DOI: 10.24996/ijs.2024.65.12.40

ISSN: 0067-2904

Land Cover Classification of Al-Jadriya Region in Baghdad Using Remote Sensing and GIS

Mohammed M. Wadod*, Faisel G. Mohammed
Department of Remote Sensing & GIS, College of Science, University of Baghdad, Baghdad, Iraq

Received: 18/3/2023 Accepted: 18/6/2023 Published: 30/12/2024

Abstract
Due to its commercial and economic significance and its adjacency to Iraq's largest university, the Al-Jadriya area in Baghdad holds vital importance. This region exhibits high population density, diverse land uses, and a wide range of land cover types. Therefore, accurately classifying the land features in this area is crucial to support decision-making and facilitate infrastructure development. This study aims to utilize remote sensing techniques and a high-resolution satellite image to classify the region. To achieve this, GIS and QGIS programs and a software package encompassing various classification methods were employed to accurately classify the features and determine the most practical classification methods for this data type. The results indicated that deep learning algorithms utilizing artificial intelligence were the most effective classification method; it achieved an 81.66% classification accuracy for the region, surpassing other techniques.

Keywords: Remote sensing; Image classification; High-resolution Satellite images; GIS

تصنيف الغطاء الأرضي لمنطقة الجادرية في بغداد باستخدام الاستشعار عن بعد ونظم المعلومات الجغرافية

محمد مظفر ودود*، فيصل غازي محمد
قسم التحسس النائي ونظم المعلومات الجغرافية، كلية العلوم، جامعة بغداد، بغداد العراق

الخلاصة
نظرا لأهميتها التجارية والاقتصادية ، فضلا عن قربها من أكبر جامعة عراقية ، فإن منطقة الجادرية في بغداد لها أهمية حيوية. تُظهر هذه المنطقة كثافة سكانية عالية ، واستخدامات متنوعة للأراضي ، ومجموعة واسعة من أنواع الغطاء الأرضي. لذلك ، يعد التصنيف الدقيق لميزات الأراضي في هذا المجال أمرًا بالغ الأهمية لدعم اتخاذ القرار وتسهيل تطوير البنية التحتية. الهدف من هذه الدراسة هو الاستفادة من تقنيات الاستشعار عن بعد وصورة عالية الدقة من الأقمار الصناعية لتصنيف المنطقة. لتحقيق ذلك ، استخدمنا برنامج GIS & QGIS وحزمة برمجيات تشمل طرق تصنيف مختلفة لتصنيف الميزات في هذا المجال بدقة وتحديد طرق التصنيف الأكثر فعالية لهذا النوع من البيانات. تشير النتائج إلى أن خوارزميات التعلم العميق باستخدام الذكاء الاصطناعي كانت أكثر طرق التصنيف فاعلية ، حيث حققت دقة تصنيف تبلغ 81.66٪ للمنطقة متجاوزة التقنيات الأخرى.

*Email: Mohammed.wado2109m@sc.uobaghdad.edu.iq

1.1 Introduction

In recent years, the remote sensing field has seen significant development in the use of high-resolution satellite images for various applications [1, 2, 3], including land use and land cover mapping [4, 5], urban planning [6], and environmental monitoring [7, 8]. One of the most challenging tasks in remote sensing is accurately classifying these images, which requires identifying and extracting specific data features and patterns. Accurate classification of Satellite images is critical and challenging, although some previous research has yielded good results [9]. Traditional methods, such as supervised classification with maximum probability and unsupervised classification using the ISO cluster technique classification tool, were widely used to classify satellite images. However, with the advent of artificial intelligence (AI), there has been a growing interest in exploring the potential of AI methods for image classification [10]. The researchers found that traditional machine learning algorithms are useful for specific applications in situations where the volume and quality of training data are limited, with recent studies showing the potential for deep learning techniques to improve detection accuracy [11]. Baghdad Governorate, Iraq, is a densely populated urban area with complex land use and land cover patterns, including residential, commercial, and agricultural areas. Remote sensing technologies, especially high-resolution satellite imagery, provide valuable information about a region's urban development and environmental conditions. By analyzing aerial and satellite imagery, researchers and planners can determine land use and changes in land cover, estimate population density and distribution, and assess environmental conditions. Environments such as air quality and vegetation, these datasets provide detailed information about the Earth's surface and can be used in various applications such as urban planning, environmental monitoring, disaster response, and military intelligence. Examples of high-resolution satellite image datasets include WorldView, GeoEye, QuickBird, Pleiades, and Sentinel-2 [12]. This study aims to compare the efficiency of traditional methods and artificial intelligence in the satellite image classification process that contains true color for the study area of Al-Jadriya, Baghdad, and to identify the strengths and weaknesses of each approach.

