Technology Development for Detecting Inhomogeneities in Agricultural Fields

Petr Skobelev, Vitaly Travin, Elena Simonova, Vladimir Galuzin, Anastasiya Galitsk

Abstract: The paper addresses the relevant problem of identifying inhomogeneities in crop development based on analysis of multispectral images obtained from Earth remote sensing (ERS) satellites and unmanned aerial vehicles. Various techniques for detection of inhomogeneities are considered, which are based on computation of normalized difference vegetation index and its analysis, but do not take into account stages of crop production. The authors propose an original method and new algorithms for detecting inhomogeneities that take into account field zoning at various stages of the plant development cycle: preparing the field for sowing, emergence, and development of seedlings, heading. The paper also describes comparative analysis of results of the algorithms described in this paper and those of system-analogs. This analysis confirms effectiveness of the proposed algorithms. The method and algorithms for detection of inhomogeneities, developed by the authors, are used in the software module of image processing and presentation of ERS results for solving problems of precision farming, providing prompt, flexible, and efficient results for consumers.

Keywords: crop production stages, field inhomogeneity, Normalized Difference Vegetation Index, precision agriculture, remote sensing.

I. INTODUCTION

At present, development of an agricultural enterprise largely depends on production of competitive products. The use of resource-saving technologies significantly reduces the cost of crop production and improves its competitiveness. One of the key elements of such technologies is precision farming [1].

Traditional monitoring of crop condition includes field survey at test sites and during route surveys. At the same time, the main observed parameters are the following: type of crop culture, development phase, plant height, crop density (number of productive stems per 1 square meter), productivity elements (number of spikelets and grains per ear/head), crop contamination, damage to plants due to adverse weather conditions, diseases, and pests, assessment of the general condition of crops, biological grain yield.

Precision farming is a combination of technologies and technical means aimed at effective management of crop productivity in conditions of inhomogeneity of the habitat and state of plants [2]. The main difference between traditional and precision farming is the use of modern information technologies for collecting, processing, and analyzing data used for making decisions, taking into account the current individual needs of plants in the specific area of the field. For implementation of precision farming, it is required to obtain data on field characteristics (chemical composition of soil, humidity level, amount of solar radiation, relief, etc.) and crop characteristics. One of the ways to obtain such data is Earth Remote Sensing (ERS) [3].

Remote sensing is a process of collecting information about an object, territory or phenomenon without direct contact with it [4]. Remote sensing includes all types of non-contact surveys that are carried out from various measurement platforms: aircrafts and spacecrafts (airplanes, UAVs, satellites, etc.), ships and submarines, as well as ground stations. A snapshot is defined as a two-dimensional metric image of specific objects, obtained as a result of remote recording or measurement of its own or reflected radiation. It represents the most appropriate form of measurement, recording and visualization of radiation carrying geographic information about the studied objects.

The main advantages of using remote sensing data for field mapping are the following: relevance of data at the time of study, high accuracy of determining boundaries of objects, higher objectivity of identifying objects and assigning an object to a particular class. In addition, when using remote sensing data, costs of assessing the general condition of crops can also be minimized by reducing field trials.

Existing methods for processing and analyzing remote sensing data allow for:
- assessment of crop acres, recognition of species and varieties of crops;
- assessment of the sanitary condition of crops, i.e. detection of foci of diseases and pests, identification of degree of weed infestation of crops;
- assessment of humidity, content of nutrients and soil acidity;
- prediction of crop biomass, etc.

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One of the methods for analyzing Earth remote sensing data is detection of inhomogeneities, as a result of which a field map with marked inhomogeneity zones is formed [5]. Using such a map, farmers have the opportunity to detect areas affected by pests or diseases at the initial stage, and more rationally allocate resources between areas of the field to avoid overspending resources where they were previously used in excess, and increase productivity of those areas that previously received less fertilizer, plowing or watering.

In order to organize decision-making support and make recommendations on coordinated management of agricultural production, a smart cloud-based management system for precision farming is developed. Its detailed description is given in the work by D. Budaev [6].

The task of detecting inhomogeneities during analysis of remote sensing data lies in assessing the state of crops based on the obtained images of fields, in order to determine deviations of the density of photosynthetically active biomass from the average value for this specific field.

