BOUNDARY DELINEATION OF AGRICULTURAL FIELDS BY APPLYING FUZZY OBJECT-BASED IMAGE ANALYSIS

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Abstract

Expected climate change can disrupt food availability, reduce access to food, and treat human beings and large living creatures in many agricultural operations worldwide, including our homeland Azerbaijan. The boundaries of agricultural fields are, therefore, important components necessary for defining the location, shape, and spatial extent of farming units commonly used to summarize production statistics at the field level. Accordingly, the current paper delineated the agricultural field boundaries from which we acquired Sentinel-2 satellite images dated 2021/06/17 inside the eCognition Developer, Version 9.5, over a small part northeast of Ganja Dashkasan and northwest Central Aran economics regions the Republic of Azerbaijan. Then, the examination was followed by applying a few Fuzzy Object-Based Image Analysis (F-OBIA) techniques inside eCognition Software. In addition, we covered edge detection approaches, watershed segmentation algorithms, and a few rule-based applications to reach the study's targeted aims. Finally, we combined edge detection features and segmented image objects with knowledge-based methods to trace agricultural fields with various Normalized Differences in Vegetation Indices. At the regional and local scales, the current methodology and associated models could be used in many agricultural operational types of research by processing high-resolution satellite imagery. The field data gave satisfactory results. Researchers could apply the proposed methodology in other Azerbaijan regions to access accurate information leading to sustainable agricultural operations.

Keywords: Fuzzy Object-Based Image Analysis, eCognition Developer, Knowledge-Based Methods, Boundary Delineation of Agricultural Fields

I. Introduction

Under climate change, climatic hazards have a higher probability of occurrence, and crop insurance has become more critical to growers. To have reasonable insurance premiums, the growers and the crop insurance agencies need precise measurements of the cropped field area and boundaries [1]. Global Navigation Satellite System (GNSS)-based on site surveys can determine field areas and boundaries, but they are costly in time and effort. The main purpose of the current article is to identify agriculture farms - examples of traditional agricultural and modern irrigation fields - based on Sentinel-2 satellite imagery. Field boundary information is often available for individual farms, but it isn't easy to collate and maintain this uniform across a region containing thousands of farms [2]. Also, physical fence lines are not the only interesting feature: several different crops are sometimes grown inside a single field. Since the final aim is to classify these crop parcels separately, subareas must also be segmented. Rydberg and Borgefors 2001 defined field boundaries as being at locations "where a change in crop type takes place or where two similar crops are separated by a natural disruption in the landscape, like a ditch or a road." To this, we add any significant differences in crop management. In practice, any boundary mapping method must be able to work across large areas, such as whole districts or full satellite scenes. It must also be easy to quickly regenerate the field boundary map from new image sequences so that we can keep up the result to date. Changes in farm type often give rise to new field layouts, and subareas of the crop within fields vary from year to year. Existing approaches for segmenting imagery include:

a) edge detection methods [3]; these accurately locate significant boundaries but do not guarantee closed polygons;

b) region-based methods involving merging adjacent areas that have similar spectral properties (bottom-up, region growing); splitting areas that have different spectral properties (top-down); or clustering spectrally similar pixels around a set of k-means [4]—all produce closed polygons, but the boundaries are not always located at the natural/visible edges of the highest gradient or linearity;

c) integrated methods that combine the advantages of edge and spectral approaches and, more recently [5]. We can combine these techniques with other metrics on potential object segments, such as shape and size. Commercial toolkits such as eCognition are available for developing segmentation and object classification algorithms [6].

According to the main aims of the current study, we applied a few simple Object-Based Image Analysis (OBIA) techniques inside eCognition Developer Software, such as covered edge detection approaches, watershed segmentation algorithm, and rule-based applications [7]. We combined edge detection features and segmented image objects with knowledge-based methods to successfully delineate agricultural fields with various normalized differences in vegetation indices. The current methodology and associated models could be used in many agricultural operational types of research by combining high-resolution satellite imagery, for example, Azer Cosmos imagery, and filed data with the aim of easy operation of agricultural methods and finally suitable agricultural products in other regions of Azerbaijan.

The Study Area:

Azerbaijan is a country located in South-Western Asia, bordering the Caspian Sea and lying on two continents: Asia and, by a small part in the north of the Caucasus range, Europe. Agriculture has been an important activity for Azerbaijan throughout its history [8]. After the rapid development in the base sectors, the contribution of agro-food businesses to the national economy has proportionally decreased. 29.5% of the population of Ganja-Dashkesan Economic Region, 58.9% of the population of the Central Aran Economic Region live in rural areas, and most of them are engaged in agriculture. Today, agriculture is the major sector providing employment and contributing to food security unless there are higher figures for other sectors. The central Aran and the low-lying areas of the Ganja-Gazakh Economic Region are highly productive areas specializing in cotton and fruit cultivation. The mountainous regions of the Ganja-Gazakh economic Region are famous for viticulture, potato growing, grain and honey production. While Central Aran are well-known for crop production, salinity is the major problem in Aran valley [9]. With this assumption, of the economic regions Nakhichevan, Central Aran and low-lying areas of the Ganja-Dashkasan seem to have relative advantages regarding cereals and dried pulses.

