Classification of crops by multispectral satellite images of sentinel 2 based on the analysis of vegetation signatures

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Abstract. This article describes crop recognition methods from multispectral satellite imagery of Sentinel 2. The feature space includes taking into account parameters such as brightness and color of optical images over the entire channel of Sentinel 2 spectrozonal satellite imagery. The signs of multispectral images for various terrain classes in satellite images are analyzed. A comparative analysis of the classification results by the methods of "Expectation Maximization" and "k - means" has been compiled.

1. Introduction

Today, the data of satellite systems for observing the Earth are one of the main sources of information about various processes in the atmosphere and on the surface of the Earth. Thanks to satellite data, it is possible to obtain uniform and comparable quality information simultaneously for large areas, which is practically impossible with any ground and near-Earth surveys. This is the reason that satellite data information is increasingly being used in a variety of fields, from purely scientific tasks to commercial projects. The ever-increasing need for data and the development of technology have led to the emergence of a large number of high-quality systems for remote sensing of the Earth from space, providing a stable and efficient receipt of information across the entire surface of the Earth. Among researchers working on mapping the Earth's landscape, optical images of the Sentinel 2a / 2b satellite [1-3] from the European Space Agency were widely used. The capture band in the multispectral coverage range of one image of this satellite is more than 52,000 km^2, which is more than twice the area of the Jizzakh region of the Republic of Uzbekistan in area. This scale of territorial coverage allows us to solve many problems in the field of agriculture, since this region of the Republic is focused on growing crops.

The aim of this type of work was to classify the types of crops of the landscape coverage of the land on multispectral images of the Sentinel 2 satellite, used for classification in geoinformation software packages and thematic mapping of the Earth's surface landscape.

To achieve this goal, the following tasks were solved:

1. Test plots were laid in the Jizzakh region of the Republic of Uzbekistan for various classes of vegetation with their geographical location on the ground in multispectral satellite images of the Sentinel 2.
2. The signs of multispectral images for various landscape classes in satellite images are analyzed: statistical characteristics, histograms of the distribution of brightness, spectral, texture and other characteristics of objects called signatures.

3. A thematic map was created on a synthesized satellite image in the SNAP 6.0 software package. By k-means and “Expectation Maximization” (EM) methods, with the subsequent identification of the most represented classes of types of ground coverage of the territory.
4. A comparative analysis of the results of EM clustering methods and "k - means".

2. Formulation of the problem

To solve the problems of deciphering the vegetation cover of agricultural lands on satellite images of medium resolution, an assessment of only one feature becomes insufficient. The characteristic space includes taking into account such parameters as the brightness and color of optical images in the visible range, as well as taking into account surface images in other spectral ranges (near infrared, medium infrared and ultraviolet).

When classifying the type of overhead coverage and identifying classified features, we used satellite multispectral images of 13 spectral ranges of the scene (S2B_MSIL1C_20190510_N0207_R034_T42TVK_20190510) of the Sentinel 2b satellite.

Table 1. Characteristics of multispectral images of the Sentinel_2b radiometer.

№	Spectral Range Name	Sentinel_2b		
		Central wavelength (nm)	Bandwidth (nm)	Spatial resolution (m)
1	Band 1 – Coastal aerosol	442.7	21	60
2	Band 2 – Blue	492.4	66	10
3	Band 3 – Green	559.8	36	10
4	Band 4 – Red	664.6	31	10
5	Band 5 – Vegetation red edge	704.1	15	20
6	Band 6 – Vegetation red edge	740.5	15	20
7	Band 7 – Vegetation red edge	782.8	20	20
8	Band 8 – NIR	832.8	106	10
9	Band 8A – Narrow NIR	864.7	21	20
10	Band 9 – Water vapour	945.1	20	60
11	Band 10 – SWIR – Cirrus	1373.5	31	60
12	Band 11 – SWIR	1613.7	91	20
13	Band 12 – SWIR	2202.4	175	20

Field studies were carried out from February to May 2019 in such a way as to take into account the density and spatial distribution of the vegetation cover on sites of 10x10 meters. Each trial plot on the outline was tied to a quarter network or the nearest well-recognized terrain object. In addition, the geographic coordinates of each trial plot were recorded using a GARMIN eTrex GPS receiver.