Complexity of this task consists in the fact that during different stages of agricultural production, inhomogeneity can mean different concepts: thus, at the stage of preparing the field for planting, weeds act as inhomogeneities, whereas at the stage of sprouting and heading, inhomogeneity is understood as vegetation in oppressed state and areas with dead crops. Moreover, at the sprouting stage, the search for inhomogeneities should be carried out in rows (the inter-row spacings are of no interest), and at the heading stage - over the whole field, distinguishing rows and inter-row spacings (between rows, inhomogeneity would be the presence of vegetation). Therefore, the method of detecting inhomogeneities used for data analysis depends on the stage of agricultural production and on the field area.

Currently, many different methods for detection of inhomogeneities are used, which are mainly based on the initial computation of vegetation index and its analysis.

The service for analyzing satellite images, developed by SAS, determines the degree of field inhomogeneity (weak, moderate, elevated, etc.) by assessing the values of field vegetation index [7].

The VEGA-PRO satellite vegetation analysis service, developed by the Space Research Institute of the Russian Academy of Sciences (VEGA-PRO – satellite vegetation analysis service [8]), allows for evaluation of field inhomogeneity in percentage, as well as the main soil factors limiting productivity on the specific field. It also analyzes the crop state using time series of vegetation indices, its seasonal and multi-year dynamics for any single point in the field or user-defined polygon.

The Geoanalitika.Agro service, developed by SOVZOND, provides the opportunity to analyze the crop state by identifying zones with different vegetation intensity within the field [9].

The EADS/Astrium Company has developed the Farmstar project (precision farming system) for wheat, maize, rapeseed, and sugar beet [10]. Its goal is to develop information products for agricultural cooperatives and farmers that will help them improve control over their crops. Farmers receive recommendations and/or field state maps during each key stage of crop growth to effectively manage their crops.

All of the above services do not take into account peculiarities of crop production and not all of them provide field zoning, i.e. do not distinguish rows and inter-row spacings.

To solve this problem, the Smart Farming system proposes to define a separate algorithm for inhomogeneity detection for each stage of crop production.

II. METHODS OF DETECTING INHOMOGENEITIES

A. Problem statement of inhomogeneity detection

The whole cycle of agricultural production is divided into three stages:

1) Preparing the field for sowing.

At this stage, there should be no vegetation in the field. Therefore, any green biomass will be considered inhomogeneity. The task of detecting inhomogeneities means searching for any plants on the field.

2) Emergence and development of seedlings.

At this stage, crops grow in rows with distinct inter-row spacings, therefore inhomogeneity would mean oppressed vegetation or lack of vegetation in the row, as well as any vegetation in inter-row spacings. The task of detecting inhomogeneities is determining the rows of crops in the image and subsequent analysis of the index image.

3) Heading.

At this stage, crops are a dense biomass with weakly expressed inter-row spacings; therefore, just as in the previous stage, oppressed vegetation, as well as absence of vegetation will be considered inhomogeneity. The task of detecting inhomogeneities is analyzing the vegetation index for the field as a whole.

Let us suppose there is a georeferenced image of the field from remote sensing. Field boundaries and the stage of agricultural production are known. The task is to search for inhomogeneities.

B. Experimental Site

For test data, the authors compiled a sample of satellite and UAV images taken from April to September 2018 in order to monitor the state of crops in the fields of ZAO S.M. Kirov, located in the Rostov region of the Russian Federation. The images were taken at the stages of agricultural crop production described in *A*.