The pilot project is being implemented in the economic districts of Ganja-Dashkesan and Central Aran in order to test the existing concepts of the OBIA research methodology. The study is limited to the north-eastern part of Samukh, the northern part of Goranboy and the north-western part of Yevlakh districts, which are located on the right bank of the Migechaur reservoir. In these regions of Azerbaijan, as is known, traditional and modern methods of farming are used. The

Mingachevir Dam is also considered to irrigation the lands in the north of the selected pilot area. By focusing on the Sentinel-2 satellite images, it is clear that the agricultural lands are mostly managed in traditional and irrigated ways [10]. Figure 1 illustrates the pilot area's location and a map overlaid on a combined RGB Sentinel-2 image.

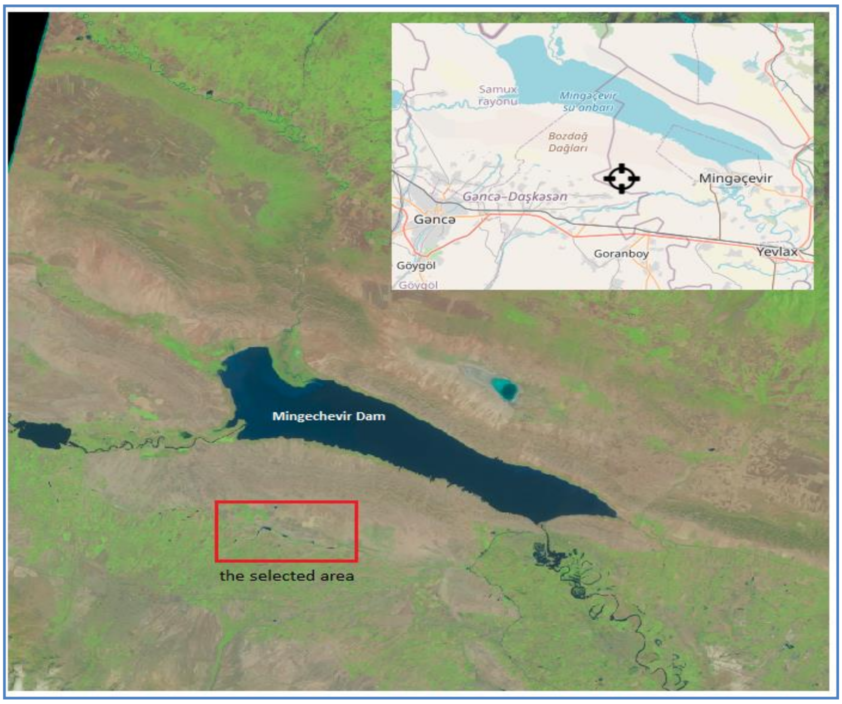


Figure 1: *The location of the selected agricultural site*

Data Analyzed:

The source of optical imagery is Sentinel-2, which is a wide-swathe, high-resolution, multispectral imaging tool that supports Copernicus land monitoring studies, including the monitoring of vegetation, soil, and water cover, as well as the observation of agricultural areas. Sentinel-2 imagery is available at various levels, level-1B and level-1C, from different sites [11]. Each tile consisted of 13 compressed JPEG-2000 images, each image representing one single band. The 13 bands had three resolutions (10, 20, and 60 m)—Notice Figure 1 for more details on the Sentinel-2 imagery. Since 2001, GloVis has been used to view easily, order, and download remotely sensed data. The current paper utilized the USGS EROS Registration System (ERS) hub to obtain the basic data. Sentinel-2 carries an innovative wide swath high-resolution multispectral imager with 13 spectral bands for a new perspective of our land and vegetation. The combination of high resolution, novel spectral capabilities, a swath width of 290 km, and frequent revisit times provides unprecedented views of Earth. The spectral and spatial resolution of Sentinel 2A, with 13 bands in total, is listed in Table 1. Four spectral bands have a 10-meter resolution, six bands have a 20-meter resolution, and the remaining 3 have a spatial resolution of 60 meters [12].

Table 1: *Sentinel 2 Spectral Bands*

Band	Description	Central Wavelength (μm)	Resolution (m)
B1	Ultra Blue	0.443	60
B2	Blue	0.490	10
B3	Green	0.560	10
B4	Red	0.665	10
B5	Visible and Near Infrared (VNIR)	0.705	20

B6	Visible and Near Infrared (VNIR)	0.740	20
B7	Visible and Near Infrared (VNIR)	0.783	20
B8	Visible and Near Infrared (VNIR)	0.842	10
B8a	Visible and Near Infrared (VNIR)	0.865	20
B9	Short Wave Infrared (SWIR)	0.940	60
B10	Short Wave Infrared (SWIR)	1.375	60
B11	Short Wave Infrared (SWIR)	1.610	20
B12	Short Wave Infrared (SWIR)	2.190	20

Also, Figure 2 illustrates the Sentinel-2 band's spectral graphical characteristics.