1.2. Related work

The application of artificial intelligence (AI) in classifying remote sensing data represented by high-resolution aerial and satellite imagery has gained significant attention in recent years. This section reviews the literature used to classify and analyze remote sensing data.

- In (2020), a new deep-learning method was proposed for detecting objects in high-resolution satellite images [11]. The authors used a combination of convolutional neural networks (CNNs) and attention mechanisms to detect satellite image objects. The results showed that the proposed method outperformed the traditional object detection methods' accuracy.
- In (2021), AI algorithms have been applied to analyze high-resolution satellite images to predict crop yields and identify potential drought areas. The authors used machine learning algorithms, including random forest and support vector regression, to predict crop yields based on satellite imagery. The results showed that the proposed method accurately predicted crop yield [13].
- In (2021), AI algorithms have been used to identify and classify different types of land cover in high-resolution satellite imagery [14]. The approach used a combination of CNNs and deep belief networks to classify land cover types.
- In (2017), a new approach has been proposed to use aerial photographs in building land use maps, combining forest rotation algorithm with object-based classification. The results showed that this approach is superior to traditional pixel-based classification methods [15].
- In (2016), they Described a deep learning approach to classify aerial images and proposed extracting features from an image via a neural network [16]. The method involved training CNN on a set of images. The results showed that it is superior to the results of traditional

machine learning and that the results of deep learning can provide the effective classification of aerial images.

- In (2017), the authors proposed a method for classifying high-resolution urban remote sensing data [17], using a random forest group to extract data and then a random field to improve classification results. The results show that it is superior to traditional methods, which can be helpful in urban planning and environmental monitoring applications.

2. Problem statement

The main problem could be summarized in the following few points:

1. Obtaining a corrected high-resolution aerial image of the study area in real-time due to the lack of a drone and a high-resolution camera, as well as security permits for this type of aircraft.
2. The image contains only visible bands (True color).
3. This type of image requires the creation of accurate categories for classification algorithms.
4. Moreover, since the study area is essential, it requires careful classification to provide results that can help make decisions related to future urban planning and environmental monitoring.

3. Study Area

Al-Jadriya, located at the Latitudes of 33.3253 to 33.3319 E and longitudes of 44.3816 to 44.3942 N, as shown in Figure 1, is a neighborhood located in the southwestern part of Baghdad city, Iraq. It is located on the eastern bank of the Tigris River, bordered westly by the Karkh district, northerly by the Al-Rusafa district, eastly by the Tigris River, and southly by the Al-Bayaa district. The region has a long history and a rich cultural heritage and includes many monuments and historical sites, such as the Shrine of Ibrahim Al-Adham, University of Baghdad, the Iraqi National Museum, and the Al-Kadhimiya Mosque [18]. Recent developments in the Jadriya neighborhood include urbanization and modernization, but the area still faces challenges such as traffic congestion, air pollution, and inadequate public services.

Figure 1: The location of the study area

4. Research Methodology

Classification methods have witnessed remarkable progress because of their potential to support land classification, land use determination, environmental information extraction, and decision-making processes. Given the wide variety of available data sources, it becomes necessary to employ diverse approaches to analyze this data and evaluate its overall outcomes. This paper aims to explore different classification methods, namely supervised classification, unsupervised classification, and artificial intelligence classification, and assess the results yielded by each method. To provide a comprehensive overview of the methodology employed, The following diagram shows the method steps applied in the present stud
y.