During compiling the test data, images from the Sentinel-2 spacecraft with resolution of 10 m in two spectral ranges: *red* (band 4) and *nir* (band 8) [11] were used.
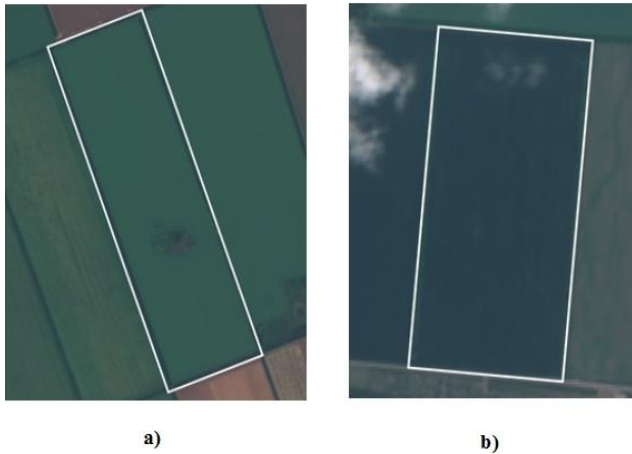
Fig. 1. Experimental fields: a) wheat, b) soybeans (Source: Sentinel-2 [11])

The UAV survey was carried out using the Survey 2 multispectral camera by MAPIR company [12], equipped with two survey channels (*red + nir*) mounted onto the DJI Phantom 3 Advanced quadrotor. As a result of shooting, a set of paired images in JPG and RAW formats was obtained. After preprocessing, a TIFF image was received from a pair of shots, which was then calibrated and geolocated.

Studies were conducted on an agricultural wheat field (Field A) with an area of 188.5 hectares and a soybean field (Field B) with an area of 97.1 hectares (Fig. 1).

C. Methods of Detecting Inhomogeneities

A characteristic feature of vegetation and its state is spectral reflectivity, characterized by large differences in reflection of radiation of different wavelengths. Based on the combination of brightness values in certain channels, informative for highlighting the studied object, and calculating the "spectral index" of the object using these values, an image is constructed corresponding to the index value in each pixel, which makes it possible to select the studied object or evaluate its state.

Calculation of most vegetation indices is based on two most stable (not dependent on other factors) regions of plant spectral reflectivity curve. The red spectrum region (0.62-0.75 micron) accounts for maximum absorption of solar radiation by chlorophyll and the near-infrared region (0.75-1.3 micron) - for maximum reflection of energy by the leaf's cellular structure. Thus, high photosynthetic activity (associated, as a rule, with large biomass of vegetation) leads to lower values of reflection coefficients in the red spectrum region and higher values in the near-infrared region. However, when the plant becomes dehydrated or sickly, the spongy layer is destroyed, and the plant ceases to reflect as much light in the near-infrared region (NIR) [13].

As one of the main indices, the Normalized Difference Vegetation Index (NDVI) is currently used to assess the state of crop vegetation. It is applicable for most cultivated crops [14].

Fig. 2 shows the scheme of generalized algorithm for detecting zones of inhomogeneities according to remote sensing data. The algorithm is based on analysis of the NDVI index:
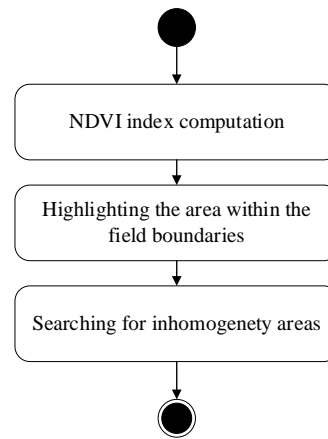

Fig. 2. Generalized algorithm for detecting inhomogeneities (Source: compiled by the authors)

$$NDVI = \frac{nir - red}{nir + red},$$

where *nir* is intensity of reflected light in the near-infrared light, *red* is intensity of reflected light in the visible red light.

The index can have values from -1 to 1. Areas without vegetation (unfertile land, rocks, sand) show very low NDVI values, less than 0.1, areas of low and rare vegetation (shrubs and grasses) show values in the range of 0.2-0.5, and trees show the highest range of 0.6-0.9 during their peak growth stage. Water shows negative NDVI values.

The input data for the algorithm is georeferenced images in the red and near-infrared spectral ranges, which are necessary for computation of vegetation index, as well as boundaries of agricultural field on which it is necessary to detect inhomogeneities.