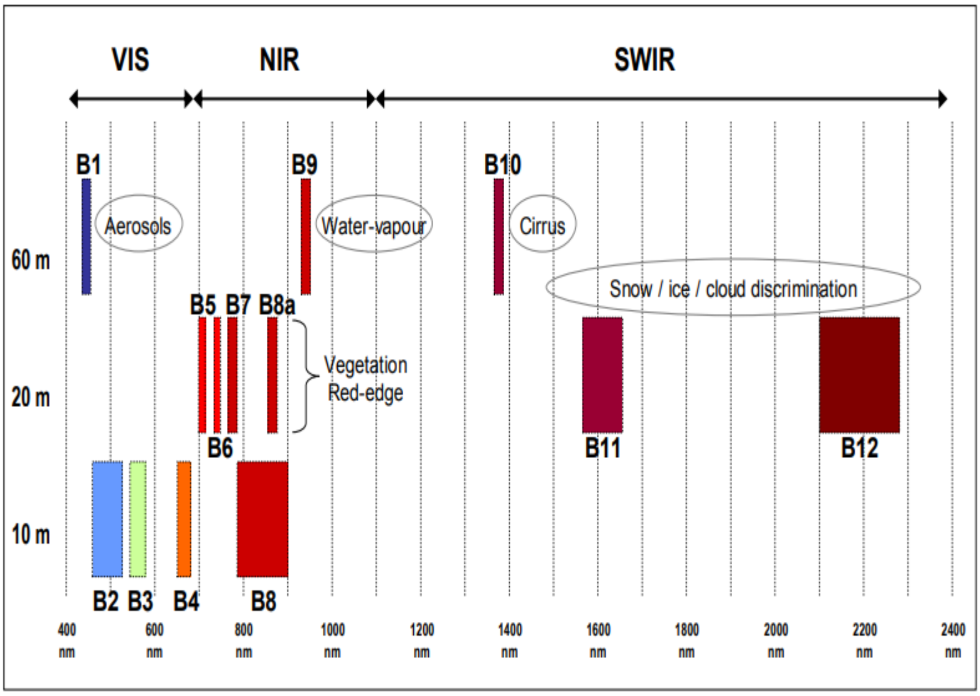


Figure 2: ***Sentinel-2 bands and spectral characteristics***

Every single satellite revisit-time is ten days. Because there are two satellites (Sentinel 2A and 2B), it has a combined constellation revisit of 5 days. To well-perform the Sentinel-2 images well, we paid attention to the following points:

✓ Usually, the Sentinel-2 images are in jp2 format and need to be converted to Geo-TIF format in SNAP or ArcGIS software.

✓ For the present exercise, we selected image bands 2, 3, 4, and 8 due to their high spatial resolution.

✓ In the current paper, the selected area is the small part of the agricultural area located southwest of Mingachevir reservoir in northwest Azerbaijan (Figure 2).

II. Methods

At a simple glance, aiming at the agricultural field boundary delineation, we applied a set of fuzzy object-based Sentinel-2 image analyses inside the eCognition software version 9.5. In the first step, we followed the main functionality of the eCognition by creating a new project inside the eCognition and setting the desired bands, such as blue, Green, Red, and NIR bands [6]. It was preferable to start with a small subsetted area from the main imagery, as you can notice in Figure

1. In step two, an Edge Extraction method based on Canny's Algorithm was applied [13]. In practice, the Canny edge detector is an edge detection operator that uses a multi-stage algorithm to detect a wide range of image edges. It could be a technique to extract useful structural information from different vision objects and dramatically reduce the amount of data to be processed. It must be mentioned that the Edge Extraction Canny enhances or extracts feature boundaries using Canny's algorithm [3].

We could use Edge extraction filters to enhance or extract feature boundaries. The resulting layer typically shows high pixel values where there is a specific change of pixel values in the original image layer. The Supported Domains are Pixel Level, Image Object Level, Current Image Object, Neighbor Image Object, Super Objects, Sub Objects, and Linked Objects. In step third, a Watershed Segmentation algorithm was applied to the data, a region-based segmentation algorithm that segments a single image layer of a scene. This algorithm is an alternative to the Multiresolution Segmentation algorithm and supports, at the moment, only small images [14]. In step fourth, a basic reshaping algorithm was applied. This technique modifies the shape of existing image objects. For example, the Remove Objects algorithm executes operations such as merging image objects and splitting them into sub-objects. Each image object is merged into the neighbor image object with the largest common border, which is especially helpful for clutter removal [15]. During step sixth, we applied two basics of spectral such as NDWI and NDVI indices. Normally, inside the eCognition software, a layer calculation algorithm inserts a new image layer by calculating any spectral indexes such as NDWI and NDVI indices [16]. These indices are numerical indicators that use spectral bands; highly associated with water and vegetation contents. The basic formula is given in Table 2, which was adjusted to the Sentinel-2 images inside the eCognition software.

Table 2: *The basic formula for different indices*

Index Name	Abbreviation	Formula
Normalized Difference Vegetation Index	NDVI	(NIR-Red)/(NIR+Red)
Normalized Difference Water Index	NDWI	(Green-NIR)/(Green+NIR)

We introduced a rule-based algorithm to the NDVI ranges in the last stage. Once we had the vegetation layer of the area in NDVI mode, we explicitly classified it by applying different thresholds and knowledge-based rule sets.

III. Results

We subsetted a small area from the main Sentinel-2 imagery. Figure 3 shows a combined image illustrating Sentinel2 blue, green, red, and NIR bands.

By applying such a simple method inside the eCognition software, the differences among different land use, such as traditional agricultural and modern farms, easily could be distinguished, even among those who have not been in the farming process. The results of a default Canny algorithm, with the single Edge-Canny (a) and Sentinel-2, combined color bands (b), are shown in Figure 4.

In most cases, after applying the Canny edging technique, some noisy object features remain on the output map. You can use one basic object reshaping algorithm to eliminate these disproportionate objects. After finishing the remove objects algorithm, you notice the results. Using this function eliminates a lot of additional objects, as shown in Figure 5.

