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Automated Decryption of Bodies of Water on the Basis of LANDSAT-8 Satellite Images with Reference to Controlled Classification

***Abstract**. An operative method of automated decryption of Landsat-8 satellite images allowing for detection of water bodies is created. Application of the developed method allows for the detection of water bodies more than 30 m in size and specifies the obtained masks of water bodies significantly.*

***Streszczenie.** Przedstawiono metodę automatycznego odszyfrowywania zdjęć satelitarnych Landsat-8 umożliwiającą wykrywanie części wód. Zastosowanie opracowanej metody pozwala na wykrycie zbiorników wodnych większych niż 30 m. **Zautomatyzowane odszyfrowywanie zdjęć zbiorników wody na podstawie obrazów satelitarnych LANDSAT-8**.*

Keywords: automatic decryption, water bodies, controlled classification, LANDSAT-8.
Słowa kluczowe: automatyczne deszyfrowanie, zbiorniki wodne, kontrolowana klasyfikacja, LANDSAT-8.

Introduction

Water is one of the most important elements necessary for the existence of different ecosystems including the existence of humanity. Both lack and excessive amounts of water may lead to extreme changes in any areas of the national economy. Therefore, the detection of water bodies and their subsequent control is an important process in academic and practical environmental research. Control over fresh water on the surface of the Earth is gaining special topicality as its volumes decrease every year. Therefore, monitoring of surface water bodies which controls the changes in the number of bodies of water, their area, shoreline, and other characteristics is carried out.

Satellite images made by systems of remote sensing of the Earth in different ranges of electromagnetic waves are used for the purposes of such monitoring. Main advantages of remote imaging include its high degree of detail, simultaneous coverage to large areas, possibility to make additional images and study hard-to-reach territories. However, the images obtained by different space vehicles vary significantly in terms of their value (the original image and its derived products).

The matter of value is often a definitive one when it comes to academic and environmental works. There is no doubt that high-resolution images provide much better possibilities for studying terrestrial surface on territories with a small area. However, due to their high price, commercial high-resolution images are not widely used in environmental projects in comparison to open access images with the medium and low definition. Medium and low definition images: from 15 m to 1000 m – the product is free and, as a rule, these images have better spectral differentiation (more spectral channels) than high definition ones.

The topic of using the images of remote sensing systems is very popular and accounts for a large number of papers [1–4]. A common feature of these publications is the development of methods and methodologies to process satellite images in order to solve environmental problems in hydrology. As a rule, the results of such processing are presented as a thematic map. Quite frequently [5–10, 13], the processing is aimed at obtaining spatial and temporal parameters of the Earth surface, including water bodies. Water mask, which allows for determining pixels with water bodies location on satellite images, is one of such parameters. To create water masks, the so-called water indices, which are a combination of relations of spectral channels, are calculated [11, 12, 14–16]. Such an approach is quite effective because it provides for the mask, whose spatial differentiation corresponds to the differentiation of spectral channels.

The aim of this paper is to develop a method for automated decryption of multispectral images made by space vehicle Landsat-8 to identify water bodies and build water masks by applying controlled classification (supervised learning) of information processing.

Methods

Landsat-8 is one of the most popular space vehicles offering multispectral images with medium spatial differentiation [16, 17]. The devices on board of the space vehicle offer multispectral (from the visible to the infrared spectrum region) images of the terrestrial surface (Fig. 1).

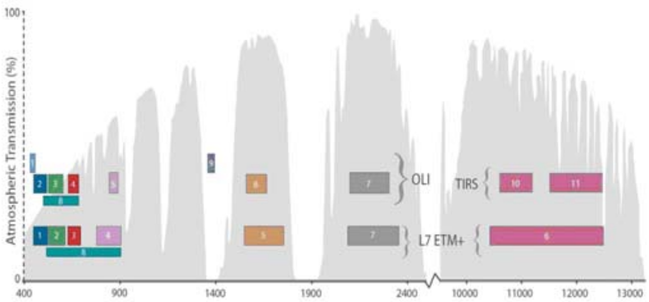

Fig. 1. Spectrum ranges of Landsat 7 and Landsat 8 channels

The images obtained require adjustment to compensate for the impact of the atmosphere connected with absorption and dispersion of radiation. The spectral range and spatial resolution of the Landsat-8 apparatus are shown in Table 1.

