Chapter 29
Methodology for Assessing the Quality of Multispectral Space Imaging Data in Landscape Element Monitoring

Viacheslav Zelentsov, Viktor Mochalov, and Natallia Lapitskaya

Abstract To determine the types and current condition of agricultural fields, methods of automated processing of multispectral space imagery are increasingly being used. One of the most relevant tasks is the semantic segmentation of landscape elements within the studied scene based on machine learning algorithms. Various algorithms are known for addressing this task, but the problem of evaluating the quality of processing results requires a better approach for solving. This paper discusses the indicators that characterize the quality of results of imagery data thematic processing when monitoring the condition of agricultural fields, using fields designated for forage preparation as an example. The methodology for assessing the quality of processed multispectral space imagery data is presented. A list and numerical values of basic quality indicators for identifying the condition of agricultural fields, considering ground survey data and hyperparameter values in machine learning algorithms, are provided. Generalized quality indicators for processing results are proposed. The role of a well-founded choice of initial data for evaluating the quality of processed imagery results is highlighted. The mathematical apparatus of fuzzy clustering is applied when forming the initial data, and the degree of membership of landscape elements to a selected cluster is taken into account when refining the initial data. The presented methodology can also be applied to determining the types and forecasting the yield of agricultural crops, detecting diseases, and solving other agricultural production issues.

V. Zelentsov (✉) · V. Mochalov
St. Petersburg Federal Research Center of the Russian Academy of Sciences (SPC RAS), St. Petersburg Institute for Informatics and Automation of the Russian Academy of Sciences (SPIIRAS), St. Petersburg, Russia
e-mail: v.a.zelentsov@gmail.com

N. Lapitskaya
Belarusian State University of Informatics and Radioelectronics, Minsk, Republic of Belarus

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29.1 Introduction

Currently, technologies for the automated processing of multispectral space imagery based on artificial intelligence technologies are being actively developed to address pressing applied problems in the field of remote sensing (RS). One of the most important tasks is semantic segmentation—the identification of landscape elements. When solving this task, each element of the image within the selected scene is assigned a label representing a surface with a known property or semantic description. Examples of semantic descriptions for agricultural production tasks may include types of agricultural crops, operations for their cultivation, field yield forecasting, types and their foci of agricultural crop diseases, and more. The physical basis and input data for solving the semantic segmentation task are the results of measuring the spectral reflectance characteristics of landscape elements in the visible and near-infrared bands of the spectrum, considering seasonal variability and the phenological phases of agricultural plant development. Technologies for measuring spectral characteristics through remote sensing, performed using onboard equipment of satellites, aircraft, and unmanned aerial vehicles, are currently being developed [1–5]. After atmospheric correction, the measurement results are input into automated processing algorithms as raw data. The most promising and increasingly widely used algorithms for automated processing are machine learning (ML) algorithms [6, 7]. The generalized scheme for processing imagery materials for this case is shown in Fig. 29.1.

In global scientific practice [8, 9], experience has been accumulated in evaluating the quality indicators of the image data processing results, particularly in remote sensing data analysis. The study [2] is dedicated to similar issues, providing a list of commonly used indicators and the procedure for their calculation.

However, the following issues remain problematic:

- The justified selection of reliable initial data, ensuring the training of machine learning algorithms and quality control of processing results;

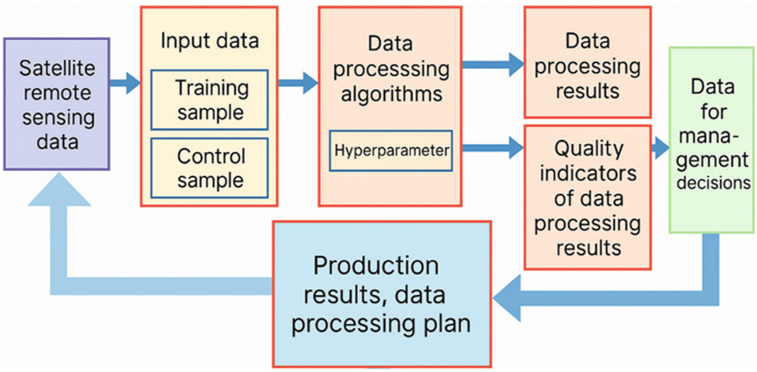


Fig. 29.1 Scheme of imagery processing

- The choice of generalized quality indicators for processing results that reflect the semantic focus of solving thematic tasks.