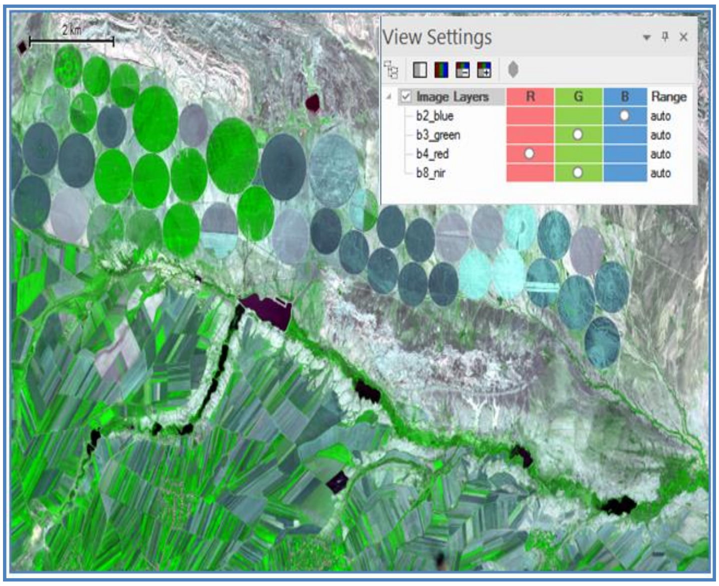


Figure 3: *A combined image illustrating Sentinel-2 blue, green, red, and NIR bands*

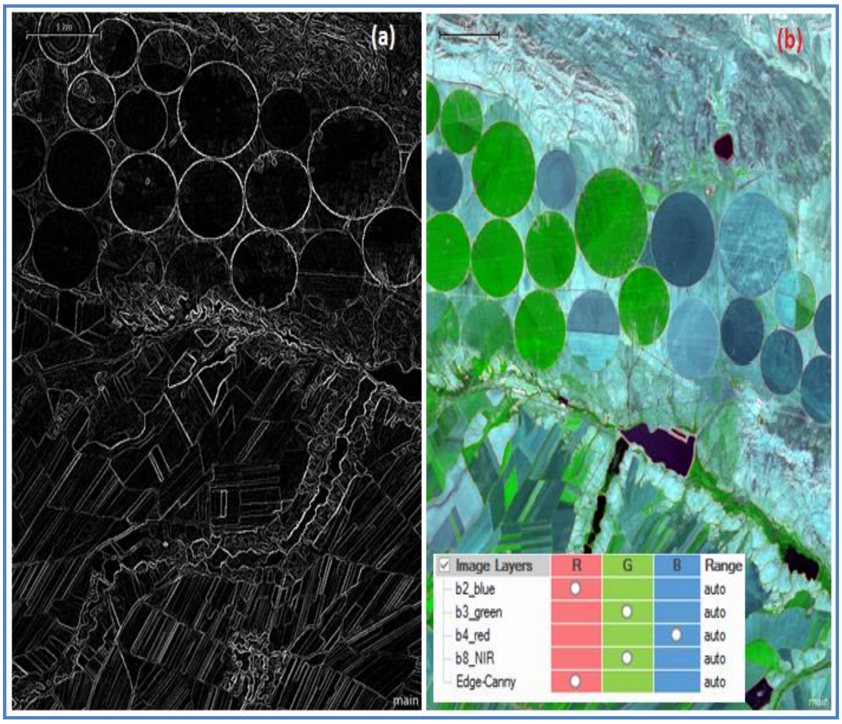


Figure 4: *The results of a default Canny algorithm, with the single Edge-Canny (a) and Sentinel-2, combined color bands (b)*

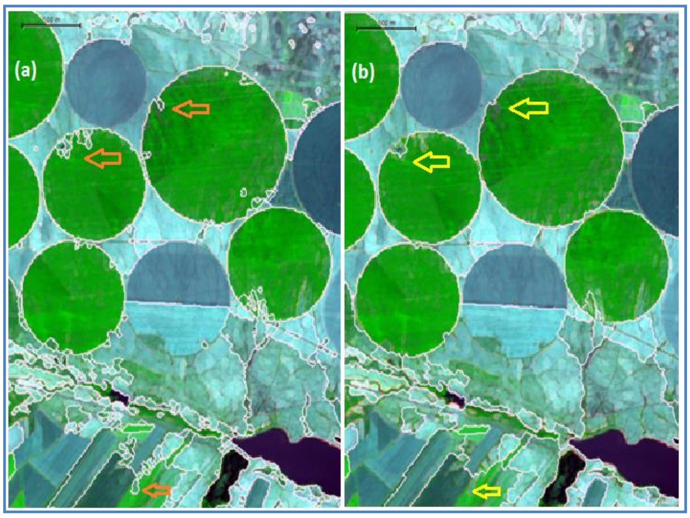


Figure 5: *The result (a) before and (b) after applying the Remove Objects algorithm*

In the implementation stage of the Watershed Segmentation algorithm, we cited the information contained in Table 3.

Table 3: *The Watershed Segmentation algorithm, the information contained in can be cited*

Stage	Parameter	Function
1	Algorithm	
2	Level	Available only if the domain is pixel-level. Select an existing level or enter a name.
3	Layer	Select the input image layer.
4	Invert layer	Specify whether to invert the image layer. The default setting is *No*. If set to *No*, dark pixels will be used as seeds; if set to *Yes*, bright pixels will be used as seeds.
5	Neighborhood	You may select option 4 - or 8 - pixel connectivity. The default setting is *8 - connected*. Specify whether seeds can grow into the four neighboring pixels (left, right, top, bottom) or into 8 neighboring pixels (i.e., they can grow diagonally). In the latter case, you can decide whether the final objects will be converted to connected objects (8- connected) or not (8-disconnected).
6	Seed criterion	With the default behavior, each initial seed (i.e., each local intensity minimum) will correspond to an object of the final segmentation. However, we can define certain criteria under which we will merge two initially distinct seeds. The criterion is always evaluated when two objects first "touch" each other, i.e., they start having a common border. Select the "l Ovfl. Height" option so that it would merge seeds with maximum intensity below the criterion into neighboring objects/seeds.
7	Threshold	Select a threshold for the seed criterion.
8	Extra seed riterion	Up to three seed criteria can be selected and combined.

