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A Comparison of Wavelet Feature-Based Minimum Distance and Rule-Based Fuzzy System for Classifying Medium-Resolution Images in Heterogeneous Landscapes

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Abstract

Classification and labeling of satellite images in remote sensing (RS), as well as improvement in their classification accuracy, have received researchers' attention for decades. The present study compares two classification methods—namely, the Rule-Based Fuzzy System and the proposed Wavelet Feature-Based Minimum Distance (W-F-M-D) algorithm—for medium-resolution images, particularly in heterogeneous landscapes. The Advanced Land Imager (ALI) was studied in an area located in southwestern Tehran, Iran. For validation, the land cover map obtained from both methods was compared with ground truth data through confusion matrix analysis, Kappa coefficient, and overall accuracy. The best results for the W-F-M-D algorithm were achieved with an overall accuracy of 93.55% and a Kappa coefficient of 0.89. Meanwhile, the results obtained from the fuzzy method were also satisfactory, with an overall accuracy of 89.27% and a Kappa coefficient of 0.84. However, the simplicity and speed of the proposed W-F-M-D algorithm constitute an additional advantage over the fuzzy method. From a different perspective, in the heterogeneous urban-agricultural area with moderate spatial resolution, the accuracy obtained for the urban area map—compared to that of bare lands—using the W-F-M-D method was evaluated as satisfactory, with producer's accuracy of 99.25% and user's accuracy of 91.67%.

Keyword: Wavelet, Feature extraction, Rule-Based Fuzzy System, Classification, medium Resolution.

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Introduction

Classification of satellite images, as one of the fundamental issues in image analysis for categorizing images into distinct homogeneous areas, has presented researchers with significant challenges (Al-Ani, 2013; Padhy et al., 2024). Landscape is defined as a set of economic, social, and cultural activities of human beings. Thus, human tendencies toward using natural spaces can significantly influence environmental processes and patterns (Turner, 1989; Kostanjšek & Golobič, 2023). Investigating changes in landscape is an important indicator for monitoring biological diversity, land use planning, land protection and management, ecosystem protection, and sustainable development. Consequently, preparing land cover maps receives high interest from organizations and officials worldwide (Bartel, 2000; Schmeller, 2008; Bunce et al., 2013; Wolf et al., 2023).

Landscape mapping is mainly performed via field studies or remote sensing observations. However, the latter approach is generally preferred due to its advantages, including large area coverage, time efficiency, and cost effectiveness (Nagendra, 2001; Petrou et al., 2014; Reyes et al., 2017; Dolman et al., 2025). To date, numerous studies have been conducted on the use of satellite images for land management and land use/land cover analysis through a combination of data and different methods. Various studies have addressed supervised classification, including those by Walker et al. (2010), Feret and Asner (2012), Longépé et al. (2011), Vyas et al. (2011), Rajesh et al. (2012), Reyes et al. (2017), Alshari and Gawali (2021), Sharma Banjade et al. (2023), Ojwang et al. (2024), Al-Aarajy et al. (2024), and Dolman et al. (2025). Other studies have focused on unsupervised classification, such as those by Muad and Foody (2012), Mwita et al. (2013), and García-Rubio et al. (2015). The common method for extracting data from satellite images includes supervised and unsupervised classification at the pixel level (Murmu & Biswas, 2015) for sensors with low and medium spatial resolution (Reyes et al., 2017).

Image classification is the process of labeling each pixel based on pixel brightness values (BVs) and investigating similarity through statistical relations. From this perspective, classification algorithms are divided into two main groups: hard computing and soft computing (Rokach and Maimon, 2005). Classification of remote sensing images is based on the hypothesis that the study area comprises a finite number of homogeneous classes. According to reflectance data and auxiliary field data, those classes can be classified (Lillesand and Kiefer, 1994). This hypothesis is not valid in areas characterized by uncertainty. This problem can be addressed via soft classification methods, such as fuzzy and sub-pixel classification methods (Murmu & Biswas, 2015). In addition, certain limitations of satellite images—including low and medium spatial resolution, poor contrast, and noise—result in low efficacy of hard classification methods (Ghaffarian & Ghaffarian, 2014). Numerous researchers have analyzed and classified images using fuzzy methods in remote sensing (Wang, 1990; Melgani et al., 2000; Bardossy and Samaniego, 2002; Wang and Jamshidi, 2004; Tang et al., 2007; Tso and Mather, 2009; Shankar et al., 2011).