The overall proposed approach to selecting quality assessment indicators is as follows: identifiable landscape elements are divided into two classes with conditionally positive and negative properties in terms of the task at hand. For example, in the task of detecting field areas, elements with negative properties include zones of disease or vegetation drying. The identification results can be represented using the following basic quality indicators [2, 10]:

- TP (True Positive)—the number of pixels representing areas with actually positive vegetation properties;
- TN (True Negative)—the number of pixels representing areas with actually negative vegetation properties;
- FP (False Positive)—the number of pixels representing areas mistakenly identified as having positive vegetation properties;
- FN (False Negative)—the number of pixels representing areas mistakenly identified as having negative vegetation properties.

The objective of this research is to develop a methodology for assessing the quality of multispectral satellite imagery processing results, considering the proposed set of generalized indicators and the justified selection of initial data for their evaluation.

29.2 Materials and Methods

The multispectral satellite imagery data considered in this study are obtained using optoelectronic equipment onboard satellites such as Kanopus-V and Resurs-P (Russia), Sentinel-2 (ESA), Landsat-8 (USA), and others. Specific examples will be shown below.

Various theoretical and practical methods were applied in the research under consideration. The composition of these methods is presented in the general scheme of the developed methodology in Fig. 29.2. The numbers in the scheme indicate the main stages of the methodology implementation, which correspond to the methods described in this section.

A preliminary analysis of the thematic task related to landscape element monitoring allows for the selection of a generalized quality indicator for the image processing results. This indicator is then assessed and analyzed for its dynamic changes based on the composition of the input data and the value of the machine learning algorithm's hyperparameter.

Stage 1: Scene and Fragment Selection.

At this stage, the operator selects a scene and its fragment within the satellite imagery frame, considering the thematic task's content. The selected fragment primarily contains identifiable landscape elements (Fig. 29.3).

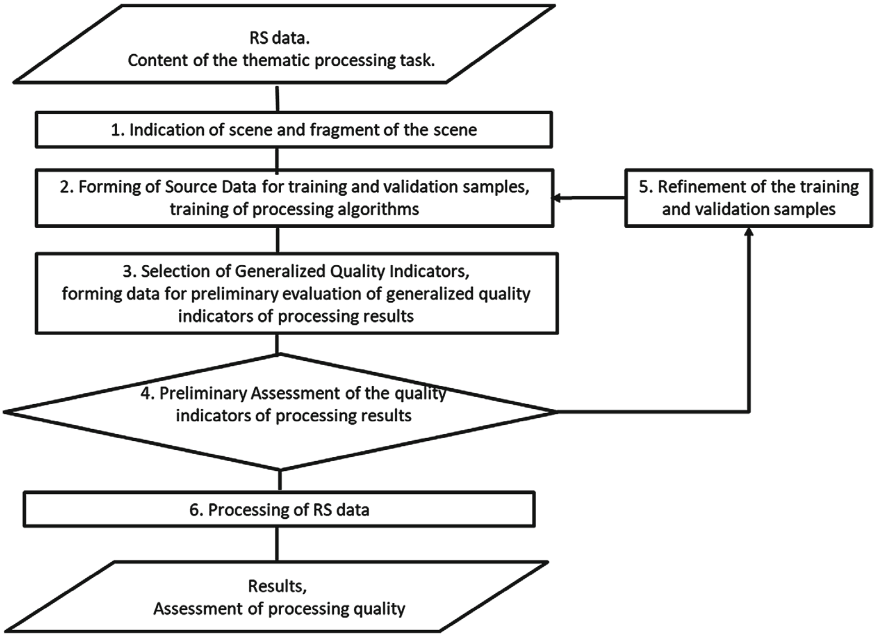


Fig. 29.2 Diagram of the methodology for assessing the quality of image processing