9	Fuse super objects	Specify whether to fuse super object. The default setting is *No*.
10	Supported Domain	Pixel Level; Image Object Level; Current Image Object; Neighbor Image Object; Super Object; Sub-Objects; Linked Objects
11	Execute	Run the algorithm

By executing the Watershed Segmentation algorithm, you will see Figure 6.

The NDVI is a numerical indicator that uses the red and near-infrared spectral bands; highly associated with vegetation content. Higher NDVI values correspond to areas that reflect more in the near-infrared spectrum and correspond to denser and healthier vegetation. In Figure 7, orange and red colors indicate vegetation covers. Also, the blue color indicates the water surface in the area.

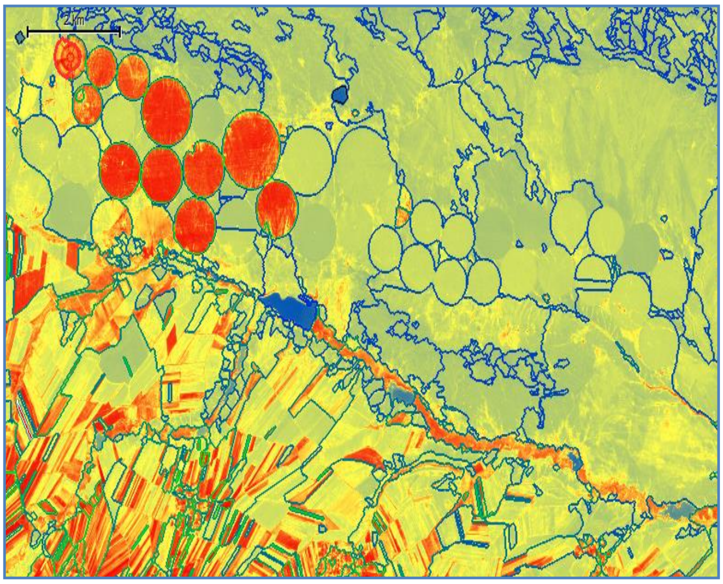


Figure 6: *The result of the Watershed Segmentation algorithm*

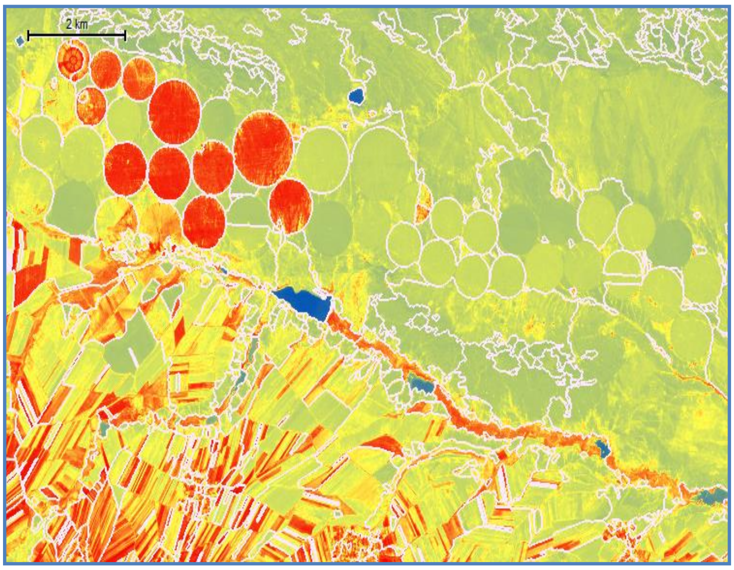


Figure 7: *The NDVI map; the higher reddish color indicates intense vegetation cover*

The vegetation cover in the modern agricultural area seems thicker than the classic cultivated areas. Meanwhile, many modern cultivated fields appeared with less or no vegetation covers. Once we created the vegetation layer of the area in NDVI mode, we classified it by applying different thresholds and knowledge-based rule sets. For this, we needed to check image object-related features inside the Image Object Information box. At the same time, we optimized the NDVI ranges indicated by the Feature View box (Figure 8).