Bethuel et al. (2025) proposed a rule-based and fusion-based classification methodology based on Dempster–Shafer theory (DST) for land cover mapping. The application of DST relied on four steps: (1) a discernment framework, (2) the assignment of mass functions, (3) the DST fusion rule, and (4) the DST decision rule. Their DST-based approach demonstrated that industrial plantations were detected with higher confidence than smallholder plantations. Wei et al. (2024) introduced a multi-level wavelet frequency decomposition module (MWFD) to extract and integrate features. To mitigate boundary uncertainty, a type-2 fuzzy spatial constraint module (T2FSC) was proposed to achieve flexible higher-order fuzzy modeling, adaptively constraining boundary features in the spatial domain by constructing upper and lower membership functions. Li et al. (2017) developed a fuzzy classification method using visual attention features (FC-VAF) for high-resolution remote sensing scene classification. Specifically, they employed wavelet transform-based visual attention feature extraction and found that the FC-VAF method improved the accuracy of high-resolution scene classification. Shankar et al. (2011) proposed a wavelet feature-based supervised scheme for fuzzy classification of land covers in SPOT and IRS images. The wavelet features obtained from wavelet transform provide spatial and spectral characteristics of pixels and can therefore be utilized effectively to improve classification accuracy, instead of using original spectral features alone.

Fuzzy logic is extensively used to address problems caused by hard classification methods at the moderate level and to cope with errors arising during processing, mainly those originating from data containing noise (Klir, 2001). Nevertheless, noise produced during the processing and acquisition of satellite images, as well as the generation of rules sensitive to rule thresholds, can affect classification accuracy. Moreover, the presentation of false rules by experts and minor changes in rule thresholds—for example, when applying this method to similar sites located in different areas—may significantly reduce classification accuracy, similar to hard classification methods (Petrou et al., 2014).

Factors such as data loss and errors caused by noise-containing data can influence the efficacy and productivity of classification methods. Such issues are common in remote sensing, particularly for data with medium spatial resolution, where various errors may be introduced during data acquisition and image processing stages, including geometric and atmospheric correction. These problems, along with memory and processing time costs and difficulties in operationalizing fuzzy logic, motivated the proposal and testing of the Wavelet Feature-Based Minimum Distance (W-F-M-D) algorithm. Wavelet transform (WT) can be used to analyze and process satellite images in both the spatial and frequency domains. Thus, WT coefficients collect data from neighboring pixels in the uncorrelated spatial domain. Several studies have employed WT for classification of remote sensing images, including Yu and Ekstrom (2003), Zhan et al. (2005), Turkoglu and Avci (2008), Shankar et al. (2011), Rajesh et al. (2012), and Garg et al. (2016).

The present study aims to identify a simple and high-performance strategy for separating urban, bare land, and residual farm classes (i.e., the ambiguous and uncertain classes) in pixel-based classification of a heterogeneous area using medium spatial resolution imagery. Accordingly, this study compares two classification methods—one based on fuzzy structure rule extraction and the proposed Wavelet Feature-Based Minimum Distance (W-F-M-D) algorithm—over a heterogeneous agricultural-urban area in Tehran City. The accuracy of these two classification approaches in producing land cover maps, particularly for extracting urban areas and urban fringe effects, was investigated using ALI data with medium spatial resolution.

The study area

Tehran Province, with Tehran City as its capital, is located in an area of 12,981 km² between 34° and 36.5° north latitude and 50° and 53° east longitude. This province is bordered by Mazandaran Province to the north, Qom Province to the south, Markazi Province to the southwest, Alborz Province to the south, and Semnan Province to the east. The study area is located approximately 10 km southeast of Tehran City, situated between 51°26' and 51°33' east longitude and 35°28' and 35°50' north latitude (Fig. 1). It is a heterogeneous area comprising agricultural fields, gardens, urban residential areas, bare land, and residual farms, which are scattered with mixed boundaries.

Materials and methods
Data

In the present study, ALI data from the Earth Observing-1 (EO-1) satellite, developed by the United States Geological Survey (USGS), were used. These data comprise nine spectral bands ranging from 0.43 to 2.35 µm, with a spatial resolution of 30 m, acquired on July 25, 2022, over an agricultural-urban area located in southeastern Tehran (Table 1).

Numerous studies have been conducted on data extraction from signals and coping with their variable behaviors. One of the methods proposed in this regard is wavelet transform, in which the spatial localization of signal frequency is preserved. In one-dimensional discrete wavelet transform (DWT), the signal is divided into approximation and detail components at each level of decomposition by concurrently applying low-pass and high-pass filters (Fig. 2). Since wavelet transform identifies the scale and space of information of phenomena, it is suitable for analyzing signal characteristics. These unique characteristics of wavelet transform are widely used for analyzing remote sensing data. By applying wavelet transform, the frequency resolution doubles, and the uncertainty of data is reduced (Shankar et al., 2011).

Given that a high degree of noise is observed in the spectral reflectance curves of heterogeneous areas, the present study employs a wavelet-based function—specifically, the Sym6 matrix—for noise reduction and spectral homogenization (based on Chavan et al., 2011; He et al., 2015; Wang et al., 2024; Khoo et al., 2025; Lu et al., 2025). Additionally, wavelet transform is applied to identify and detect spectral characteristics.