First, vegetation index is calculated. Then, in the resulting image, the area inside the field boundaries is highlighted (Fig. 3).
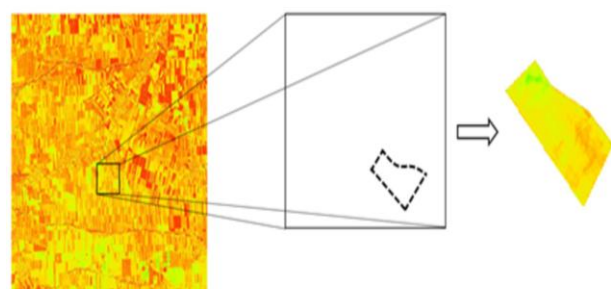

Fig. 3. Selection of the area on the index image along the field boundaries (Source: compiled by the authors)
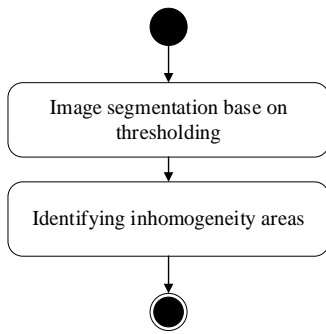
Fig. 4. Inhomogeneity detection algorithm at the stage of field preparation (Source: compiled by the authors)

At the stage of searching for inhomogeneity areas, analysis of the index image is performed. At the same time, for each selected agricultural production stage, different search algorithms are used (Figs. 4, 6, 7).

a. Inhomogeneity Detection at the Stage of Field Preparation

Fig. 4 shows the scheme of detecting inhomogeneities at the stage of field preparation. Initially, the index image is segmented, in order to highlight areas in which pixel values fall within the range of index values corresponding to vegetation. The pixels of the final image will get a value equal to one, provided that on the original image the index value in this point falls into the desired range. Otherwise, the new pixel value becomes zero. As a result of segmentation, a binary image is obtained (Fig. 5).

After that, a search is made for contours of inhomogeneity zones obtained as a result of segmentation, by applying the method of contour analysis. A contour is a certain object boundary separating it from the background. In a binary image, object boundaries are specified explicitly. A set of pixels that makes up the object boundary is its contour. Result of the search is a set of contours encoded with the Freeman chain code [15]. Moreover, the contour boundary is represented as a sequence of straight line segments of a certain length and direction.

b. Inhomogeneity Detection at the Stage of Sprouting

Fig. 6 shows the scheme of inhomogeneity detection at the stage of sprouting.

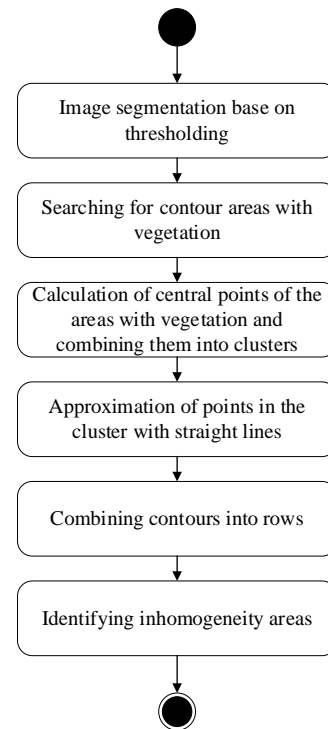**Fig. 5. Result of segmentation as a binary image (Source: compiled by the authors)**

Fig. 6. Algorithm for inhomogeneity detection at the stage of emergence and development of seedlings (Source: compiled by the authors)

At the beginning, just as in the previous step, the index image is segmented in order to highlight areas with vegetation and determine their contours. Then, for recognition of rows, central points of the found areas are calculated. After that, the central points close to each other are combined into clusters so that points in the obtained clusters can be later approximated by a straight line.

After clustering the points, they are approximated by a linear function $y=ax+b$ and slope angles of approximating lines are calculated. The dominant angle of the straight line is taken as the slope angle of rows in the image.

After finding the slope angle of rows, clustering is repeated and approximation is done taking into account the fact that rows must be located in the given direction. Then, the average distance between approximating lines is calculated and clusters that fall in the inter-row spacings are filtered.

Finally, areas with vegetation are combined into rows, according to clusters.

The next stage is to directly search for inhomogeneities in rows and inter-row spacings. For inter-row areas, the algorithm is similar to the one given in *a*.