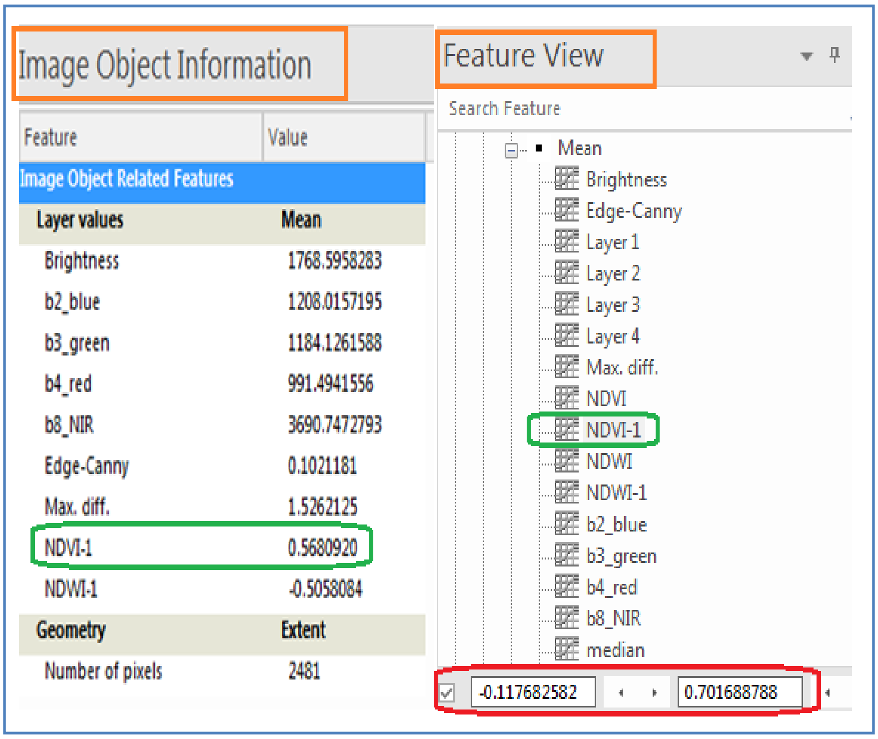


Figure 8: *Information for features is indicated by the Image Object Information and the Feature View boxes*

The results of thresholds and knowledge-based rule sets on NDVI layer information are indicated as a range of algorithms on the Process Tree (Figure 9).

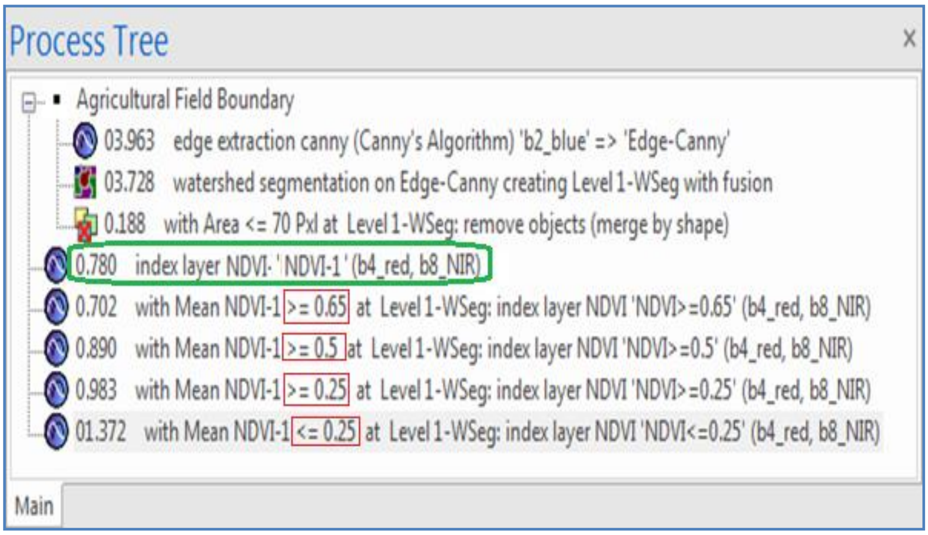
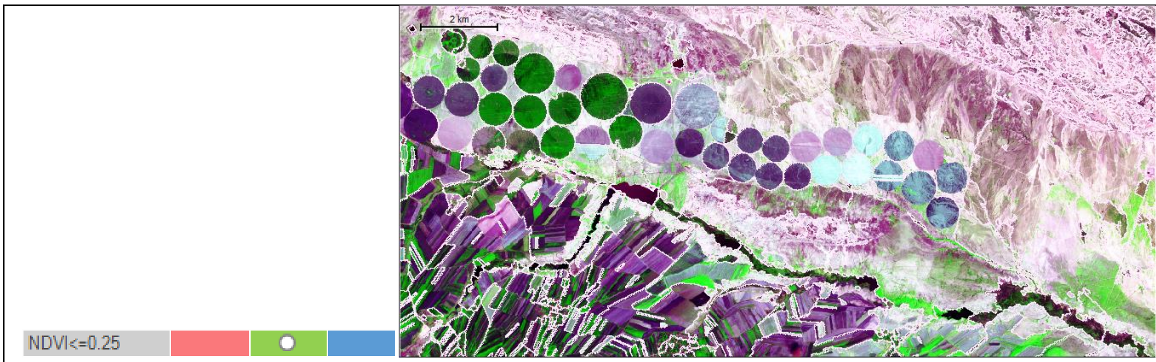
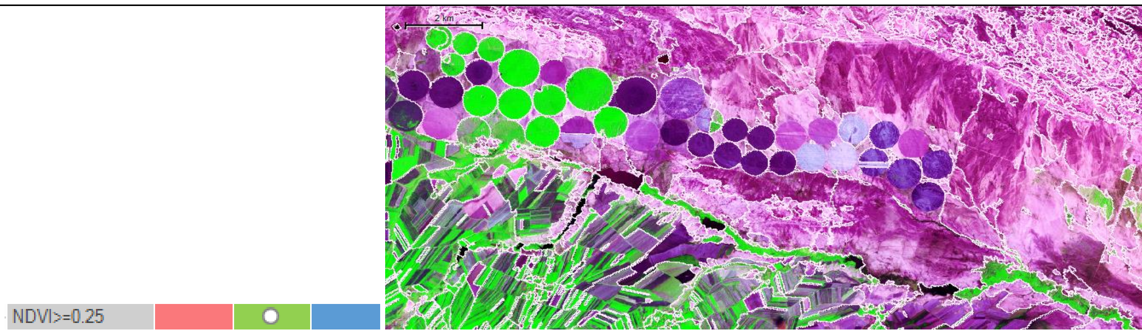