Recognition of landscape objects in multispectral images is usually based on identifying differences in the spectral characteristics of the studied types of ground cover. Under the classification of satellite images is understood the process of selecting objects of a raster image to one of the predefined thematic classes. The basis of this process is the use of differences between the spectral brightness of the selected classes in different spectral channels of the image. Both classification processes (controlled and uncontrolled) of images are based on the use of sets of spectral, texture, and other characteristics of objects called signatures [4]. Each given cluster corresponds to its own signature, which is used to establish belonging to it classified objects of the image of the earth's surface.

In terms of satellite data, in addition to spatial and temporal resolution, it is very important to know what spectral channels are available.

Different natural objects have different reflectivity in the spectral regions; it is customary to characterize such a property of the objects by the coefficient of spectral brightness.

Spectral Luminance Coefficient (SLC) is a photometric function showing the ratio of brightness in a given direction (ϑ, φ) to the brightness (in the same direction) of an orthotropic surface in a specific wavelength range $(\lambda, \lambda + d\lambda)$ under given lighting conditions.

$$\rho\lambda(\vartheta, \varphi) = B\lambda(\vartheta, \varphi)/B_0(\vartheta, \varphi)$$

where $B\lambda(\vartheta, \varphi)$ is the brightness in this direction; $B_0(\vartheta, \varphi)$ - brightness in the same direction of the orthotropic surface.

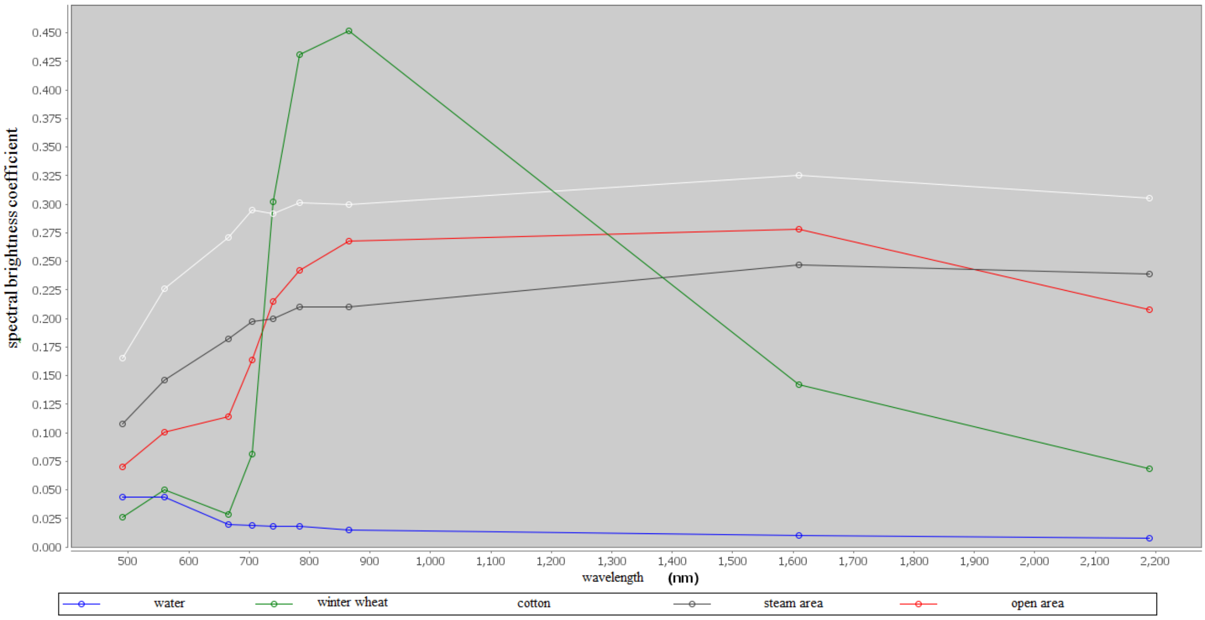

Figure 1. Spectral reflection of vegetation.