The discrete wavelet transform (DWT), like the Fourier transform, is used to transform the spectrum into another space through meaningful features. The DWT is given by:

$$x(t)=\sum_{j=1}^{l}\sum_{k=0}^{2^{l}} c_{j,k}\psi_{j,k}$$

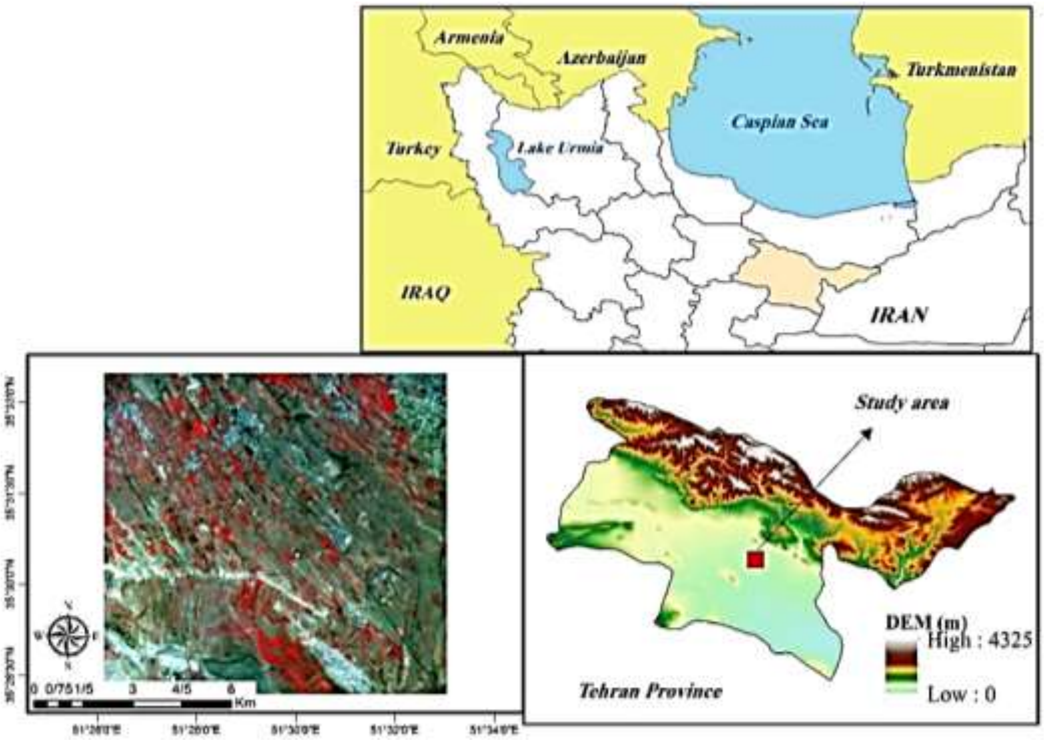

Fig. 1. The False color composite (RGB: 5, 4, 3 bands) of ALI image of Tehran in IRAN from July 2022 and DEM of Tehran.

Table1, List of data used in this study and its characteristics

Acquisition date	Data type	Path/Row	Bands	Wavelength(micrometers)	resolution
2022.07.25	EO-1-ALI	164/35			
			Band 1 - Blue	0.43 - 0.453	30
			Band 2 - Blue	0.45 - 0.515	30
			Band 3 - Green	0.525 - 0.605	30
			Band 4 - Red	0.63 – 0.69	30
			Band 1 - NIR	0.775 – 0.805	30
			Band 2 – SWIR1	0.845 – 0.89	30
			Band 3 – SWIR2	1.2 – 1.3	30
			Band 4 – SWIR3	1.55 – 1.75	30
			Band 4 – SWIR4	2.08 – 2.35	30

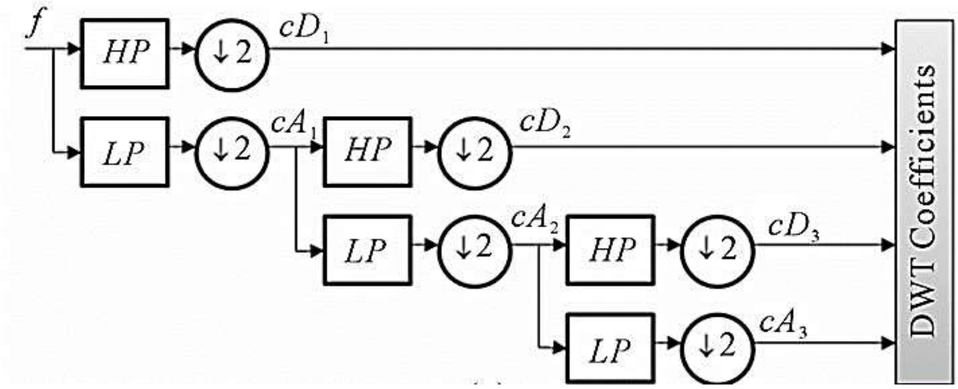

Fig. 2. The DWT at three levels and production of approximation (cA) and details (cD) components (Vermaak et al., 2016)