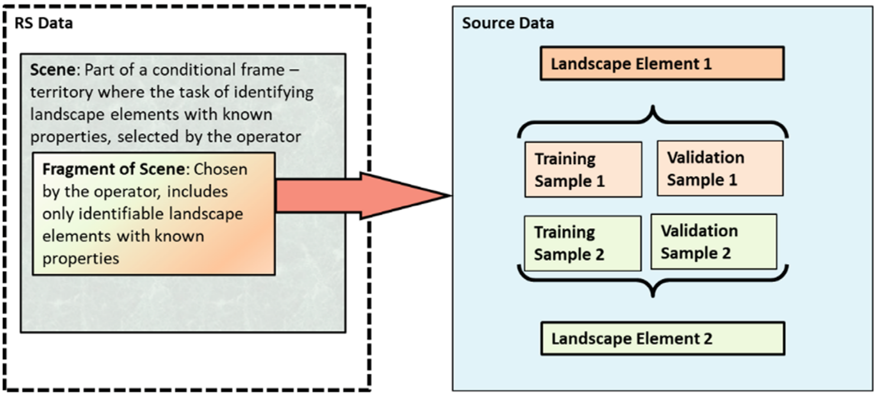


Fig. 29.3 Composition of initial data

The evaluation of properties or the semantic description of landscape elements is typically performed through field surveys or based on other reliable data sources.

Stage 2: Landscape Element Boundary Detection Using Fuzzy Clustering.

At this stage, the boundaries of landscape elements within the selected scene fragment are determined using the fuzzy c-means (FCM) clustering method [11].

This approach allows for the division of landscape elements into a predefined number of clusters with established properties.

The use of FCM is justified because, during the formation of training and validation datasets, it is often challenging for an operator to visually identify the precise boundaries of landscape elements with known properties in the scene. This difficulty arises primarily due to the homogeneity of the image in the visible spectral range within the chosen fragment. Similar challenges are also encountered during field surveys, as navigating through certain landscape areas can be complicated.

The issue of image segmentation of landscape elements is characterized by uncertainty. Therefore, it is advantageous to apply fuzzy logic-based clustering algorithms to address it [12].

Traditionally, a function calculated by the Euclidean metric can be employed as a function of the distance $d\left(r_i, r_q\right)$ in the l-dimensional space of spectral characteristics:

$$d\left(r_{i,}r_q\right) = \sqrt{\sum_{j=1}^{l}(r_i^j - r_q^j)^2}, \tag{29.1}$$

where R is a set of multispectral image points to be segmented. Each point corresponds to a vector of numerical values $(r_i = (r_i^1, r_i^2, \ldots r_i^l)$, where r_i^j is the numerical value of the j spectral characteristic for the$i$ point $(i = \overline{1, n}; j = \overline{1, l})$. For Sentinel-2 survey materials, l can be taken equal to 13.

The proposed improved apparatus for image segmentation and subsequent identification of the main types of landscape elements is based on the detection and further analysis of the membership function matrix. The initialization of the matrix of membership functions $\boldsymbol{U}$, which determines the degree of belonging of the i-pixel to the k-cluster, is carried out as follows:

1. It is calculated the distance between the center of the class $R_k^э = \left\{r_{kl}^э\right\}$ and each pixel brightness vector $R_i = \{r_{il}\}$ where l is the wavelength number.

