-1571.2018.

[13] I. Zaitoun, N. Almasri, L. Taha, and M. Alshraideh, "Satellite Image Cloud Classification Using Fuzzy Logic," *International Journal of Imaging & Robotics,* vol. 19, no. 1, p. 2109.2019.

[14] H. K. Abbas, N. A. Fatah, H. J. Mohamad, and A. A. Alzuky, "Brain tumor classification using texture feature extraction," in Journal of Physics: Conference Series, 2021, vol. 1892, no. 1, p. 012012: IOP Publishing.

[15] R. R. Daphne, J. WinowlinJappes, and N. Brintha, "An Unsupervised Drowsiness Detection Architecture Using Fuzzy Classifier," in *2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS)*, 2022, pp. 1734-1742: IEEE.

[16] H. K. Abbas, A. H. Al-Saleh, H. J. Mohamad, and A. A. Al-Zuky, "New algorithms to enhanced fused images from auto-focus images," Baghdad Science Journal, vol. 18, no. 1, pp. 0124-0124.2021.

[17] H.M. Abduljabbar, A.J. Hatem, A.A. Al-Jasim "Desertification Monitoring in the South-West of Iraqi Using Fuzzy Inference System" NeuroQuantology | May 2020 | Volume 18 | Issue 5 | Page 01-11 |.

[18] The World Factbook: https://www.cia.gov/the-world-factbook/countries/iraq/map/

[19] F. P. Salcedo, P. P. Cutillas, J. J. A. Cabañero, and A. G. Vivaldi, "Use of remote sensing to evaluate the effects of environmental factors on soil salinity in a semi-arid area," *Science of The Total Environment,* vol. 815, p. 152524.2022.

[20] L. Tao, D. Ryu, A. Western, and D. Boyd, "A new drought index for soil moisture monitoring based on MPDI-NDVI trapezoid space using MODIS data," *Remote Sensing,* vol. 13, no. 1, p. 122.2020.

[21] M. A. Raheem and A. J. Hatem, "Calculation of Salinity and Soil Moisture indices in south of Iraq - Using Satellite Image Data," Energy Procedia, vol. 157, pp. 228-233.2019/01/01/ 2019.

[22] A. K. Saha, M. M. Hasan, M. R. A. Khan, and M. Al-Amin, "Prediction of spatial saturated hydraulic conductivity at the upper soil layer using soil class and terrain attributes," Modeling Earth Systems and Environment, vol. 8, no. 3, pp. 3591-3605.2022.