Where $\psi_{0,0}$ is the father wavelet out of which other wavelets $\psi_{j,k}$ are derived. $x(t)$ shows the spectrum, l is the decomposition level for the DWT and $c_{j,k}$ represents wavelet coefficient calculated by the inner product between $x(t)$ and $\psi_{j,k}$ (Donald, 2012):

$$c_{j,k} = \langle x(t) | \psi_{j,k} \rangle$$

The spectral vector of ALI image bands in the heterogeneous area is highly variable and complex; consequently, features cannot be easily detected. To extract features from satellite images and prepare land cover maps, the spectral properties of image features were considered. The spectral properties of an object in images are typically obtained through statistical measurements of spectral values, such as mean, standard deviation (SD), and pixel spectral ratios.

In the present study, the spectral ratio of the vectors of all bands to band 9 was considered. Through this process, variability was reduced, and the vectors were normalized. Finally, to extract land cover using the extracted spectral features, the minimum distance classification method was employed. This simple yet efficient method is used to classify unknown image pixels into classes with the objective of minimizing the distance between image data and class centers in the multi-feature space. This minimum distance serves as a similarity indicator, whereby the minimum distance corresponds to maximum similarity. The Euclidean distance is used in cases where the variances of class populations differ from one another. The Euclidean distance is given by (Del Giudice, 2023):

$$D^2_k = (X-\mu_k)^t (X-\mu_k)$$

The Rule-Based Fuzzy System

In areas with obscure and uncertain boundaries and uncertainty in feature extraction—particularly in urban areas—the use of fuzzy logic appears appropriate (Longley et al., 2001). In fuzzy logic, the properties of a feature are explained through the definition of a membership function. The class of each feature is described via a rule-based fuzzy system that establishes relationships between each feature and its properties (Sebari and He, 2013).

An object class rule constitutes a conjunction of propositions regarding the properties describing that class. Generally, it follows this form:

IF X_1 is P_1 AND …… AND X_i is P_i AND ….. X_n is P_n THEN Y is C_i

Where ≪X_i is P_i≫ is a fuzzy proposition on a property and ≪Y is C_i≫ the conclusion translating membership to the class C_i. The degree of satisfaction of a rule is obtained by using a fuzzy aggregation operator which aggregates the membership degrees like a logical ‘‘AND’’ (Sebari and He, 2013). We used the Fuzzy inference systems (FIS) for creating fuzzy rules. Fuzzy inference is the process of mapping functions from a given input to an output using fuzzy logic (Matlab, 2015). FISs also known as fuzzy rule-based systems, fuzzy model, fuzzy expert system, and fuzzy associative memory consists of inputs and their membership functions; output and its membership functions; and rules for the memberships (Asklany et al., 2011).

Results and Discussion

Due to the creation of high levels of combination among different bands and classes, the CreateFuzzyRules function in MATLAB was used to generate fuzzy rules. Figure 3 presents an example of the fuzzy membership functions used in this research, illustrating a triangular function type along with its minimum, mean, and maximum values for each class. Figure 4 also displays some of the rules of the fuzzy model developed for accessing the classes.

In this study, a total of 216 fuzzy rules were generated based on the number of bands and classes. Representative examples of the fuzzy model rules developed in this study are as follows:

If (Band2 is Class 1) AND (Band7 is Class 1) AND (Band9 is Class 1) THEN (Class is Class 1)

If (Band2 is Class 4) AND (Band7 is Class 2) AND (Band9 is Class 2) THEN (Class is Class 2)