This is a typical vegetation reflection curve. The abscissas are the wavelength of the electromagnetic spectrum, and the ordinates are the coefficients of the spectral brightness of the vegetation. This vegetation reflection curve has several important points, for example, the red channel, the wavelength (0.65 -0.68) is the absorption line of chlorophyll, the more chlorophyll the deeper the gap, both the concentration of chlorophyll and the total chlorophyll reserve due to green biomass. There is practically no absorption at the next point, here the greatest reflection is the near infrared channel wavelength (0.8-0.9) [5].

Due to the reflection features in the near infrared and red regions of the spectrum, natural objects not related to vegetation have a fixed spectral brightness value (which allows using this parameter for their identification).

Chlorophyll of plant leaves reflects radiation in the near infrared range of the electromagnetic spectrum and absorbs in red. The ratio of brightness values in these two channels allows you to clearly separate and analyze vegetation from other natural objects (Fig. 2).

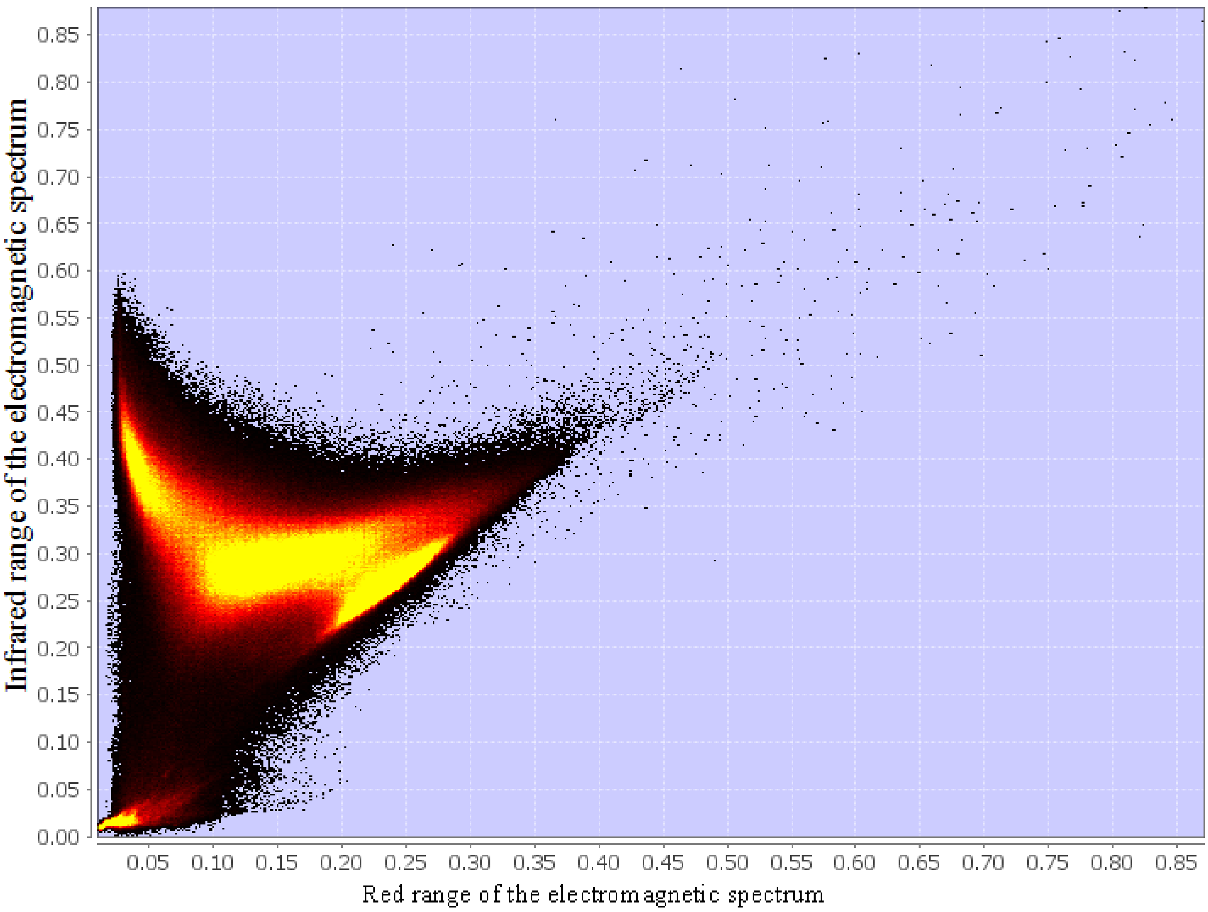

Figure 2. Relationship between pixel brightness values in the near infrared and red regions of the spectrum

3. Solution methods