In the standard algorithm, the distance from a pixel to a cluster is taken as the Euclidean (29.1). However, for mixed landscape elements, this choice is not always justified. It is valid only if there is no inversion between the spectral signatures of individual species of landscape elements. In the formula (29.1), the sum of the squared differences is used as a criterion for a pixel to belong to a cluster. Sometimes, it is more efficient to use the Mahalanobis distance [7] for the analysis of vegetation cover, which is a complex unit of objects with different spectral reflective properties. However, in the case of hyperspectral data, there may be issues with inversion of the covariance matrix. Therefore, it was proposed to use the Terebizh metric [13] as a distance measure:

$$d_{ik} = \sum_{j=1}^{l}(R_i(\lambda_j) - R_k^э(\lambda_j))^2/R_k^э(\lambda_j). \tag{29.2}$$

As a result, the $n \times p$ matrix $\boldsymbol{D}$ is formed from d_{ik}, where n is the number of clusters, p is a number of pixels of a hyperspectral image.

2. The elements of the membership function matrix $\boldsymbol{U}$ are calculated

$$u_{ik} = 1/(\sum_{q=1}^{n} t_{ikq}), \tag{29.3}$$

where $t_{ikq} = (d_{ik}/d_{iq})^{-2/(m-1)}$ form the matrix $\boldsymbol{T}$, m is the fuzzificator.

3. The objective function, which must be minimized, is estimated like this:

$$F = \sum_{i=1}^{p}\left(\sum_{k=1}^{n} d_{ik}^{2}\mathrm{u}_{ik}^{m}\right). \tag{29.4}$$

4. If the number of specified iterations is not completed and the specified classification accuracy is not achieved ε: $|F(j) - F(j-1)| \leq \varepsilon$, then new class centers are calculated by the formula:

$$r_{kl}^{э} = \sum_{i=1}^{p}(\mathrm{u}_{ik}^{m} r_{il}) / \sum_{i=1}^{p}\mathrm{u}_{ik}^{m} \tag{29.5}$$

and steps 1–3 are repeated.

At stage 3, the data for preliminary quality assessment of thematic image processing results are generated. After clustering the image data within the scene fragment, training and validation datasets are created for the landscape elements under consideration, typically in a 1:1 ratio. During the training of processing algorithms, additional vegetation indices may be calculated if necessary.

The following key operations are performed at this stage:

construction of a histogram representing the distribution of pixels in the training dataset based on the calculated index values (Fig. 29.4); selection and visualization of a hyperparameter defining the threshold between the segmented landscape elements, which is also displayed on the histogram (Fig. 29.4);

calculation of basic and generalized quality indicators to assess the accuracy of image processing results (Fig. 29.4, Table 29.1).

In Fig. 29.4, the abscissa axis represents conditional threshold numerical values reflecting the position of the hyperparameter or the separating surface (Threshold) on the identifiable landscape elements. The ordinate axis displays the histogram values representing the number of pixels corresponding to the landscape elements.

The elements with conditionally positive properties (P) are depicted by Row 2, while those with conditionally negative properties are depicted by Row 1. The current position of the hyperparameter is indicated by a red line.

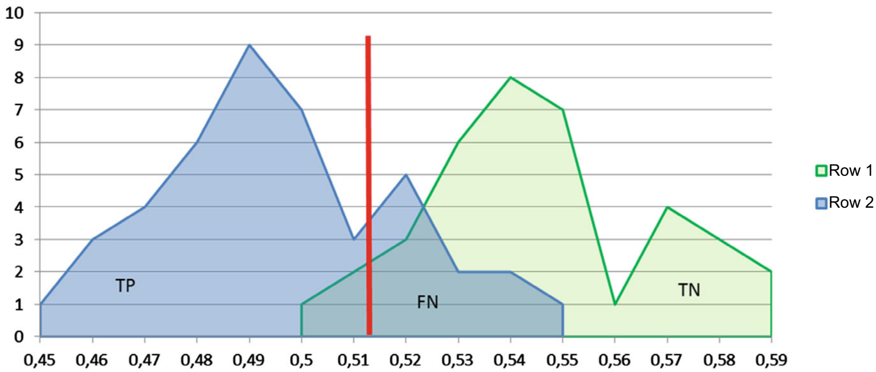


Fig. 29.4 Example of determining basic quality indicators of processing results

Table 29.1 Examples of tasks and generalized quality indicators of processing results