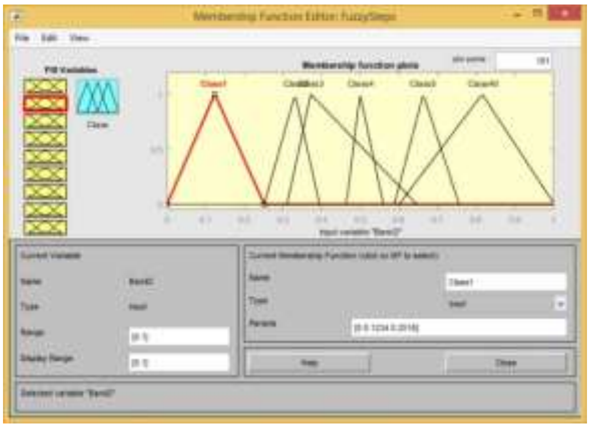

Fig. 3. Fuzzy membership functions of with a triangular function type

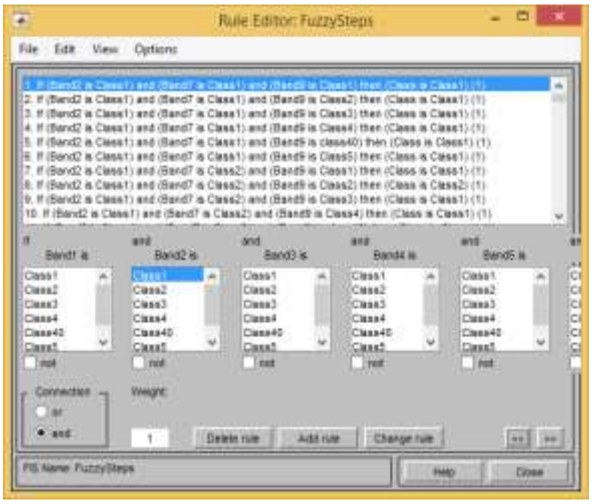

Fig. 4. Some Fuzzy rules of this research

For qualitative assessment of the proposed method in the present study and comparison with fuzzy logic, the output maps of these two methods are presented in Figure 5. Figure 5 generally shows that there is no significant difference between the two classification methods for the urban labeled class. However, upon closer examination of the results, it is evident that the W-F-M-D method is more objective; particularly in

Regions 2, 3, and 4, the results are more consistent with the satellite image and ground truth data and are therefore more accurate. In Region 1, the results obtained from fuzzy logic are more consistent with the ground truth data.

In conventional classification methods such as artificial neural networks and maximum likelihood, urban areas cannot be accurately detected in satellite images with medium spatial resolution and are consequently classified as bare land. However, in both the fuzzy and the proposed W-F-M-D methods, areas with high fuzziness can be successfully detected.

Considering Regions 1 and 2 in Figure 6, the fuzzy output map shows that some pixels are incorrectly and inaccurately classified under the Garden class instead of the Rest Farm class. Although in the proposed W-F-M-D method, there are some parts classified under the Agriculture class instead of the Garden class in Regions 1 and 2, the Rest Farm class has been classified more accurately in those areas. In contrast, in Regions 3 and 4 of Figure 6, the proposed W-F-M-D method extracts the Agriculture lands class more accurately and correctly than fuzzy logic.

Although there are some notable differences between the results of Garden and Agriculture classification in the two methods compared to the images and ground truth data, the results of the proposed W-F-M-D method are generally less problematic and more reliable. The Agriculture class was obtained with very little deviation from the ground truth data using the proposed W-F-M-D method.

Figure 7 clearly indicates that the Bare Land and Rest Farm classes are classified with greater accuracy by the proposed W-F-M-D algorithm than by fuzzy logic. Furthermore, it is readily observed that the proposed W-F-M-D algorithm is more efficient in classifying roads than fuzzy logic. A considerable amount of bare land has been classified as part of the Rest Farm class in the fuzzy logic method, whereas those areas actually belong to the Bare Land class.