The process of searching for water bodies on the basis of multispectral images allows for their detection on the basis of the reflecting power characteristics. Water bodies are characterized by the lowest values of the reflection index in comparison to other natural objects. All other natural objects, even in moisturized condition, have a higher reflection index. This fact is used to detect water bodies on a satellite image.

Table 1. Names of spectral channels, spectral range and spatial differentiation of Landsat-8 equipment

Channel name	Wavelength range [µm]	Spatial differentiation [m]
Band 1 Coastal	0.43–0.45	30
Band 2 Blue	0.45–0.51	30
Band 3 Green	0.53–0.59	30
Band 4 Red	0.64–0.67	30
Band 5 NIR	0.85–0.88	30
Band 6 SWIR 1	1.57–1.65	30
Band 7 SWIR 2	2.11–2.29	30
Band 8 Pan	0.50–0.68	15
Band 9 Cirrus	1.36–1.38	30
Band 10 TIRS 1	10.6–11.19	100
Band 11 TIRS 2	11.5–12.51	100

Primary data for work are multispectral Landsat-8 images with Level 1 processing presented in GeoTIFF format with WGS84 (UTM) binding.

A fragment of an image made by Landsat-8 equipment in Zhytomyr City in combination 4-3-2 natural colors is presented in Fig. 2.

Fig. 2. A fragment of the image made by Landsat-8 equipment in Zhytomyr in combination 4-3-2 natural colors

The method of automated decryption is presented as a list of logical stages.

1. *Identifying the parts of the image where the bodies of interest are located*. This operation is necessary to reduce the size of the image and accelerate the processing operations.

2. *Creation of a multispectral image*. Due to the fact that Landsat-8 images with Level 1 processing are presented separately to each channel, it is feasible to combine channels 2-7 into one multispectral image for the purposes of controlled application classification.

3. *Creation of an image in artificial colors for a combination of channels*

$$R \to B_5, G \to B_6, B \to B_4 ,$$

where R, G, B – red, green and blue channels respectively; B_n– designation of the channel with number *n* for equipment of Landsat-8.

This combination of the near, medium and infrared channels and red visible channels ensures clear differentiation between water and land and accentuation of the hidden details that are poorly visible if only visible range channels are used. Water bodies within land will be detected with high precision. This combination reflects vegetation in different shades of brown, green, and orange.

4. *Determination of reference areas (areas of interest).* This approach is characterized by the fact that the subsets of elements of the input image (picture) – reference areas – are used as reference images. The choice of reference areas is aimed at determining the fragments of the image that have uniform brightness and location.

The inclusion of reference areas into certain classes of objects under research is determined in advance:

on the basis of the preliminary visual decryption using additional deciphering signs;

by results of field deciphering;

by results of previous investigations held in this area or on the basis of other accessible information.

According to the empirical rule, each reference area shall contain 10–100 times more pixels than the number of spectral channels of the image. Such important characteristics as representativeness, homogeneity differentiation, and similarity with normal distribution are considered in the process of evaluating the quality of reference images as training samples.

The number of reference areas should correspond to the necessary number of classes of the output image. In the process of water bodies isolation, it is feasible to distinguish from 3 to 5 classes with the main ones being the open areas of water surface. Other classes, like forests, fields, and others, are necessary only to differentiate the main objects.

5. *Controlled classification of the image (classification with training).* Modern processing complexes usually have a certain number of procedures for controlled classification: spectral angle of minimum distance, parallelepipeds; maximum likelihood procedure; Mahalanobis distance; binary coding.

It is commonly believed [18, 19] that it is most feasible to use the binary coding procedure for two classes (for example, water and land). In the case of binary coding, all pixels are assigned one of two values on the basis of comparison with the values of model sampling. In the course of classification, the value of each pixel is compared with a mean value of the model sampling. A binary image is obtained as a result. However, it is quite difficult to obtain such a clear division of an image with different terrain elements into two classes in practice. As a rule, a number of other elements with similar spectral characteristics are included in the water class.

The procedure of spectral angle is expedient in the process of creating water body masks. This procedure offers good results when it is necessary to classify the objects that have similar brightness values in all spectral ranges. In addition, this method does not consider the values of pixel brightness, which means that flash effects do not influence the results.