Figure 9: *Process Tree; main appended and inserted child algorithms*

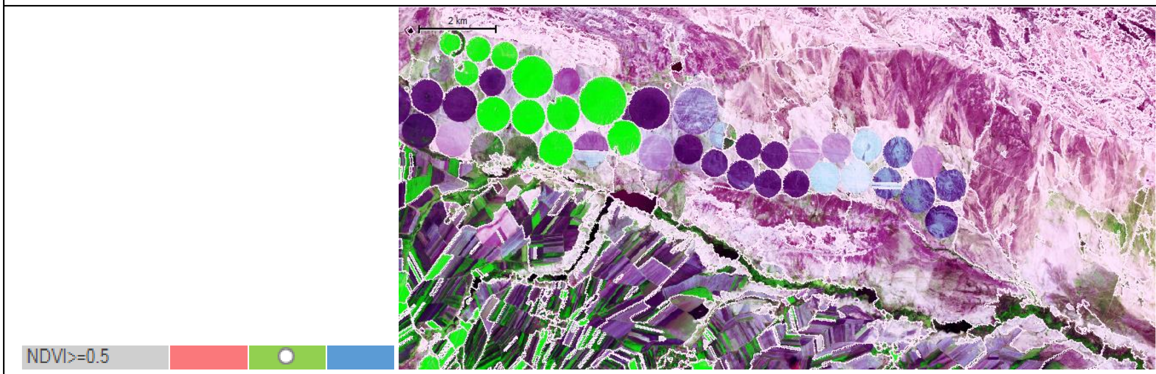
Remember that we had to modify the "Edit Process dialog box content," with the threshold condition as NDVI> =0.65 value.



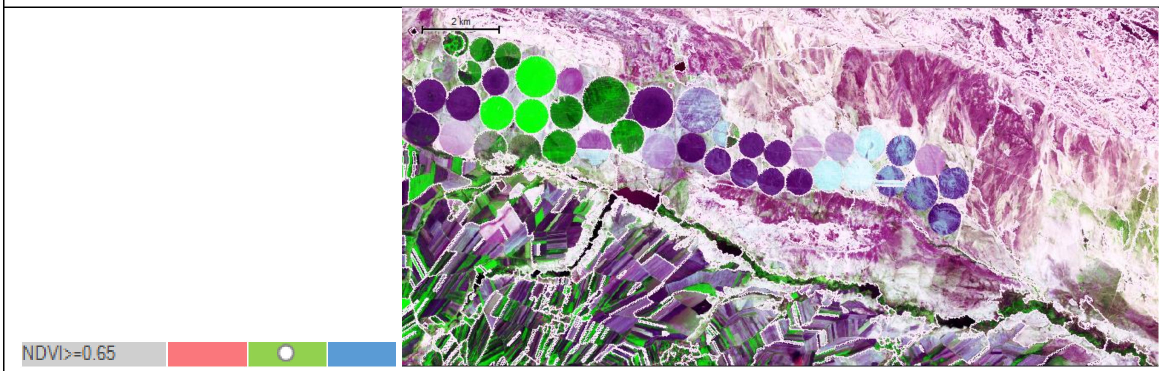
with Mean NDVI-1 <= 0.25



with Mean NDVI-1> =0.25



with Mean NDVI-1> =0.5



with Mean NDVI-1> = 0.65

Figure 10: *Final classified NDVI values for different threshold ranges, green colors indicate the associated NDVI values*

Above-mentioned threshold has to be repeated three times more: with conditions Mean NDVI> = 0.5;> = 0.25; and <= 0.25 values. Final classified NDVI values for different thresholds are shown in Figure 10, and greenish colors indicate the associated NDVI values for each NDVI category. Note that describing and interpreting the results of the current paper would be different depending on the image processing data and distinguished purposes.

IV. Discussion

Small-scale farms generally do not use modern technology to improve the product's quality (hygiene, cooling, storage, etc.) and increase production (productivity-enhancing methods using modern equipment, fertilizers, seeds, etc.). They cannot afford the investment in these inputs. For bulk production and low-value agricultural commodities, present farming methods may be appropriate. Yet, as demand for high-value food commodities increases, driven by rising income, urbanization, and changing preferences, a transition towards using more up-to-date quality-enhancing technologies is necessary. In the current paper, we used a few simple OBIA techniques inside eCognition 9.5, such as covered edge detection approaches, watershed segmentation algorithm, and rule-based applications to successfully delineate agricultural fields with various NDVI values [17]. Agricultural land use maps are more informative per field than per-pixel. It requires up-to-date field boundary maps potentially covering large areas containing thousands of farms, especially in remote areas where land access is very difficult. Although this kind of map is usually difficult to obtain, you have learned to develop a set of combined edge detection and image-segmented object methods to some extent. Meanwhile, by deriving sets of closed polygons around traditional and modern agricultural fields by processing Sentinel-2 imagery, the NDVI indices will be needed [7,18]. In more detailed research, you may compare the greenery obtained from traditional and modern patrol methods during the growing season to estimate the ultimate agricultural harvested products.