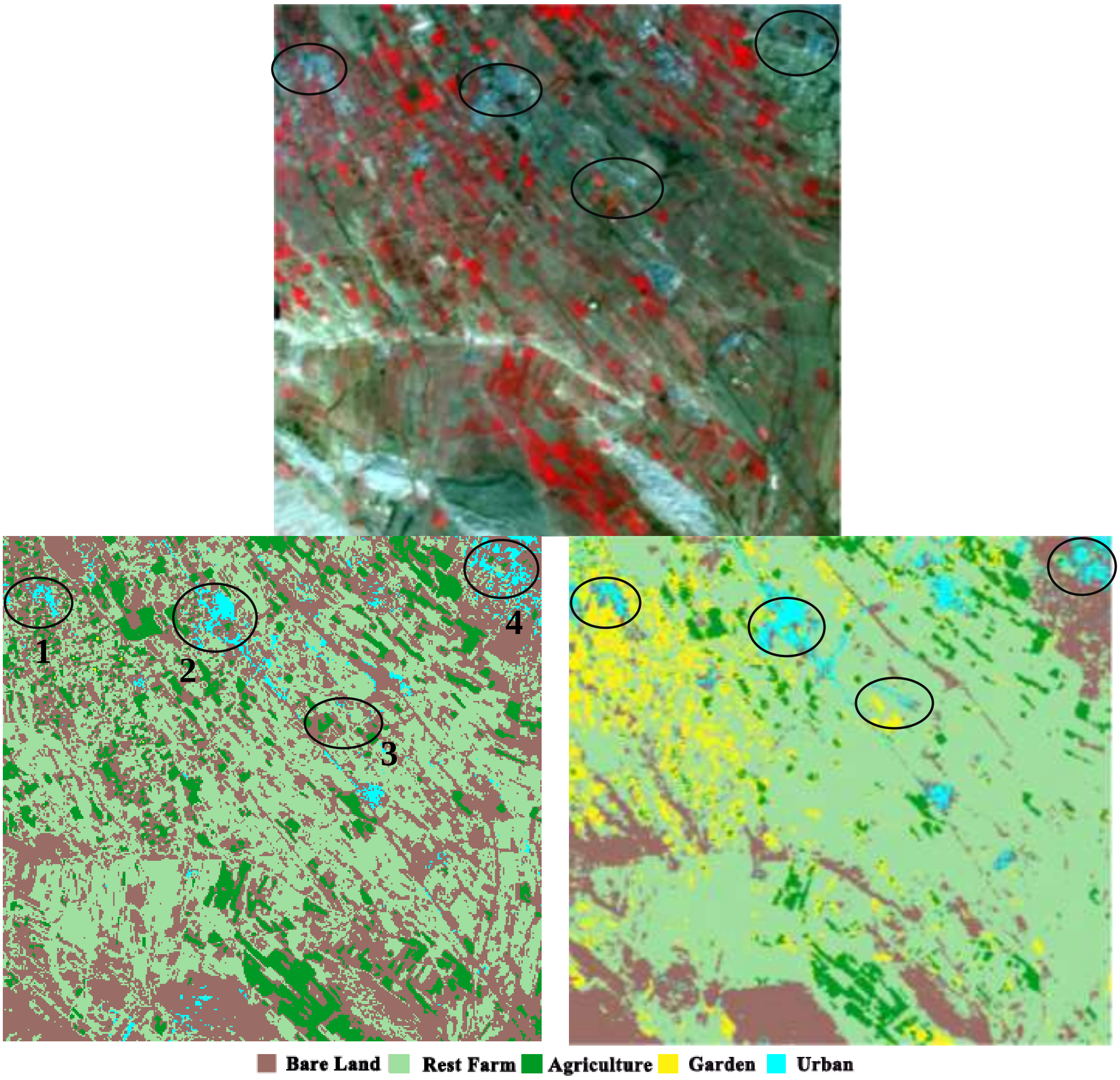

Fig. 5. Land cover extracted by the proposed W-F-M-D method and Fuzzy logic are shown in left and right sides, respectively. The upper one is the image of this study area.