First, reference areas are created. All pixels of an image, including the reference ones, are considered as vectors in the space of spectral indicators.

A maximum allowable spectral angle is set, i.e. if the angle between the reference vector and pixel vector being classified is less than maximum, this pixel belongs to this class, if it is bigger, it does not belong to this class (Fig. 3).

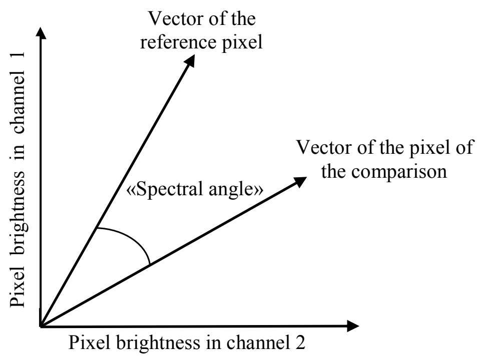

Fig. 3. Illustration of the classification by spectral angle method

Spectral angle is calculated using the following formula:

(1) $$S(\vec{x}_1, \vec{x}_2) = \frac{\vec{x}_1 \vec{x}_2}{|\vec{x}_1||\vec{x}_2|},$$

where $\vec{x}_1, \vec{x}_2$ are reference vector and pixel vector correspondingly.

The advantage of this method lies in the fact that classes received by spectral angle method depend on the angle between the vectors of pixel brightness and do not depend on the vector length (brightness value).

6. *The procedures of post-classification are used to improve the quality of classification*

Among the range of procedures of post-classification it is worth using the procedures of pixel grouping ("Clumping classes") and "class screening".

Classified images are often characterized by insufficient positional connection (spots or gaps in classified areas). The "Clumping classes" procedure is intended to group similar adjacent areas under classification using morphological operators. The classes selected are grouped using the expansion operator and later smearing operator on the classified image using the given kernel size.

The "class screening procedure" is used to solve the problem of isolated pixels, which is encountered during image classification. Class screening deletes isolated classified pixels using drop grouping. The "pixel screening" procedure considers the adjacent 4 or 8 pixels to determine whether a pixel is grouped with pixels of the same class. If the number of the grouped pixels in the class is lower than the value indicated, the pixels will be deleted from the class. When pixels are deleted from the class using the screening procedure, black (unclassified) pixels remain.

Often, the problem of isolated pixels can be solved using the medial filtering with 3×3 aperture.

7. *Quality evaluation of the results of classification and creation of the water body mask*.

Evaluation of quality of water body detection is done by dividing the difference model according to the number of classified pixels of the water body and the general number of water pixels by the number of water pixels of the reference mask.

(2) $$D = \frac{|N_v - N_e|}{N_e} \times 100[\%],$$

where N_v is the number of classified water pixels on the image under analysis; N_e is the number of water pixels on the reference mask.

Another classification precision measure is the kappa parameter (κ) [18], whose value lies in the range [–1; 1]. A positive value of kappa parameter indicates high precision, while zero and negative value indicate the lack of correlation in the classification. It is calculated by multiplying the general number of pixels in all land-based verification classes (N) by the sum of diagonal elements of the matrix of failed classifications ($\sum_k x_{kk}$),subtraction of the sum of land-based verification pixels in the class multiplied by the sum of classified pixels in the same class, summing all classes ($\sum_k x_{k\Sigma}\, x_{\Sigma k}$), and dividing by the general number of pixels squared minus sum of verification pixels in this class multiplied by the sum of classified pixels in this class, summing all classes ($\sum_k x_{k\Sigma}\, x_{\Sigma k}$).

(3) $$\kappa = \frac{N\sum_k x_{kk} - \sum_k x_{k\Sigma}\, x_{\Sigma k}}{N^2 - \sum_k x_{k\Sigma}\, x_{\Sigma k}}.$$

Results. The results of researching the method for different ways of controlled classification are summarized in Table 2. It is noteworthy that the quality of classification is to a great extent dependent on the types, number, and combination of bodies on an image. Therefore, the research was done for a complicated case: when an image contains the following: water, forests, field, roads, and settlements.

