Multi-Spectral Image Segmentation Based on the K-means Clustering

Mohamed A.Hamada, Yeleussiz Kanat, Adejor Egahi Abiche

Abstract: Agriculture is one of the oldest economic aspects of human civilisation, and it is still undergoing a dynamic makeover in the course of the application of IT innovative mechanisms in farming methodology. Remote sensing has vied a significant role in crop classification, crop health and yield assessment. Multispectral remote sensing plays a vital role in providing enhancement of more detailed analysis of crop segmentation. In this article, pixel-based clustering of 12 channels is carried out using the satellite image from Sentinel 2 remote sensing satellite via k-means clustering. K-means clustering algorithm is usually a better method of classifying high-resolution satellite imagery. The extracted regions are classified using a minimum distance decision rule.

Keywords: k-means a clustering, agriculture, remote sensing, Sentinel-2

I. INTRODUCTION

Agriculture forms the essential instrument for property development and better economic condition, particularly in developing countries as it plays essential and significant roles in their economic developments. Long since the earliest stages of crop classification with digital remote sensing, information has varied approaches supported with the application of supervised and unsupervised classification techniques that are accustomed to map geographic distributions of crops which characterize cropping practices, such as counting on geographical region, crop diversity, field size, crop phenology, and soil condition, with totally different band ratios of multispectral knowledge and classification schemes application (M. Duane Nellis. et al[8]

One of the most useful methods of classifying the pixels of an image correctly in a decision-oriented application is Image Segmentation. In field-areas such as health care, image processing, traffic image, pattern recognition and so forth, image segmentation is tremendously valuable(Nameirakpam D. et al, 2015)[10].

The purpose of image segmentation is the pixels within the image to get importantly significant data for helpful information extraction. Through classification of satellite imaging, thematic maps bearing the data like registry information, types of soil, crop and vegetation types, may well be obtained [1].

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Ways of classifying image classification could be sorted into two main classes depending on the image primitive used mostly via pixel-based or object-based ways.

On the one hand, Pixel-wise based is primarily based on ways of classifying individual pixel of the image while not taking into consideration any abstractive information of the pixel and the spectral patterns that are exclusively used. On the other hand, the object is primarily based on ways of trying to cluster pixels into objects by a picture segmentation method supported by a selected similarity, such as texture, color, intensity and so use the spectral abstraction and discourse info inherent in these objects to classify the full image. It emerged as a superior means of doing image classification. One in every one of its strength is the ability to extract global objects; correct in form and correct in classification. It eliminates the mixed picture element drawback suffered by most picture element primarily based ways. The segmentation of the remote sensing imagery has done mistreatment to color k-means clustering algorithm, wherever the image was classified into numerous categories with a read to work out the foremost optimum clusters supported Apriori data of the imagery. The aim has been to spot and classify crops for statutory environmental functions. The study of combinations of channels from the satellite Sentinel 2 to adopt the classification algorithm for agricultural fields in the territory of the Republic of Kazakhstan. The task of implementing this project is to develop the concept of an algorithm and methodology for computer-mathematical modelling of a measurement method and a computer network for spectral reflectivity data (Spectral Response) of light emission of minerals, soil, vegetation and biomass reflected at wavelengths (Wavelength, nm) in the range 350 to 2500 nanometers derived from both spectrometers and Sentinel-2A and Sentinel-2B satellites. Which are used as useful tools for classification, monitoring and control acreage of crops on the online platform for remote sensing technologies of the Earth. Tiang-Xiang Z. et al[9], asserted that in data resources, Landsat 8 and Sentinel-2A is the most popular as it has the finest properties which usually include increased number of bands, shorter revisit time, higher spatial resolution, and the provision of more details in NIR and SWIR band ranges, that are helpful in classification of land covering, agricultural precision and applications of forest monitoring among many others.

II. LITERATURE REVIEW

Wen C. et al. [2], presented a Satellite image classification method using color and Satellite Imagery of Land Cover Classification; using k-means Clustering Algorithm, Computer Vision for Environmental Information Extraction and classification of high resolution.