Based on multispectral images, a classification of types of crops was carried out and a thematic map of the main landscape objects of the studied region was built. For this, each pixel of the spectral image must be assigned to one of five types of overground cover: 1) Cotton field (CP); 2) Winter wheat (WW); 3) Steam areas (SA); 4) Pond (P); 5) Open areas (OA). Deposits were assigned to open areas, perennial grasses are represented mainly by young spring grass formed after rain.

Objects were classified by two methods of “Expectation Maximization” and “k - means”.

Method «k-means»

A thematic map was created for the study area using the “k-means” method of uncontrolled classification [6].

The action of the k-means algorithm seeks to minimize the total quadratic deviation of cluster points from the centers of these clusters:

$$V = \sum_{i=1}^{k} \sum_{x \in S_i} (x - \mu_i)^2$$

where k is the number of clusters, S_i are the resulting clusters, $i = \overline{1,k}$, μ_i is the center of mass of all vectors x from the cluster S_i.

The k-means clustering tool implemented in SNAP is able to work with arbitrary large scenes. Given the number of k classes, the k-means algorithm is implemented by the step procedure described below:

Step 1. Randomly select k pixels, samples of which determine the initial centers of the clusters.
Step 2. Assign each pixel to the nearest center of the cluster in accordance with the Euclidean distance.
Step 3. The centers of the clusters are recalculated as the arithmetic mean for all samples of all pixels in the cluster.
Step 4. The second and third steps are repeated until the convergence criterion is reached.