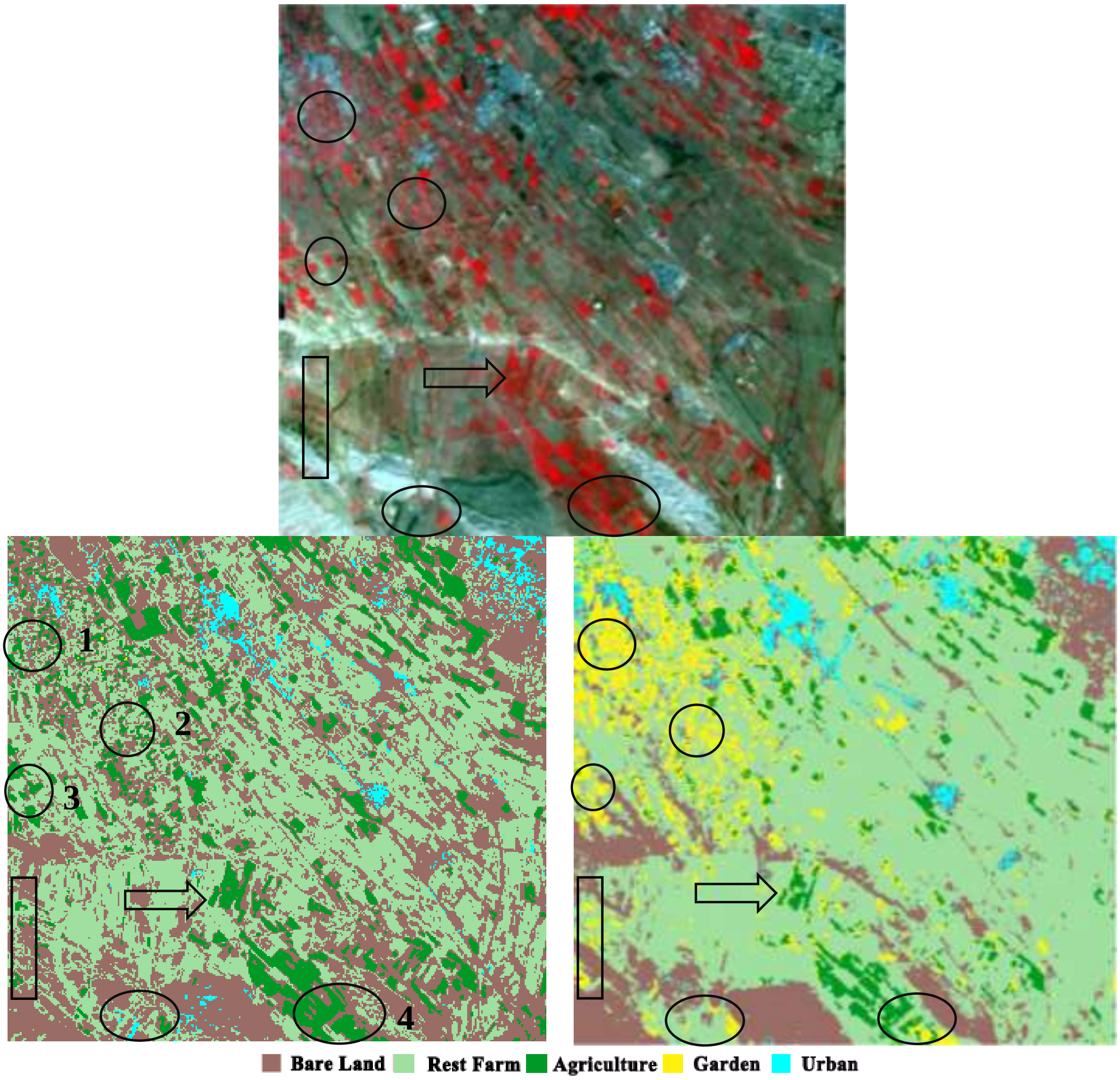

Fig. 6. Land cover extracted by the proposed W-F-M-D method and Fuzzy logic are shown in left and right sides, respectively. The upper one is the image of this study area.

The Rest Farm class is usually classified falsely under the Bare Land class in most pixel-based classification methods applied to satellite images with medium spatial resolution. However, in the proposed W-F-M-D algorithm, the Rest Farm class is classified more appropriately than in the fuzzy logic method.

Therefore, based on qualitative assessment of the classification results, it can be concluded that the proposed W-F-M-D algorithm is more accurate than fuzzy logic with respect to the classification of the Rest Farm class, as well as the extraction of roads, agriculture, and urban regions.

Furthermore, examination of the overall accuracy and Kappa coefficient values for both methods reveals that the proposed W-F-M-D algorithm, with values of 93.55% and 0.89, respectively, is more efficient than fuzzy logic, which achieved values of 89.27% and 0.84 for the classification of this heterogeneous area with medium spatial resolution. Accordingly, the confusion matrix values (producer's accuracy, user's accuracy, commission, and omission) for the proposed W-F-M-D algorithm are presented in Tables 1 and 2. As observed from the results, only the Garden class was not accurately classified, whereas the other classes were properly classified. Notably, the Urban class—which is typically classified under the Bare Land class in medium-resolution images—was classified properly in terms of producer's accuracy (99.25%) and user's accuracy (91.67%) using the proposed method.

It is concluded that the structure of the proposed method performs well in heterogeneous areas due to noise reduction and spectral homogenization achieved through wavelet transform. Wavelet transform, like the Fourier transform, is used to identify and detect spectral characteristics and to transform the spectrum into another space using meaningful features. Furthermore, in heterogeneous areas, spectral feature extraction using statistical measurements, combined with the minimum distance classification method as a similarity indicator, can introduce greater accuracy in separating ambiguous and uncertain classes such as Rest Farm, Bare Land, and Urban classes, particularly in urban areas.

All stages of this research were conducted on a computer system (a laptop) with the following configurations: an Intel Core i7 processor with 2.8 GHz and 8 GB of RAM. The rules for fuzzy logic and the proposed W-F-M-D algorithm were developed in MATLAB. The structure and implementation of the proposed W-F-M-D algorithm are not only simple but also require lower processing memory and time costs. Specifically, the processing times for the W-F-M-D and fuzzy methods were 22.296 seconds and 55.296 seconds, respectively.

Conclusion

In this research, fuzzy logic and the proposed Wavelet Feature-Based Minimum Distance (W-F-M-D) algorithm were used to classify ALI satellite imagery of an urban-agricultural heterogeneous region with medium spatial resolution. Despite the simplicity of the proposed W-F-M-D algorithm, it not only requires less memory but also demands less processing time for execution. Furthermore, the accuracy obtained from the proposed algorithm—in terms of overall accuracy, Kappa coefficient, producer's accuracy, and user's accuracy—is higher than that achieved by fuzzy logic. Notably, the proposed algorithm demonstrated superior accuracy in segregating urban areas from bare lands. This algorithm can also be applied in other disciplines that require automatic clustering algorithms. Although longer computation time is expected for hyperspectral images with 220 bands, the simple W-F-M-D algorithm may still prove more efficient. Additionally, incorporating other features in combination with wavelet transform could lead to even more accurate classification of satellite images. It is recommended that future studies compare the results of the proposed method with machine learning and deep learning approaches, as well as conduct multi-scene and experimental analyses to enhance generalizability.