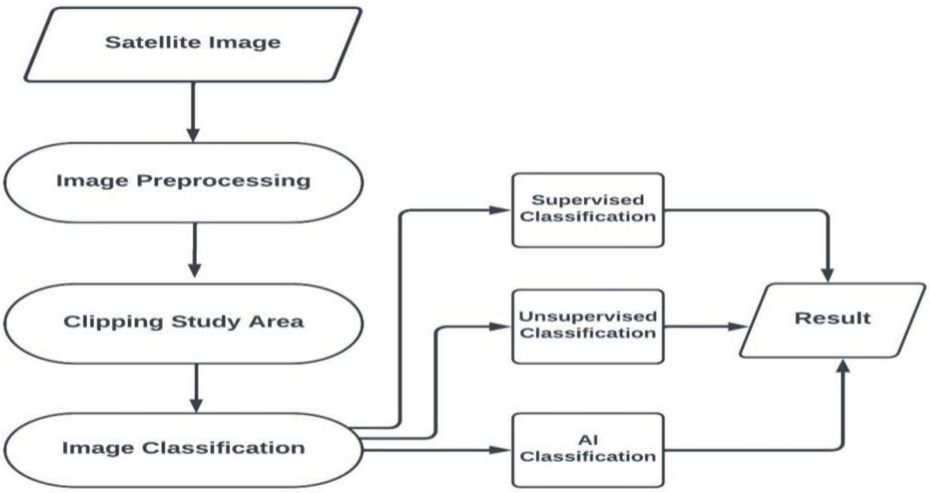

Figure 2: Block diagram of the current research work steps

4.1. Data acquisition

High-resolution satellite images can take detailed pictures of the Earth's surface using visible light [19]. These images have a high spatial resolution, which means they capture fine details of objects on the ground. High-resolution satellite imagery is helpful for various applications, including urban planning, environmental monitoring, disaster response, and military monitoring. Images can also monitor land use, vegetation, and coastal erosion changes. With technological advances, the quality of high-resolution satellites has improved significantly, allowing researchers and analysts to gain valuable insights about the Earth's surface at a level of detail previously unattainable.

The study area was classified using a satellite image from the Esri Image Collection. The image was acquired using a remote sensing platform that captures data in the visible spectrum and has a high spatial resolution of 30 cm, allowing detailed analysis and interpretation of the study area. The satellite images used contain only true colors. The resulting image has been visually interpreted and categorized into different land cover categories based on image characteristics.

4.2. Image pre-processing

The first step for pre-processing was to export the aerial image to the QGIS program and adjust the images according to the coordinate reference system for a region (WGS 1984 UTM

ZONE 38 N). After georeferencing, the second step was to crop the image using the clip tool to remove areas outside the study area in the QGIS program.

4.3. Classification method

Land cover classification is crucial in ecology, agriculture, urban planning, and climate change research. It involves identifying and classifying land cover types in a study area using software tools like GIS and QGIS. Remote sensing techniques, such as satellite imagery, provide data for processing and analysis. Traditional methods like supervised and unsupervised classification were commonly used. However, recent advances in artificial intelligence (AI) have introduced new methods like deep learning and convolutional neural networks (CNN) that improve accuracy with less human intervention. Accurate land cover classification aids in land management, decision-making, and research on climate change and urban planning. Traditional methods have limitations, but AI-based methods offer opportunities for improved accuracy. The choice of method depends on the purpose, data accuracy, and study area characteristics. Improved land cover classification methods will continue to advance the understanding of land dynamics [20, 21].

4.4. Supervised maximum likelihood classifier

The formula for maximum likelihood (MHL) classification follows the principle of maximum likelihood estimation, involving determining the class parameters that maximize the likelihood of the observed data. The probability distribution of the observed data in the case of maximum likelihood classification was assumed to be a multivariate normal distribution.

Suppose a group of training data for a specific land cover class contains n pixels represented by a vector x that shows their spectral signatures. To estimate the mean vector and covariance matrix for this class, the following equation was used [22] :

$$\mu = (1/n) * \sum(i = 1 \; to \; n) \; zi$$
$$\Sigma = (1/n) * \sum(i = 1 \; to \; n) \; (zi - \mu) * (zi - \mu)T \qquad (1)$$

where (μ) is the estimated mean vector, (Σ) is the covariance matrix, and (zi) is the spectral signature for i the pixel. By considering these estimates, the probability density function for the multivariate distribution can be calculated through the following equation [22]:

$$p(z \mid \mu, \Sigma) = (1/((2\pi)^\wedge(q/2) * |\Sigma|^\wedge(1/2))) * exp(-0.5 * (z - \mu)T * \Sigma^\wedge - 1 * (z - \mu)) \qquad (2)$$

Where q is the number of spectral bands in the image, |Σ| is the determinant of the covariance matrix, and exp. () is the exponential growth.