Task	Indicator	Task description	Equation
A	Overall Accuracy	Homogeneous landscape elements, the requirements for identification accuracy are comparable	$\mathrm{OA} = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}}$
B	Recall	Identification of areas that require planned activities, which do not involve significant material costs	$\mathrm{REC} = \frac{\mathrm{TP}}{\mathrm{TP+FN}}$
C	Precision	Identification with maximum accuracy of only those landscape elements that require immediate response, such as costly measures	$\mathrm{PRE} = \frac{\mathrm{TP}}{\mathrm{TP+FP}}$
D	Comprehensive indicator F_β	The possibility of harmoniously accounting for the priority of planned and operational tasks, depending on the situation, is provided	$F_\beta = \frac{(1+\beta^2)\cdot\mathrm{PRE}\cdot\mathrm{REC}}{\beta^2\cdot\mathrm{PRE}+\mathrm{REC}}$ $\begin{cases}\beta < 1 \to \mathrm{PRE}\\ \beta > 1 \to \mathrm{REC}\end{cases}$

To the left of the red line, the blue surface, enclosed by a blue contour, corresponds to the value of TP (True Positive), while the area enclosed by the green contour corresponds to FP (False Positive).

To the right of the separating surface, the green figure, enclosed by a green contour, corresponds to TN (True Negative), while the area outlined by the blue contour corresponds to FN (False Negative).

At stage 4, the values of basic and generalized quality indicators of the image processing results [2, 10] are analyzed in relation to the specified requirements for monitoring the condition of landscape elements. If the requirements are not met,

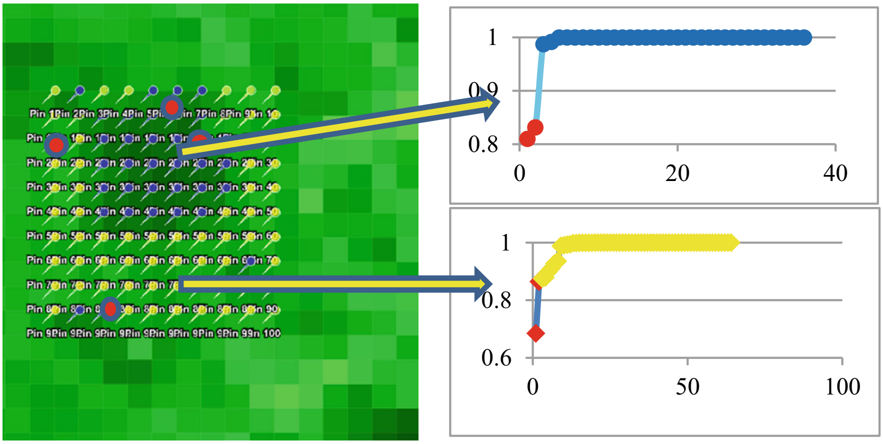


Fig. 29.5 Scene fragment and raw data for processing image materials

a decision is made to proceed to stage 5 and the subsequent stages, following the diagram shown in Fig. 29.2.

At stage 5, the composition of the initial data is refined in terms of the training and validation datasets. This refinement is carried out by excluding selected pixels from the initial dataset or by conducting additional field surveys.

The decision to exclude pixels from the training and validation datasets is based on the analysis of the degree of membership of each pixel to the considered cluster (Fig. 29.5), using the Student's t-test criterion [14]. The degree of membership of each pixel to the considered cluster was determined in stage 2 using the fuzzy clustering mathematical framework. A confidence interval is then calculated:

$$\overline{X} = t_{\propto} * \frac{S}{\sqrt{n}}, \tag{29.6}$$

where: S—standard deviation; n—number of pixels in the sample (degrees of freedom in the critical values table of the Student's t-test); $t_{\propto}$—critical value from the Student's t-distribution table at a significance level of $\alpha = 0.05$, corresponding to a 95% confidence level, for a given number of degrees of freedom; $\overline{X}$—confidence interval.