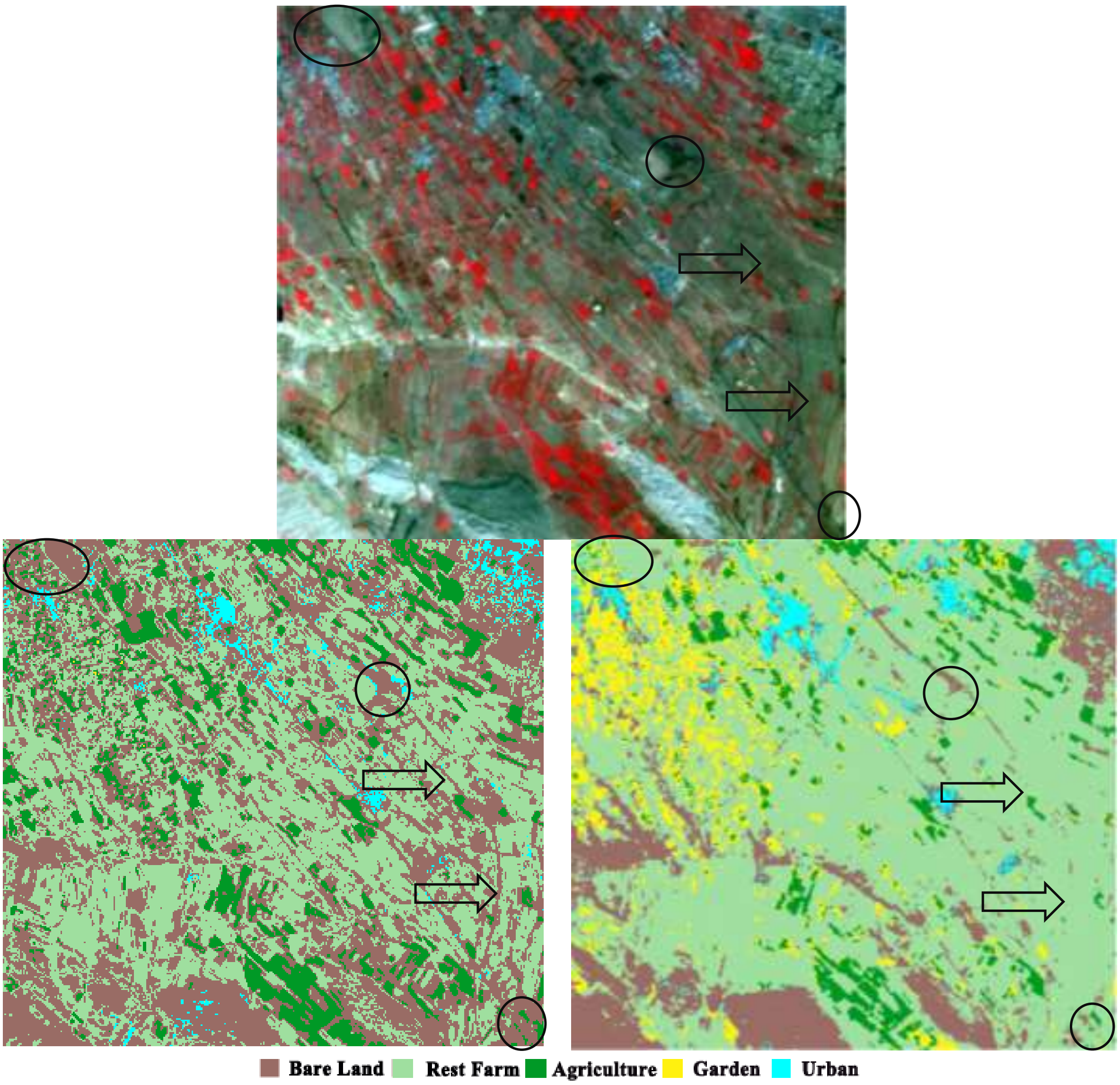

Fig. 7. Land cover extracted by the proposed W-F-M-D method and Fuzzy logic are shown in left and right sides, respectively. The upper one is the image of this study area.

Table2, The Confusion matrix of the proposed W-F-M-D algorithm

	Ground Truth (Pixels, Percent)					
	Class	Agriculture	Garden	Rest Farm	Bare Land	Urban
Classification	Agriculture	176, 96.17	19, 63.33	0	0	0
	Garden	7, 3.83	11, 36.67	0	0	0
	Rest Farm	0	0	328, 96.19	13, 4.48	0
	Bare Land	0	0	11, 3.23	267, 92.07	1, 0.75
	Urban	0	0	2, 0.59	10, 3.45	132, 99.25
	Total	183	30	341	290	133

Table3, The prod. Acc., user. Acc., commission and omission of the proposed W-F-M-D algorithm

	Class	Prod. Acc. (%)	User. Acc. (%)	Commission (%)	Omission (%)
Classification	Agriculture	96.17	90.26	9.74	3.82
	Garden	36.67	61.11	36.84	63.33
	Rest Farm	96.19	96.19	3.81	3.81
	Bare Land	92.07	95.7	4.3	7.93
	Urban	99.25	91.67	8.33	0.75

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