A pixel with spectral signature z is classified by calculating the PDF for each land cover class, and the class with the highest likelihood is chosen for the pixel.

$$p(cf \mid z) = (p(z \mid \mu f, \Sigma f) * pf) / \sum(j = 1 \; to \; f) \; p(z \mid \mu j, \Sigma j) * pj \qquad (3)$$

Where p(cf | z) denotes the posterior probability of class k given the pixel's spectral signature z, μf, and Σf are the estimated mean vector and covariance matrix for class f, pf denotes the prior probability of class f, and f denotes the total number of land cover classes. The class with the highest posterior probability is assigned for each pixel in the image, and the process is repeated for all pixels [23].

4.5. Unsupervised ISO Cluster Classifier

The ISO cluster classification method is unsupervised, meaning it does not need training data or knowledge of the image classifications beforehand. The stages listed below can be used to summarize the algorithm:

• Initialization: Pick an initial set of seed pixels to represent the classes.
• Assignment: Based on spectral similarity, classify each pixel in the image to the nearest group. The spectral values of each pixel can be compared to the mean spectral values of each class using a distance measure, such as the Euclidean distance or Mahalanobis distance.
• Update: Based on the newly allocated pixels, recalculate the mean spectral values of each class and modify the class boundaries.
• Repetition: The stopping criterion, such as a predetermined number of iterations or a minimum change in class membership, must be satisfied before repeating steps 2 and 3.

The clustering principle, which tries to classify similar pixels in an image into separate groups based on spectral properties [24], is the basis of the ISO cluster classification algorithm. The method is unsupervised because it does not need prior knowledge of the image classes or training data. Instead, to distinguish between different classes in the image, the method relies on the iterative calculation of mean spectral values and comparing pixel spectral values to these means.

The equation for the distance measure can be written as [25]:

$$d(z,x) = \left|\left|i(z) - M(x)\right|\right| \tag{4}$$

Where ||.|| represents the Euclidean distance, i(z) is the spectral vector of the zth pixel, M(x) is the mean spectral vector of the xth class, and d(z,x) is the distance between the zth pixel and the xth class. The class with the least distance is given the pixel.

4.6. Map flow AI Classifier

A machine learning platform for modeling and analyzing geographical data is called Mapflow AI. As a result, it employs a range of machine learning algorithms and techniques to identify patterns in the input data and create predictions and classifications. The particular equations that Mapflow AI uses will vary depending on the algorithm and methodology. Here are a few illustrations:

Linear regression takes the form of [26]:

$$m = zx + b \tag{5}$$

Where the coefficients (z and b) are obtained by fitting the model to the training data, this equation describes the relationship between the target variable (m) and the input variables (x).

In a decision tree, the equation is represented as [26]:

$$m = f(x) \tag{6}$$

The target variable (m) is determined based on the binary decisions made from the input variables (x).

A random forest combines multiple decision trees to generate a tree ensemble that predicts or classifies the target variable (m) based on the multiple input variables (x1, x2, ..., xn). The final prediction is computed by aggregating the results of all the individual trees.

The equation is expressed as [27] :

$$m = f(x1, x2, ..., xn) \tag{7}$$

In a neural network, the equation is expressed as [28]:

$$m = f(w1x1 + w2x2 + ... + wn*xn + b) \tag{8}$$

Where the weights (w1, w2, ..., wn) are determined by the network's hidden layers, and the bias term (b) adjusts the overall prediction. The weighted sum of the input variables (x1, x2, ..., xn) determines the target variable (m).

Mapflow AI employs numerous machine learning algorithms and techniques, and the equations used for modeling and analysis depend on the specific data and analysis requirements [29].

5. Results and discussion

Satellite images of the study area were classified using three different methods: supervised maximum likelihood, unsupervised ISO set, and artificial intelligence through the Mapflow tool. Table 1 and Figures 3-6 include the classification results for all methods used in the research paper.