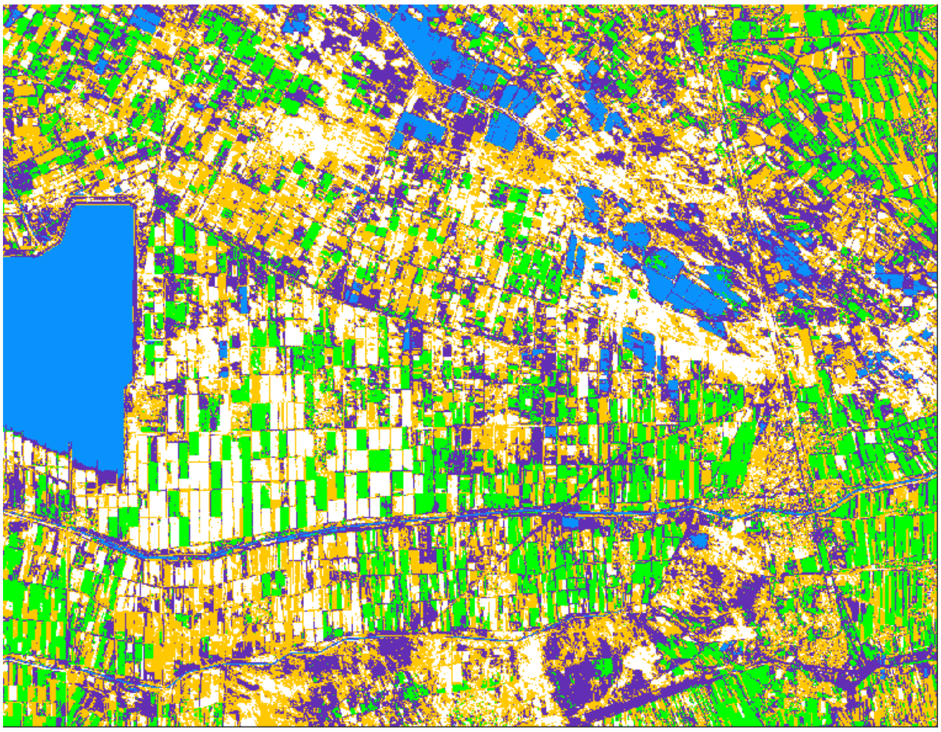

Figure 3. Thematic map obtained by the method of "k-means". Highlighted classes by color: blue – water, white – cotton field, green – winter wheat, orange – steam areas, purple – open areas.

Method «Expectation Maximization» (EM)

The EM method implemented in SNAP can be considered as a generalization of the k-means algorithm [6]. The main differences are:

1. Pixels are not assigned to clusters. The membership of each pixel to a cluster is defined by a (posterior) probability. For each pixel, there are as many (posterior) probability values as there are clusters and for each pixel the sum of (posterior) probability values is equal to unity.
2. Clusters are defined by a prior probability, a cluster center, and a cluster covariance matrix. Cluster centers and covariance matrixes determine a Mahalanobis distance between a cluster center and a pixel.
3. For each cluster a pixel likelihood function is defined as a normalized Gaussian function of the Mahalanobis distance between cluster center and pixels.
4. Posterior cluster probabilities as well as cluster centers and covariance matrixes and are recalculated iteratively. In the *E-step*, for each cluster, the cluster prior and posterior probabilities are recalculated. In the *M-step* all cluster centers and covariance matrixes are recalculated from the updated posteriors, so that the resulting data likelihood function is maximized.

5. When the iteration is completed, each pixel is assigned to the cluster where the posterior probability is maximal.

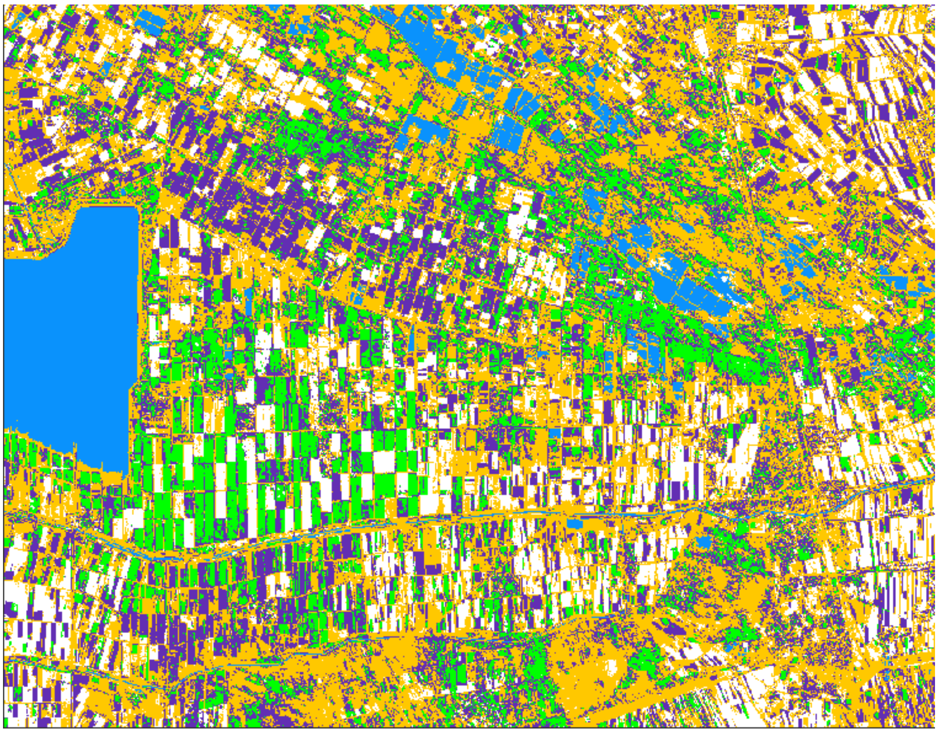

Figure 4. Thematic map obtained by the EM algorithm (unmanaged classification). The distinguished classes by color: blue – water, white – cotton field, green – winter wheat, orange – steam areas, purple – open areas.