We have developed a segmentation method that is tailored to identify fields in an agricultural landscape [4]. The method has enabled regional-scale analysis of farming patterns by producing field polygons. This technique allows for classifying fields as whole objects, which is more accurate than classifying individual pixels. The area that can be segmented is essentially unlimited because the imagery is tiled for processing. The locational accuracy of boundary line work is approximately half the pixel size of imagery used to produce it. Comparison with hand-drawn reference boundaries has shown a high degree of segmentation correctness, meaning that the segments seldom merge two different land uses [19]. These observations mean that the resulting field boundaries are suitable for input into a land-use classification process. Comparison against two existing segmentation methods shows straighter, cleaner linework and results in agricultural lands not being disrupted by data gaps [5]. The researchers could adjust the current paper methods to other Azerbaijan agricultural fields. We used the same parameters in all cases, showing that our method is robust in the context of the medium-resolution satellite imagery we typically use for field-scale mapping. The conclusion is that the Canny edge detector provides finer edges than others. In addition, a watershed segmentation outperforms multi-resolution and multi-threshold segmentation for field boundary delineation. Due to the dynamic nature of field crops, a multi-temporal NDVI is essential for accurate agricultural information [20]. Finally, more information delineates agricultural farms by processing different topographies and satellite sensors.

References

[1] Willer H. and Lernoud, J. eds. (2016), The World of Organic Agriculture. Statistics and Emerging Trends 2016, Research Institute of Organic Agriculture (FIBL), Frick and IFOAM-Organics International, Bonn.

[2] Yan, L. and Roy D. P. (2014), Automated crop field extraction from multitemporal web-enabled Landsat data. Remote Sens. Environ., vol. 144, pp. 42–64.

[3] Canny, J. (1986), A computational approach to edge detection. IEEE Trans. Pattern Anal. Mach. Intell., vol. PAMI-8, no. 6, pp. 679–698.

[4] Pal, S. K. and Mitra, P. (2002), Multispectral image segmentation using the roughest initialized EM algorithm. IEEE Trans. Geosci. Remote Sens., vol. 40, no. 11, pp. 2495–2501.

[5] Graesser, J., and Ramankutty, N. (2017), Detection of cropland field parcels from Landsat imagery. Remote Sens. Environ., vol. 201, pp. 165–180.

[6] Trimble, eCognition Developer 9.5 (2019), Reference Book. Trimble Company, Munich, Germany.

[7] Rasouli, A.A., Asgarova, M.M., Safarov, S.H. (2021), Mapping of LC/LU Changes Inside the Agdam District of Karabakh Region Applying Object-Based Satellite Image Analysis//Journal of Life Science and Biomedicine, Baku, 13p.

[8] Khalilov, H., Shalbuzov, N., Huseyn, R. (2015), Country Report: Azerbaijan. Research Institute of Agricultural Economics, Azerbaijan.

[9] Ministry of Economic Development of Azerbaijan Republic, Economic Development Scientific Research Institute (2016), Reports.

[10] ESA's Sentinel-2 Team (2015), Color Vision for Copernicus, The story of Sentinel-2. ESA Bulletin No 161, May 11, 2015, pp. 2–9.

[11] Copernicus, Sentinel-2 (2020), Satellite Missions – eoPortal Directory. eoportal.org, It retrieved it on March 5.

[12] Rasouli, A.A.; Mammadov, R.; Safarov, E.; Mohammadzadeh, K. (2018c), Fuzzy Object-Based Landcover/Use Mapping of The Karabagh Region by Processing of Sentinel Satellite Imageries. Eurasian GIS 2019 Congress 04–07 September 2018 – Baku/Azerbaijan.

[13] Hu, Y.; Chen, J.; Pan, D. and Hao, Z. (2016), Edge-guided image object detection in multi-scale segmentation for high-resolution remotely sensed imagery. IEEE Trans. Geosci. Remote Sens., vol. 54, no. 8, pp. 4702–4711.

[14] Woodcock, C., and Harward, J. (1992), Nested-hierarchical scene models and image segmentation. Int. J. Remote Sens., vol. 13, no. 16, pp. 3167–3187.

[15] North, H.C; IEEE, M.; Pairman, D.; and Belliss, S. E. (2019), Boundary Delineation of Agricultural Fields in Multitemporal Satellite Imagery, IEEE Journal of Selected Topics in Applied Earth Observation and Remote Sensing. VOL. 12, NO. 1.

[16] Dobrowski, S.Z., Safford, H.D., Cheng, Y. Ben, & Ustin, S.L. (2008), Mapping Mountain vegetation using species distribution modeling, image-based texture analysis, and object-based classification. Applied Vegetation Science 11: 499–508.

[17] Rydberg, A. and G. Borgefors, (2001), Integrated method for boundary delineation of agricultural fields in multispectral satellite images. IEEE Trans. Geosci. Remote Sens., vol. 39, no. 11, pp. 2514–2520.

[18] Asgarova, M.M. Application of GIS technologies in soil fertility management. 3rd International November 24 Head Teacher Education and Innovative Sciences Symposium, Baku, Azerbaijan. May24-25 2021, P.58-63, www.24kasim.org

[19] Trimble, eCognition Developer 10.2 (2021), Detection of cropland field parcels from Landsat imagery. Remote Sens. Environ., vol. 201, pp. 165–180.

[20] Benz, U. C.; Hofmann, P.; Willhauck, G.; Lingenfelder, I.; and Heynen, M. (2004), Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. ISPRS J. Photograms. Remote Sens., vol. 58, pp. 239–258.