Table 1: Classifications result for area features of the region using the three methods

Method	Vegetation (km^2)	Bare soil (km^2)	Road (km^2)	Building (km^2)
MHL Classification	1.667	2.686	0.967	1.914
ISO Classification	2.582	2.301	1.096	1.255
AI Classification	0.845	0.378	0.408	1.249

Figure 3: Image classified using Maximum likelihood classifier technique

Figure 4: Image classified using the Iso technique

Figure 5: Image classified using AI technique

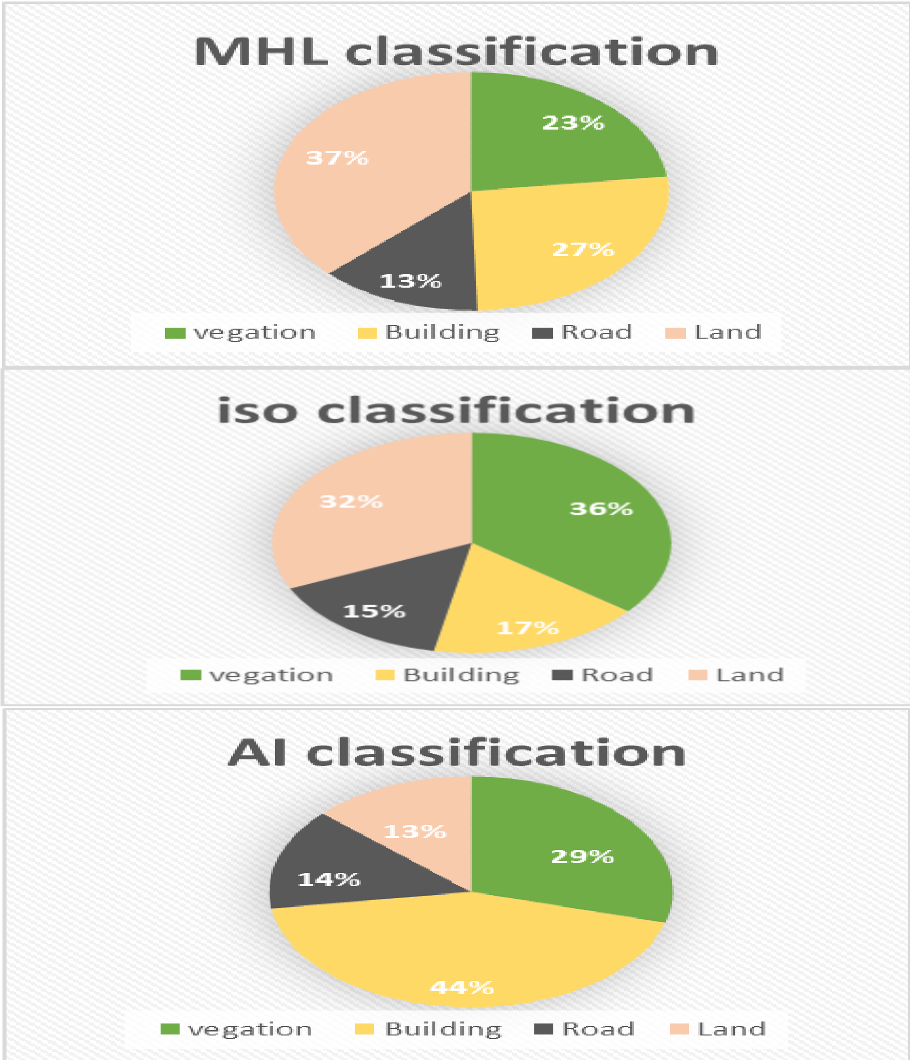

Figure 6: Illustration of the percentage of classes in each method

The rating results showed that the Mapflow AI tool outperforms the other two methods regarding accuracy. The classification accuracy for Mapflow was 81.66%, which is higher than the accuracy of the maximum likelihood (71.66%) and ISO range (69.16%). However, weaknesses were noted in areas with significant overlaps, such as between short weeds and Bare Soil. Mapflow could not identify some low-rise buildings, indicating the need for more training on these points, as shown in Figure 4.

Regarding supervised classification, maximum likelihood resulted in errors, as there was overlapping classification in some image treatments. Despite the amount of accuracy used in determining the training models, they showed weakness, especially in the overlap between shade areas and plants, where the shade areas in the image were classified as plants, in addition to a significant overlap in the classification of bare soil areas and buildings, where some parts of the buildings were classified as Dirt lands due to the layer of dust formed on the roof of the building, as shown in Figure 2.