4. Discussion of results and conclusions

In the process of field research, five geographical coordinates of the pixels of each class were fixed using a GPS receiver. The coordinates of these pixels were marked on thematic maps obtained using the above methods. Recognition results are presented in the form of cross tables.

Table 2. Result of object recognition using the “k – means” method.

Class name	Geographical coordinate of the object		On the map “k-means”
	Longitude	Latitude	
water	68.44524588167907	40.35159785667743	water
water	68.48351908511692	40.366730340236735	water
water	68.47009922446162	40.30558715308188	water
water	68.48456758088538	40.2908773037337	water
water	68.49610238040434	40.29020737159608	water
cotton field	68.55029402979487	40.2792591465666	cotton field
cotton field	68.60141053642371	40.26827494053153	cotton field
cotton field	68.6198032084448	40.3022118940378	***stream area***
cotton field	68.61471992646867	40.28561794636098	cotton field
cotton field	68.63688260980136	40.27704066149216	cotton field
winter wheat	68.5853913914764	40.272182763744574	winter wheat
winter wheat	68.59571053916635	40.277444692903956	winter wheat
winter wheat	68.62600942900377	40.28637573377269	winter wheat

winter wheat	68.65381245987419	40.278714232653584	winter wheat
winter wheat	68.83206874777738	40.40271734973886	***open areas***
steam area	68.62915831435248	40.2792591465666	steam area
steam area	68.53846051097975	40.26827494053153	***cotton field***
steam area	68.88479809416262	40.3022118940378	steam area
steam area	68.82917347172125	40.28561794636098	steam area
steam area	68.81038054901592	40.27704066149216	steam area
open area	68.62733028164061	40.21718797139858	open area
open area	68.71763040952986	40.20717270051893	open area
open area	68.79059114729898	40.24895127896414	***cotton field***
open area	68.85228903237817	40.20922474553532	open area
open area	68.7815161854052	40.36515463861321	***cotton field***

Table 3. The result of recognition of objects by the method of “Expectation Maximization”.

Class name	**Geographical coordinate of the object**		**On the map EM**
	Longitude	**Latitude**	
water	68.44524588167907	40.35159785667743	water
water	68.48351908511692	40.366730340236735	water
water	68.47009922446162	40.30558715308188	water
water	68.48456758088538	40.2908773037337	water
water	68.49610238040434	40.29020737159608	water
cotton field	68.55029402979487	40.2792591465666	***stream area***
cotton field	68.60141053642371	40.26827494053153	***stream area***
cotton field	68.6198032084448	40.3022118940378	***stream area***
cotton field	68.61471992646867	40.28561794636098	cotton field
cotton field	68.63688260980136	40.27704066149216	cotton field
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winter wheat	68.83206874777738	40.40271734973886	***open areas***
steam area	68.62915831435248	40.2792591465666	steam area
steam area	68.53846051097975	40.26827494053153	***cotton field***
steam area	68.88479809416262	40.3022118940378	***cotton field***
steam area	68.82917347172125	40.28561794636098	steam area
steam area	68.81038054901592	40.27704066149216	steam area
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open area	68.79059114729898	40.24895127896414	***cotton field***
open area	68.85228903237817	40.20922474553532	open area
open area	68.7815161854052	40.36515463861321	***cotton field***

Analyzing the results of Tables 2 and 3, we can conclude that in this task, the “k-means” and “Expectation Maximization” methods recognize water and wheat well, this is because the spectral brightness coefficients of these objects differ well in the red and near infrared channels. In other objects (cotton, clean steam and open areas) there are recognition errors, errors arise from the fact that the Sentinel 2 multispectral image was dated 05/10/2019, at this time the vegetation index [7] of the cotton field and pure steam slightly differ from each other.

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