To detect inhomogeneities in rows with crops, the average value of NDVI index is first calculated for all rows. Then, in each row, areas with specified deviations from this value are allocated.

c. Inhomogeneity detection at the heading stage

Fig. 7 shows the scheme of inhomogeneity detection at the heading stage.
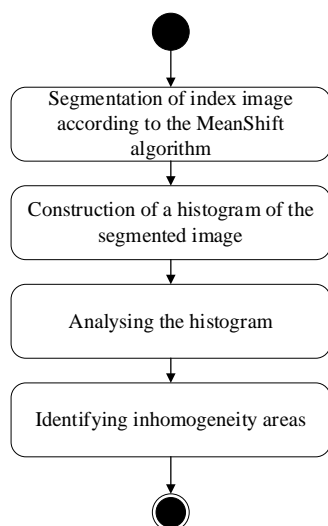
Fig. 7. Algorithm for inhomogeneity detection at the heading stage (Source: compiled by the authors)

First, the index image is segmented according to the MeanShift algorithm, which groups objects with similar features [16]. Pixels with similar index values are combined into one segment. The output is an image with homogeneous areas (Fig. 8).

For the obtained image, a histogram of index value distribution is plotted. The areas corresponding to histogram columns with low probability will be defined as inhomogeneity areas.

III. RESULTS AND DISCUSSION

Experimental images for each of the stages of agricultural production, obtained from the Sentinel-2 satellite and unmanned aerial vehicle (UAV), are shown in Figs. 9-11.

Results of the field survey were taken as the reference sample. During this survey, boundaries of inhomogeneity areas were noted by experts using a GPS tracker. The total area of inhomogeneities is calculated in percentage to the total field area.

At the stage of preparation of Field B, as a result of manual analysis, total area of 6.3 hectares (Fig. 9b) was noted as inhomogeneity (6.5% of the total field area). Whereas, the algorithm analysis noted 5.9 hectares (6.1%). This inaccuracy in results of detection is associated with a decrease in vegetation density at the boundaries of inhomogeneity areas.

At the stage of emergence and development of soybean seedlings in Field B, a UAV image with 19 rows of planted crop with a total length of 133 m was used to detect inhomogeneities (Fig. 9a). As a result of manual analysis, sections with a total length of 14 m (Fig. 9b) were noted as inhomogeneities, which accounted for 10.5% of the total length of landings. Whereas the algorithm noted 20 m (15%). This inaccuracy in results of inhomogeneity detection is associated with uneven planting density. In some cases, empty spaces between neighboring seedlings were marked by the algorithm as seeds that did not sprout.

At the heading stage in Field A, as a result of manual analysis, the total area of 5.4 hectares was noted as inhomogeneity (Fig. 11b), which accounted for 2.9% of the

Fig. 8. Result of segmentation of the index image according to the MeanShift algorithm (Source: compiled by the authors)

total field area. Whereas the algorithm noted 3.8 ha (2%). This inaccuracy in results of inhomogeneity detection is associated with an increase in vegetation density at the boundaries of inhomogeneity areas.

To evaluate effectiveness of the algorithms, a comparative analysis was performed: results of the algorithms described in this paper were compared to those of the system analogs discussed in Section 1 for a sample of 100 images for each stage of agricultural production. The value of standard deviation from the result of manual analysis was considered as an indicator of algorithm efficiency. Results are shown in Table 1.

TABLE I. EXPERIMENT RESULTS

Stage	SAS	VEGA	Geoanalitika. Agro	Algorithms presented in the paper
Field preparation	3.1%	2.5%	1.8%	1.7%
Emergence and development of seedlings	14.9%	17.5%	12.4%	5.8%
Heading	4.2%	3.7%	1.8%	1.9%