At stage 6, the image data are processed using algorithms that have been trained based on the training dataset, considering the selected value of the hyperparameter. By way of explanation, especially, the task of semantic segmentation of landscape elements within the scene is addressed. The final evaluation of the processing quality of the image data is carried out using the operations described in stage 3, where, instead of the training dataset, the values of the validation dataset are considered.

As the output data of the methodology presented in Fig. 29.2, the results of the automated processing of the image data within the scene and the results of the quality assessment of the automated identification of landscape elements are presented.

29.3 Results

The validation of the developed methodology was applied to the Sentinel-2 image: S2A_MSIL2A_20230617T092031_N0509_R093_T35VPG_20230617T132300 dated June 17, 2023. A fragment of the scene and the data for forming the training and validation datasets are shown in Fig. 29.5

In Fig. 29.5, the blue pixels on the left represent landscape element №1, while the yellow pixels represent landscape element №2. For example, two types of landscape elements may correspond to two states of agricultural crops. The red dots indicate pixels with a low degree of membership to the considered clusters, which, if necessary, should be excluded from the initial data. The membership graphs for the pixels corresponding to the clusters are shown on the right. In the graphs, the ordinate axis represents the number of pixels, while the abscissa axis represents the degree of membership of the pixels to the considered clusters. The histograms for determining the basic quality indicators of the processing results are shown in Fig. 29.6a, b.

In Fig. 29.6, the abscissa axis represents the value of the index used in the adopted machine learning algorithm. The red line indicates the selected hyperparameter value, which is 0.45. The numbers in the columns represent the number of pixels from the initial dataset for which the algorithm's index value falls within the corresponding range on the abscissa axis.

Figure 29.6b differs from Fig. 29.6a in that it shows the refined values of the initial data, from which pixels with the lowest degree of membership to the corresponding cluster (Fig. 29.5) have been excluded.

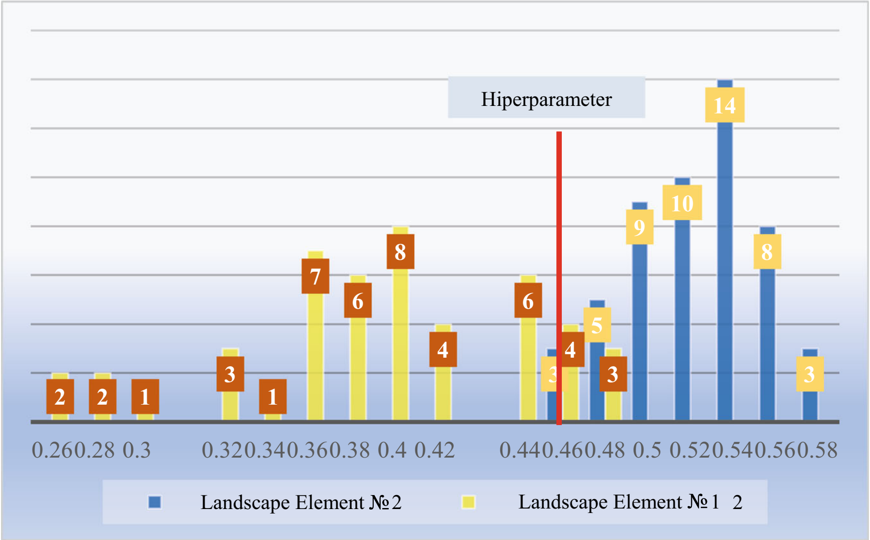
Table 29.2 presents the results of calculating the basic and generalized quality indicators of the processing results [15]. For the calculations, the initial data values displayed in Fig. 29.6 are utilized.