Satellite imagery is a challenging problem because it is no longer meaningful to carry out this task on a pixel-by-pixel basis. The excellent spatial resolution implies that each object is an aggregation of several pixels in close spatial proximity, and accurate classification requires that this aspect be subtly considered. K-means clustering algorithm is a better method of classifying high-resolution satellite imagery. The extracted regions are classified using a minimum distance decision rule. Several regions are selected as training samples for region classification. Each region is compared to the training samples and is assigned to its closest class. The procedure significantly reduces the mixed pixel problem suffered by most pixel-based methods. In this paper, we used k-means clustering algorithm to classify satellite imagery into specific objects within it for cadastral and environmental planning purposes. Zhang T. et al. [3], getting a better segmentation and classification performance can be achieved by directly using the three selected channels of all 13 channels and can further improve performance application to Sentinel-2 satellite images. Sachin D. et al. [4], described the image segmentation technique for plant disease detection. In image segmentation, K-means clustering algorithm is applied for separating foreground and background images. Clustering in segmentation is based on subtracting the clustered leaf images and intensity mapping for high-lighting leaf area. The K-means clustering is a very useful and simple method for detection analysis. Mayank T.[5], provided an insight into the application of feed-forward neural networks in the area of satellite image classification. The different image classification methods were compared using satellite images by Aykut A. et al. [6]. Out of their work, the maximum likelihood method was found more applicable and reliable for the type of satellite image classification.

Mayank T. [10], provided an insight into the application of feed-
forward neural networks in the area of satellite image classification

III. METHODOLOGY

Satellite Sentinel 2 has 12 channels which consist of three types of resolution: 10, 20 and 60 meters. Our task is to distinguish between crops and weeds, so the use of 60-meter canals is not practical because proximity challenges. To study the channel combinations, channels with a resolution of 10 and 20 meters were selected.

#	Title	Wavelength nm	Wavelength width nm	Resolution m
1	Band 2 – Blue	496.6	98	10
2	Band 3 – Green	560.0	45	10
3	Band 4 – Red	664.5	38	10
4	Band 5 – Vegetation Red Edge	703.9	19	20
5	Band 6 – Vegetation Red Edge	740.2	18	20
6	Band 7 – Vegetation Red Edge	782.5	28	20
7	Band 8 – NIR	835.1	145	10
8	Band 8A – Narrow NIR	864.8	33	20
9	Band 11 – SWIR I	1613.7	143	20
10	Band 12 – SWIR II	2202.4	242	20

Figure 1: The name of the channels of the satellite Sentinel 2 and their characteristics

The European Space Agency (ESA) has released an open access application for all Sentinel satellites. The application is called SNAP (Sentinel Application Platform). This application allows the processing of data from Sentinel satellites 1, 2, 3. Moreover, it also allows the experiment with the combinations of various satellite channels. In these applications, we can find the official data on standard combinations with the following parameters:

The name of the combination	R band	G band	B band
Natural colors	B4 Red	B3 Green	B2 Blue
False colors	B8 NIR	B4 Red	B3 Green
Crops	B11 SWIR I	B8 NIR	B2 Blue
Healthy vegetation	B8 NIR	B11 SWIR I	B2 Blue
Soils and water	B8 NIR	B11 SWIR I	B4 Red
Natural colors with atmospheric core	B12 SWIR II	B8 NIR	B3 Green
Vegetation analysis	B11 SWIR I	B8A Narrow NIR	B4 Red

Figure 2: The name of the combination and their parameters from SNAP

To visualize the result of a combination, only three channels are used, which can be arranged in the order of RGB. According to Figure 2 above, it can be seen that B2 stands for Blue, B3 Green, B4 Red. B8A Narrow NIR, B8 NIR, B11 SWIR I and B12 SWIR II channels, which are used to study vegetation and crops. A significant advantage of the Sentinel satellite is the availability of additional channels such as SWIR II and Narrow NIR [3].

NDVI = (B8A Narrow NIR - B4 Red)
/ (B8A Narrow NIR + B4 Red)

This solution allows the improvement on the quality of the vegetation index due to a narrower infrared channel.

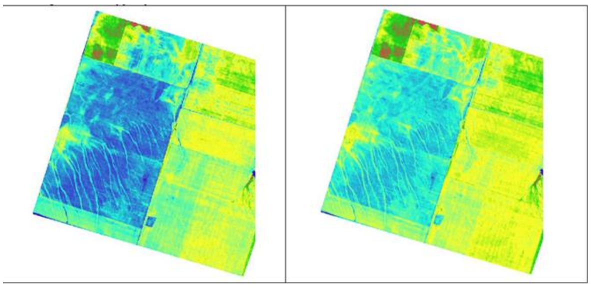

Figure 3: NDVI results using the NIR channel (left) and the Narrow NIR channel (right)