The unsupervised classification results using the ISO ensemble showed high randomness, with no clear boundaries between the different land cover types, as illustrated in Figure 3. This method may not be suitable for the exact classification of land cover types for this data type.

It is possible that supervised and unsupervised classification methods can be effective with images containing multispectral bands, as these provide greater reflectivity than images with only visible bands. Therefore, satellite images with multispectral bands may be essential for studies requiring precise results.

5.1 Classification Accuracy Assessment

An essential step in the classification process is to assess the accuracy of the classification results for the methods used to determine the effectiveness of the method used. To evaluate the classification results, 120 points were randomly selected across the study area for each method used; each point was assigned to one of the land cover categories in the special classification scheme. Google Earth Pro was used to check the land cover type at each point by comparing the images visually with the classified map.

The overall accuracy [30] and user's and producer's accuracy, and kappa coefficient [31] for each land cover category were calculated using the following equations:

$$over\ all\ accuracy = \frac{Total\ number\ of\ coorectly\ classified\ pixles}{Total\ number\ of\ refrence\ pixels} \times 100\% \tag{8}$$

$$User's\ Accuracy = \frac{Total\ number\ of\ coorectly\ classified\ pixles\ in\ each\ category}{Total\ number\ of\ classified\ pixels\ in\ that\ category\ (Row\ Total)} \times 100\% \tag{9}$$

$$Producer\ Accuracy = \frac{Number\ of\ coorectly\ classified\ pixle\ in\ each\ category}{Total\ number\ of\ classified\ pixels\ in\ that\ category\ (column\ Total)} \times 100\% \tag{10}$$

$$\text{Kappa coefficient} = \frac{N(\sum_i^r=1\ Xii) - (\sum_i^r=1\ (xi+.x+i)}{N^2 - (\sum_i^r=1\ (xi+.x+i)} \tag{11}$$

Where r =number of rows in error matrix, Xii = number of observations in row I and column i

Xi= total of observations in row I, X+i= = total of observations in column I, N= total number included in the matrix.

The results of the accuracy assessment, including the error matrix and kappa coefficient, for each of the three methods used in the classification was presented below:

Maximum likelihood classifier:

The error matrix for the maximum likelihood classifier is shown in Table 2. All accuracy for maximum likelihood is 71%, and the kappa coefficient is 0.62; the user's and producer's accuracy for each land cover category are presented in Table 3.

Table 2: Error matrix for maximum likelihood classifier

Classified	Building	Land	Road	vegetation	user's
Building	20	9	1	0	30
Land	6	21	1	2	30
Road	4	4	20	2	30
vegetation	1	2	2	25	30
producer's (Total)	31	36	24	29	71%

Table 3: User's and producer's accuracy for maximum likelihood classifier

Classified	Building	Land	Road	vegetation
User's accuracy	66.67%	70%	66.67%	83.33%
producer's accuracy	64.5%	58.33%	83.33%	86.26%

Map flow AI Classifier:

The error matrix for the Map flow AI Classifier is shown in Table 4. All accuracy for maximum likelihood is 81.6%, and the kappa coefficient is 0.75; the user's and producer's accuracy for each land cover category are presented in Table 5.

Table 4: Error matrix for Map flow AI Classifier

Classified	Building	land	Road	vegetation	user's
Building	23	3	0	4	30
Land	5	24	0	1	30
Road	0	3	25	2	30
vegetation	0	2	2	26	30
producer's (Total)	28	32	27	33	81%

Table 5: User's and producer's accuracy for Map flow AI Classifier

Classified	Building	Land	Road	vegetation
User's accuracy	76.67%	80%	83.33%	86.67%
producer's accuracy	82.14%	75%	92.59%	78.78%

ISO Cluster Classifier:

The error matrix for ISO Cluster Classifier is shown in Table 6. All accuracy for maximum likelihood is 69.16% and kappa coefficient 0.59; the user's and producer's accuracy for each land cover category are presented in Table 7.