After analyzing the results obtained, it is clear that all systems at the field preparation stage, on average, show results close to those of the manual analysis. However, the SAS and VEGA services provide a wider range of estimates. For the stage of emergence and development of seedlings, deviations from the reference standards are very large for all systems-analogs. At the heading stage, the Geoanalitika. Agro service shows the closest estimates to the reference standards. Only the algorithms presented in the paper show results closest to the reference ones for all stages of agricultural crop development.
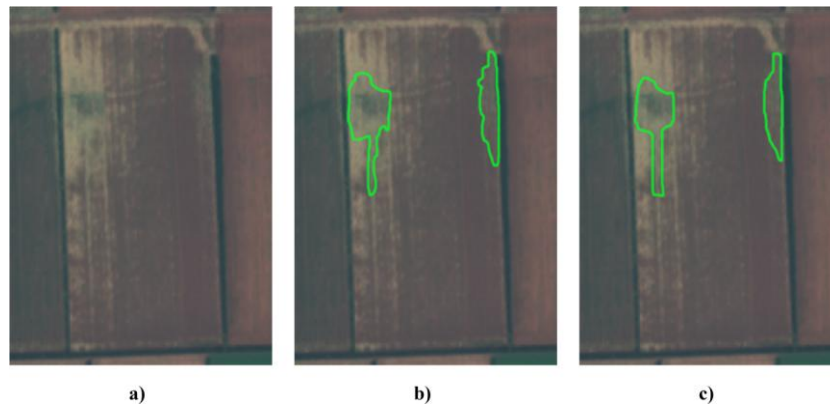
Fig. 9. Experimental image for the field preparation stage: a) source image (Source: Sentinel-2 [11]), b) manual analysis results (Source: compiled by the authors), c) analysis results using the algorithm presented in the paper (Source: compiled by the authors)
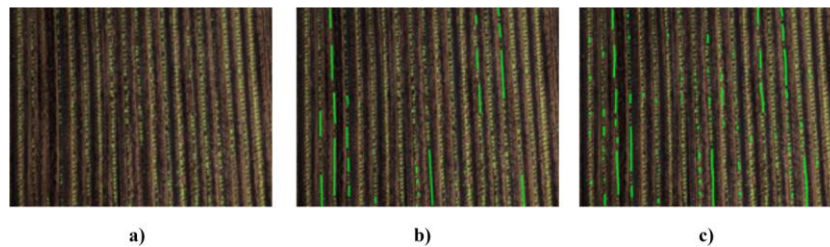

Fig. 10. Experimental image for the stage of emergence and development of sprouts (UAV): a) source image (Source: Sentinel-2 [11]), b) manual analysis results (Source: compiled by the authors), c) analysis results using the algorithm presented in the paper (Source: compiled by the authors)
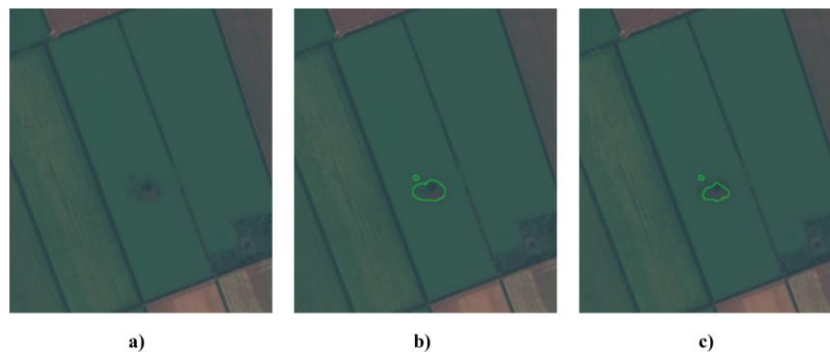

Fig. 11. Experimental image for the heading stage: a) source image (Source: Sentinel-2 [11]), b) manual analysis results (Source: compiled by the authors), c) analysis results using the algorithm presented in the paper (Source: compiled by

IV. CONCLUSIONS

Based on the described algorithms of field inhomogeneity detection, an image processing software module for precision farming is implemented within the Smart Farming system. It allows users to calculate indices of biomass development and detect inhomogeneities of various types (sowing defects, oppressed plants, etc.). Algorithms presented in the paper are new, as they take into account development stages of agricultural crops tend field zoning. They show high efficiency in solving problems of precision farming in comparison with existing methods.

Further research will focus on development of algorithms for determining the causes of detected inhomogeneities for a more detailed analysis and clarification of their causes. It should ultimately provide significant reduction in the time interval from problem detection to its successful resolution, which is the critical factor for precision farming.

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