The presented example illustrates the possibility of obtaining quality assessments of the image processing results and analyzing the quality of processing depending on the composition of the initial data and the applied processing algorithm. In particular, an analysis of the values provided in Table 29.2 allows us to conclude that the overall quality of the image processing results is high when solving the task of semantic segmentation of specific landscape elements based on the formed initial data. It is shown that refining the composition of the initial data leads to an improvement in the values of the considered quality indicators. Furthermore, the choice of a specific quality indicator for processing depends on the semantic content of the practical task being addressed.

29.4 Discussion and Conclusion

The paper presents a methodology for evaluating the quality of image processing results in multispectral imaging for monitoring the condition of landscape elements, using the example of identifying the state of agricultural production objects. The

(a)



(b)

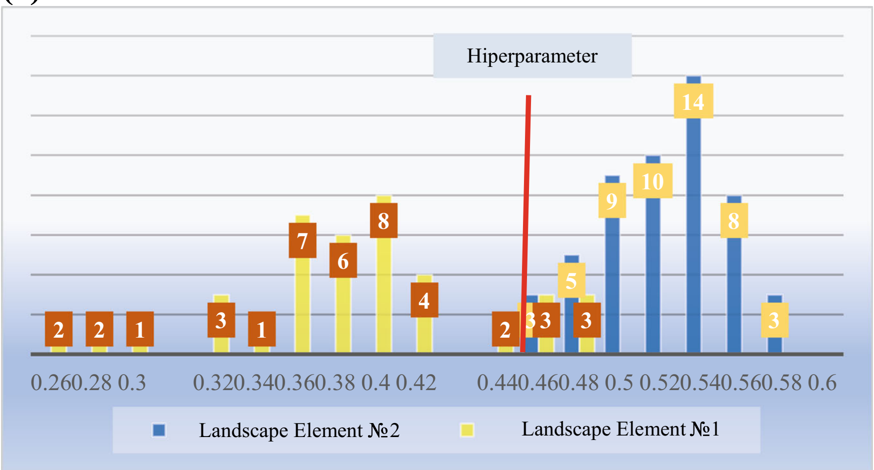


Fig. 29.6 **a** Histogram for assessing the preliminary values of basic quality indicators of the processing results; **b** histogram for assessing the refined values of basic quality indicators of the processing results

application of the methodology allows for supplementing the processing results with quality indicators, thereby determining the degree of confidence in these results and creating the possibility of selecting the most reliable algorithm and its parameters for solving each specific thematic task. This advantage determines the novelty of the

Table 29.2 Quality indicator values of the processing results

Quality indicator of processing results	For preliminary values of the initial data	For refined values of the initial data	The absolute value of the improvement in processing results, ΔA	Relative value of the improvement in processing results, δ, %
TP	40	40		
TN	52	52		
FP	0	0		
FN	7	3		
REC	0.85	0.93	0.08	8.51
PRE	1.00	1.00		
OA	0.93	0.97	0.04	4.04
F_β	0.92	0.96	0.04	4.60

approach considered and enables practitioners to make more informed decisions to assess the current situation in agriculture fields, monitoring and other applications.

Additionally, the preliminary evaluation of the quality indicators of thematic processing results allows for analyzing the adequacy of the pre-formed initial data, including the spectral reflectance characteristics of typical landscape elements, to address current practical tasks in various fields of activity.

After performing spectral energy calibration of the image materials, data from various aircraft- and space-based instruments can serve as sources of initial data. A necessary preparatory step in implementing the methodology is semantic description and selection of a scene fragment. In this regard, utilizing fuzzy clustering methods to form training and validation datasets represents an innovative solution, ensuring a well-founded choice of initial data. An important feature of the methodology is the capacity to justify the correction of the composition of the initial data, which ensures the formation of reliable training and validation datasets and ultimately improves the quality of image processing results.

The developed methodology can also be applied in such areas as:

- Justifying the requirements for image materials in terms of their spectral, energy, and spatial resolution;
- Selecting machine learning algorithms based on the specific thematic monitoring issue;
- Choosing the values of hyperparameters and threshold values for intermediate indicators used in data processing algorithms.

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