Table 6: Error matrix for ISO Cluster Classifier

Classified	Building	Land	Road	Vegetation	user's
Building	22	8	0	0	30
Land	2	21	7	0	30
Road	2	6	22	0	30
vegetation	0	3	9	18	30
producer's accuracy	26	38	37	18	69%

Table 5: User's and producer's accuracy for Map flow AI Classifier

Classified	Building	Land	Road	vegetation
User's accuracy	73.33%	70%	73.33%	60%
producer's accuracy	84.61%	55.26%	59.45%	100%

6. Conclusion

The study presented three methods for classifying aerial images: supervised maximum likelihood, unsupervised ISO set, and artificial intelligence through the Mapflow tool. The Mapflow AI tool outperformed the other two methods in accuracy, with a classification accuracy of 80%. However, weaknesses were noted in areas where there were significant overlaps. The maximum likelihood method resulted in some errors due to overlapping classification, and the unsupervised ISO ensemble showed a high degree of randomness, making it unsuitable for precise land cover classification. Using aerial images with multispectral bands may be essential for studies that require exact results. Overall, the study highlights the importance of selecting an appropriate classification method based on the research question and available data and suggests that the AI-based approach holds promise for future research in this area.

References

[1] N. S. Abd-Alwahab and N. K. Ghazal, "Change Detection between Landsat 8 images and Sentinel-2 images," *Iraqi Journal of Science,* vol. 60, no. 8, pp. 1868-1876, 2019.

[2] M. F. Allawai and B. A. Ahmed, "Using Remote Sensing and GIS in Measuring Vegetation Cover Change from Satellite Imagery in Mosul City, North of Iraq," *IOP Conference Series: Materials Science and Engineering,* vol. 757, no. 1, p. 012062, 2020.

[3] B. S.Ismaal, B. A.Alazaq, Z. F.Rasheed and E. F.Khanjer, "Change Detection Study of Al Razaza

Lake Region by Image Classification Using Gaussian Mixture Model," *Indian Journal of Natural Sciences,* vol. 9, no. 51, p. 15521_15525, 2018.

[4] H. F. Difar and F. M. Abed, "Automatic Extraction of Unmanned Aerial Vehicles (UAV)-based," *Iraqi Journal of Science,* vol. 63, no. 2, pp. 877-896, 2022.

[5] A. S. Mahdi, "The Land Use and Land Cover Classification on the Urban Area," *Iraqi Journal of Science,* vol. 63, no. 10, pp. 4609-4619, 2022.

[6] F. K. Mashee, O. H. Mutlag and M. J. Rasheed, "Spectral indices analysis for Al-Gharaf River basin land," *EurAsian Journal of BioSciences,* vol. 14, no. 2, pp. 3367-3375, 2020.

[7] F. G. Mohammed, M. H. Ali, S. G. Mohammed2 and H. S. Saeed, "Forest Change Detection in Mosul Province using RS and GIS Techniques," *Iraqi Journal of Science,* vol. 62, no. 10, pp. 3779-3789, 2021.

[8] S. M. Ali, A. S. Mahdi, Q. M. Hussan and F. W. Al-Azawi(b), "Fluctuating Temperatures as one of the Important Causes for Desertification in Iraq," *British Journal of Science,* vol. 7, no. 2, p. 26_32, 2012.

[9] Q. Wu, Ruofei Zhong, W. Zhao, H. Fu and K. Song, "A comparison of pixel-based decision tree and object-basedSupport Vector Machine methods for land-cover classification based on aerial images and airborne lidar data," *International Journal of Remote Sensing,* vol. 38, no. 23, p. 7176–7195, 2017.

[10] P. Wang, E. Fan and P. Wang, "Comparative analysis of image classification algorithms based on traditional machine learning and deep learning. Pattern Recognition Letters," *Journal Pre-proof,* vol. 145, pp. 32-39, 2021.

[11] W. Cui, X. H. ORCID, M. Y. Z. Wang, J. Li, Y. Hao, W. Wu and H. Zhao, "Landslide Image Captioning Method Based on Semantic Gate and Bi-Temporal LSTM," *ISPRS International Journal of Geo-Information,* vol. 194, p. 1_29, 2020.

[12] S. Martinis and J. Skaloud, " Performance evaluation of data compression for high-resolution optical satellite imagery," *Remote Sensing,* vol. 5, no. 7, pp. 3324-3349, 2013.

[13] A. Shah, A. Adnan, S. Khalid Hussain and S. Anwar, "Predicting crop yield and identifying drought areas using high-resolution satellite imagery and machine learning algorithms," *Computers and Electronics in Agriculture,* vol. 181, p. 105976, 2021.