We are using the example of agricultural fields near the village known as the Motherland in (Figure 3). It can be seen that the NDVI vegetation index using the Narrow NIR channel (on the right) captures small (low) vegetation (which may consist of young weeds) in the lower right corner of the image. We have chosen the channel B8A Narrow NIR instead of the channel B8 NIR as it provides more efficient data. The Mechanical and chemical processing of fields to control weeds has been enforced between three and six decades after planting, depending on the type of soil and the level of humidity. The height of crops is usually between 10–15 cm. During this period, most weed-cultures in Kazakhstan have a tubular appearance with minimal vegetation. While many types of weeds have already had their leaves dissolved, in this case, it would be more useful to use the channels B3 Green and B4 Red and thus, excluded the B2 Blue channel from the list. After analyzing and studying the articles, we decided to select the following five channels for further work: B3 Green, B4 Red, B8A Narrow NIR, B11 SWIR I, and B12 SWIR II.

Results from the spectrometer Quality Spec Trek.

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In the same report, the reasons were described (in bold letters) the combination of channels: "The data obtained in the jpeg format were studied and visualized using the overlay of an additional layer — the wavelength spectrum.
The spectral signature allows the understanding of the reaction of different wavelengths (from visible to short-wave infrared - SWIR). The combination of spectral channels allows the enhancement or weakening of the wavelength response to the reflecting surface. Thus, enhancing the contrast of the image to identify the heterogeneity of the fields ".

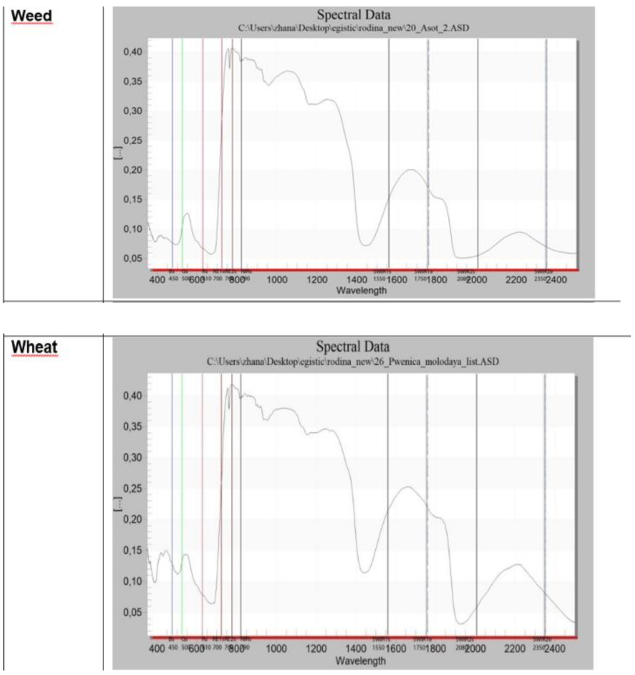

Figure 4: Spectral signatures of crop species and weeds

As can be seen from Figure 4 above, the shape of the spectral signatures in all types of vegetation (crops and weeds) have similar forms of bending lines. However, after studying more than a hundred samples captured in the fields of the Akmola region in Kazakhstan, small differences in the amplitude values (Y-axis) became noticeable.
QGIS is a user-friendly geographic information system (GIS) with an open code distributed under the GNU General Public License. QGIS is a project of the Open Source Geospatial Foundation (OSGeo). It works on Linux and Windows Operating Systems(OSs) and supports many vectors, raster formats, databases, and it has more extensive capabilities for analyzing spectral signatures.
In the final result, the following channel combinations received the most optimal visual result:
- R band = SWIR I + SWIR II;
- G band = Narrow NIR - Green;
- B band = SWIR I - Green.