Table 2. Different types of controlled situation

Classification procedure	D [%]	κ
Spectral angle	96.8	0.68
Minimum distance	90.4	0.54
Parallelepiped	88.7	0.51
Maximum likelihood	96.3	0.67
Mahalanobis distance	83.5	0.37
Binary coding	87.1	0.34

Fig. 2 shows a fragment of an image of Landsat-8 equipment near Zhytomyr in natural colour combination 4-3-2. Near-infrared artificial colour, B_4 is fed to channel R, medium infrared artificial colour B_3 is fed to channel G, and red artificial colour B_2 is fed to channel B for combination 4-3-2 (see Table 1). The vegetation is shown in shades of brown, orange, green and red colours for this combination. For example, coniferous forests appear brown and forests with mixed tree species appear in red and orange (Fig. 4). Water objects appear in dark (close to black) colours.

It is easier for the operator to identify the reference areas for training (Fig. 5), since water objects are more visible.

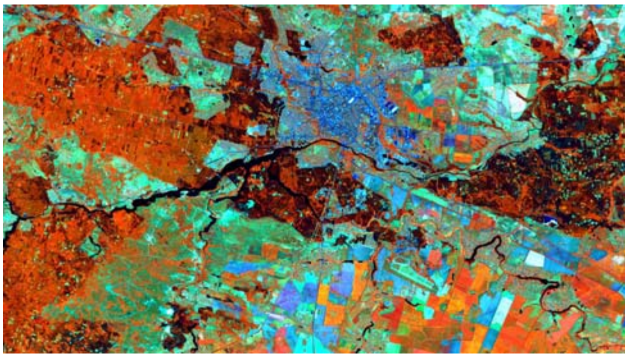

Fig. 4. Fragment of an image made by Landsat-8 equipment in Zhytomyr in combination 5-6-4 artificial colors

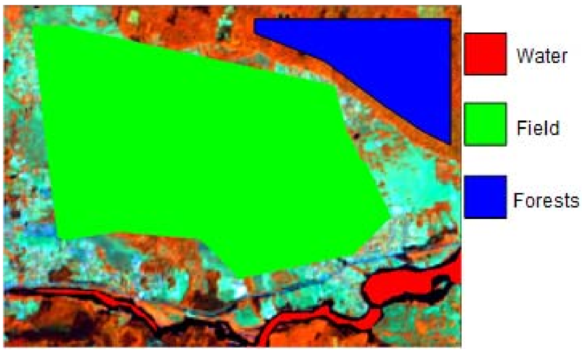

Fig. 5. Determination of reference areas

The mask image is obtained after the completion of items 5–7. The binary mask of water bodies calculated using the spectral angle method is presented in Fig. 6. The best kind of mask is selected using Table 2.

The coefficients D and κ are calculated by the formulas of paragraph 7.

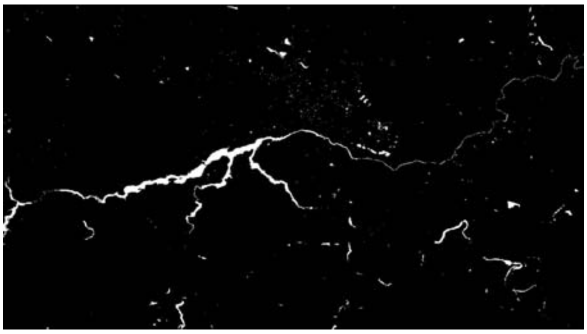

Fig. 6. The binary mask of water bodies calculated using the method of spectral angle

Conclusions

Thus, a method for automated interpretation of Landsat-8 satellite images has been developed in this paper, which enables the effective detection of water objects and the construction of their binary images.

The automated interpretation method contains the following steps:

- cutting out from the picture the part in which the objects of interest are;
- creating a multispectral image;
- creating an image in artificial colors;
- selecting the reference areas (areas of interest);
- classification with image training. It is expedient to use the spectral angle method when creating binary images of water objects. This method gives good results when you need to classify for objects that have similar values of brightness across all spectral ranges. In addition, since this method does not take into account the pixel brightness value, the image overexposition also do not affect the results;
- using post-classification procedures to improve the quality of the classification;
- evaluating the quality of the classification results and creating the binary image of a water object.

The outcome of the study of this method indicates that the best results of the application of the technique can be achieved by using methods of spectral angle or maximum likelihood for classification. The application of the developed method allows the detection of water objects larger than 30 m and substantially refines the obtained binary images of water objects.

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