[14] A. Garg, R. Shukla, P. Chaudhary and S. Kanga, "Land cover classification in high-resolution satellite images using a deep learning approach," *Journal of Applied Remote Sensing,* vol. 15, no. 1, p. 016503, 2021.

[15] Ö. Akar, "The Rotation Forest Algorithm and Object Based," *Geocarto International,* vol. 33, no. 5, p. 538–553, 2017.

[16] G. John Ray, C. Persello and C. Gevaert, "A deep learning approach to the classification of sub-decimetre resolution aerial images," *2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS),* pp. 1516-1519, 2016.

[17] X. Sun, X. Lin, S. Shen and Z. Hu, "High-resolution remote sensing data classification over urban areas using random forest ensemble and fully connected conditional random field," *ISPRS International Journal of Geo-Information,* vol. 6, no. 8, p. 245, 2017.

[18] A. M. Al-Quraishi, "Urban growth and land use changes in Baghdad city using remote sensing and GIS techniques," *Journal of Civil Engineering and Architecture,* vol. 12, no. 1, pp. 1-8, 2018.

[19] G. O. Reddy, "Satellite remote sensing sensors: principles and applications," in *Geospatial technologies in land resources mapping, monitoring and management*, 2018, pp. 21-43.

[20] M. Mohammady, H. R. Moradi, H. Zeinivand and A. J. A. M. Temme, "A comparison of supervised, unsupervised and synthetic land use classification methods in the north of Iran," *Int. J. Environ. Sci. Technol,* vol. 12, no. 5, p. 1515–1526, 2015.

[21] P. Helber, B. Bischke, A. Dengel and D. Borth, " A novel dataset and deep learning benchmark for land use and land cover classification," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* vol. 12, no. 7, pp. 2217-2226, 2019.

[22] T. Lillesand, R. W. Kiefer and J. Chipman, "Remote Sensing and Image Interpretation," *John*

Wiley & Sons, 2015.

[23] J. Richards, "Feature reduction," *in Remote Sensing Digital Image Analysis: An Introduction, 2nd ed., Springer-Verlag, Berlin, Heidelberg,* pp. 343-380, 2013.

[24] R. G. Congalton and K. Green, "Assessing the Accuracy of Remotely Sensed Data," *in Proceedings of the 31st International Symposium on Remote Sensing of Environment (ISRSE),* 2008.

[25] G. M. Foody, "Non-parametric classification and class composition by decision tree analysis," *International Journal of Remote Sensing,* vol. 15, no. 2, pp. 331-336, 1994.

[26] K. B. Korb, C. S. Caetano and A. R. Tavares, "Machine Learning Techniques for Geospatial Analysis," *in Geographic Information Systems: Concepts, Methodologies, Tools, and Applications, IGI Global,* pp. 1256-1277, 2017.

[27] M. F. Goodchild and T. J. Cova, "Introduction to Geospatial Technologies for Emergency Management," *in Geospatial Analysis of Environmental Health,* pp. 29-42, 2019.

[28] A. B. Kibria, K. S. Hasan and S. Sultana, "Machine Learning Techniques for Spatial Data Analysis: A Review," *in Journal of Big Data,* vol. 7, no. 1, pp. 1-27, 2020.

[29] M. Kanevski and A. Pozdnoukhov, "Geostatistical and Machine Learning Approaches for Spatial Data Analysis," *in Handbook of Regional Science,* pp. 1-32, 2021.

[30] S. S. Rwanga and J. M. Ndambuki, "Accuracy Assessment of Land Use/Land Cover," *International Journal of Geosciences,* vol. 8, no. 4, pp. 611-621, 2017.

[31] R. Congalton, "A Review of Assessing the Accuracy of Classifications of," *Remote Sensing of Environment,* vol. 37, pp. 35-46, 1991.

[32] R. G. Congalton and K. Green, "Assessing the Accuracy of Remotely Sensed Data," *in Proceedings of the 31st International Symposium on Remote Sensing of Environment (ISRSE),* 2008.

[33] K. B. Korbo, C. S. Caetano and A. R. Tavares, "Machine Learning Techniques for Geospatial Analysis," *in Geographic Information Systems: Concepts, Methodologies, Tools, and Applications, IGI Global,* pp. 1256-1277, 2017.