Furthermore, an analysis of various methods of image segmentation was carried out. Image segmentation is necessary to split the image into many small divisions (islands). Pixels inside islands have common spectral data and characteristics that belong to the same class of crops or weeds.
The k-means segmentation algorithm is suitable for the task of defining crops in this particular research. However, it has one drawback: The k-means algorithm should be able to specify the number of classes in the image. For our task of automating the process, this flaw is fundamentally essential.
In the article "Multiresolution Segmentation: An Optimized Multi-Scale Image Segmentation" by M. Baatz and A. Shape [7] describe a segmentation method based on K-means. This method is called the Multiresolution Segmentation. Its feature is the automatic determination of the number of classes in the image. This effective segmentation method is available in the "eCognition" program. This program is available in its free version. For Multiresolution Segmentation, we used the following channels: R band (SWIR I + SWIR II), G band (Narrow NIR - Green), B band (SWIR I - Green).
The problem of vegetation-cover classification could be solved with the help of controlled learning algorithms. Controlled classification builds an implicit connection between the feature vector and the target variable. With the help of a trained classification model, it is possible to predict new object data so that its class type can be determined. Various classification algorithms have been developed in science, including decision trees, discriminant analysis, support vector machines (SVM), the nearest neighbor, a neural network, and many others.
The Machine Learning algorithm consists of two processes. In the first process, it is necessary to create a model from spectral data. To create an entire base, it is necessary to carry out fieldwork every decade, starting from the first shoots of crops to their full maturity. Next, the spectral data are processed manually, and a table is created with averaged values characteristic of a particular type of culture.
The test model was created based on spectral data captured in the Akmola region in Kazakhstan in September 2018. The spectral data is in ASCII format, as shown in a simple table (Figure 6) below. It contains the sequence of number; the value of the wavelength is in nm and the value of the spectral radiant. The spectral radiant determines the energy brightness of a pixel at a given wavelength.

#	Wavelength nm	The value of the spectral radiant
1	350,000	0,584
2	351,000	0,571
3	352,000	0,562
4	353,000	0,551
5	354,000	0,542
6	355,000	0,536
7	356,000	0,523
8	357,000	0,512
9	358,000	0,507
10	359,000	0,496
...	...	...
2147	2496,000	0,024
2148	2497,000	0,024
2149	2498,000	0,024
2150	2499,000	0,024
2151	2500,000	0,024

Figure 6: Spectral data in ASCII format from a Quality SpecTrek spectrometer

In building the model, it is necessary to calculate the average value of the pixel energy brightness over the channel wavelength. The value of the spectral radiant is calculated using the following formula (Watt per Meter² per Steradian per Micrometer):

$$Wm^{-2}sr^{-1}\mu m^{-1}$$

In the second stage of the algorithm after segmentation, the constructed model is applied. The data from the model are compared with the values of the segmentation clusters. In the case of data equality, the algorithm decides on the assignment of the class type to the cluster.

IV. RESULTS

The field map after segmentation has clearly defined the heterogeneity of the contours of the field. Thus, it shows the distinct differences between the accumulation of different types of vegetation, as well as different degrees of crop maturation. The next step is going to determine the type of class (wheat, corn, weed, and so forth.) for each contour using a model based on the spectral signature of crops and weeds.

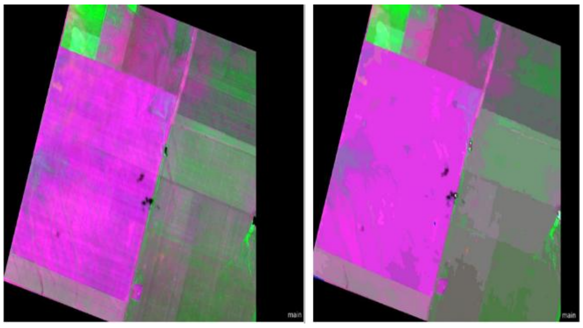

Figure 5: Image before segmentation (left), and after segmentation (right)

Figure 5 above, shows the classifier which constitutes: the water bodies, crops, pairs, soil and weed accumulation that are classified on the map. The Unknown class is used when machine learning is not able to find similar spectral data. During the fieldwork, we found that this field was sown with barley and wheat for livestock feed. In this case, the pixel value is mixed with spectral data of barley and wheat. Hence, their spectral data differ from the data of individual wheat and barley.

V. CONCLUSION

The machine learning algorithm used could work in automatic mode. The accuracy of the result of the classification of crops and weeds depends on the accuracy and size of the spectral data model. We have studied many models of segmentation and classification of remote sensing data for agriculture and select the most effective for our tasks. Channels R-band (SWIR I + SWIR II), G-band (Narrow NIR - Green), B-band (SWIR I - Green) are optimal for field segmentation. However, the highest result is obtained by segmentation of each field (under one cadastral number) separately. It is also more efficient to carry out the classification for each field separately. The improved k-means segmentation method with automatic determination of the number of classes together with the constructed machine learning algorithm can be used to run the project to automate processes.

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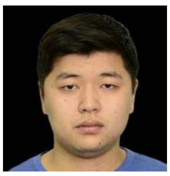

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