Satellite monitoring and visualization of vegetation indices for assessing crop productivity

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Abstract. The article discusses approaches to the use of remote sensing and satellite monitoring tools for assessing the productivity of agricultural crops based on the recognition of high-resolution aerial photographs, followed by numerical calculation of vegetation indices and visualization in cross-platform geoinformation systems.

1. Introduction
With the development of remote sensing and satellite monitoring technologies, as well as the increasing availability of satellite images around the world, precision (coordinate) farming systems are beginning to be introduced into agriculture. The key task of precision farming in the production of agricultural crops is to maximize the yield, financial benefits and minimize capital investment, environmental impact. The scientific concept of precision agriculture is based on the idea of the existence of inhomogeneities within a single field. An inhomogeneous field contains damaged areas – areas that, for one reason or another, may yield a lower yield. The definition of such heterogeneous areas allows you to reduce the required area of tillage, optimize the consumption of fertilizers used and generally reduce the average cost of the field, while increasing the yield.

When identifying the state of vegetation, vegetation indices are usually used, which are linear or fractional-linear combinations of two spectral channels: 0.6 -0.7 microns (red range of the spectrum) and 0.8-0.9 microns (near IR range of the spectrum). The most resistant to various factors: the type of shooting equipment, the height of the Sun and the scanning angle of the satellite, the density of the atmosphere, etc. is the normalized vegetation index NDVI, which is the difference between the values of the near-IR and red channels divided by the sum of these values.

An example of visualization of the resulting index is shown in Figure 1.
Despite the above advantages of using this technology, at the moment the percentage of farms using elements of precision farming in Russia is still low: no more than 20-25% of the total number. This may be due to the high cost of introducing new technologies: the cost of weather stations and sensors installed on agricultural equipment can reach up to several million rubles. There is also another urgent problem in the field of monitoring the state of vegetation – the problem of atmospheric pollution. Vegetation indices, including NDVI, are calculated from images obtained using optical equipment that cannot penetrate through the dense atmospheric layer. Therefore, it is impossible to build yield maps in cloudy weather, as well as in the dark, which can significantly delay updating data on the state of crops. Currently existing products that provide remote sensing capabilities of the earth, at the moment can not offer an unambiguous solution to this problem. However, in recent years, the number of studies has increased, considering the use and processing of satellite images with radar equipment as a proposed solution.

This work is aimed at studying the existing methods of using radar data to solve the problem of updating vegetation maps in cloudy weather. The paper considers the development of a geoinformation system for monitoring the state of vegetation that is independent of weather conditions.

2. Materials and methods

Monitoring and assessment of the state of vegetation is carried out using various vegetation indices, which are calculated from images obtained using optical equipment. However, in modern research [1-3], more and more attention is paid to radar data of remote sensing of the earth in order to use them for the needs of agriculture. An example of a radar image is shown in Figure 1. The most effective application of radar data at the current moment is the mapping of the dielectric characteristics of the reflecting surface (humidity, freezing/thawing, salinity, clay and iron oxides content in soils. Slightly less significant results were obtained by researchers who studied the use of remote sensing radar data for identifying crops, assessing the structure of vegetation cover, monitoring vegetation growth, and predicting yield [3]. This is due to the emergence of specific difficulties in processing radar images. These images are complicated by speckle noise, since coherent electromagnetic waves of reflected intrinsic radiation are recorded.

The classical methods of processing radar images are:
1. Speckle filtering of images.
2. Correction of the relief.
3. Modeling of a multispectral image using various polarization filters.
4. Refinement of orbits using these correction files.
Figure 2. An example of a radar image of an agricultural plot

The NDVI indicator of crops can be estimated at different scales: from the survey of a small plot of crops using portable devices to the assessment of vegetation at the regional level using remote sensing. The NDVI indicators of agricultural crops are determined from high-resolution satellite images using Spot-5 satellites (spatial resolution of the red and near-infrared channels of 10 m), Spot-6 (resolution of 6 m) and Eros B (resolution of the panchromatic channel of 0.7 m).

Figure 3. Visualization of the results of recognition of field crops and plant objects based on a high-resolution satellite image and the value of the NDVI index

To verify the NDVI index indicators obtained using these images, the results of ground surveys using manual yield sensors are used. The initial preparation of satellite images includes atmospheric and spatial correction. To calibrate the images, information about the reflectivity and NDVI indicators of objects of various nature adjacent to the field is used: water (ponds), man-made (roofs of buildings
and asphalt surfaces) and plant (forest belts and sports lawns). An example of processing and visualization of satellite images in the QGIS program is shown in Figure 3.

To calculate the NDVI of different crops from satellite images in the QGIS program, several test lines are laid on each image along the field territory in different directions. For calibration, "NDVI constants" are used as reference (standard) NDVI, which have been repeatedly confirmed during several growing seasons by field ground studies. The strongest differences between the results of the ground and satellite NDVI scores (up to 0.3 units) on experimental fields are noted in the summer period. On winter wheat crops in variants without fertilizing: the NDVI indicator in the end-flowering phase is 0.39-0.48, and according to satellite data - 0.65-0.70. This significant discrepancy is due to the insufficient resolution of satellite images (6 and 10 m / pixel) when evaluating experimental plots with a width of 3 m. When assessing the NDVI of production crops, such small-contour heterogeneity does not have a significant impact, therefore, the resolution of satellite imagery is sufficient.

Figure 4. Dynamics of the state of plants according to the vegetation index

The results of the NDVI assessment of field crops from satellite images may differ significantly from the data of ground surveys. When comparing the NDVI indicators obtained by remote and ground surveys for three years of observations, it was found that for cereals, the greatest discrepancies between the results of ground and remote assessment were noted in the initial phases of development (20-35%), and the smallest – at the time of reaching the peak of NDVI in the earing phase (2-11%). In particular, for potatoes, the NDVI indicators obtained from satellite images were significantly lower compared to the results of ground-based studies using active sensors.

3. Conclusion

After studying the approaches to the use of remote sensing and satellite monitoring tools for assessing the productivity of agricultural crops, it can be concluded that radar data can be used on a par with optical data for such tasks as determining soil moisture, identifying agricultural crops. However, it is necessary to continue working in this area to improve methods for obtaining alternative vegetation indices for monitoring the state of vegetation. It is necessary to conduct a number of experiments with the processing of radar data and to derive indicators correlating with NDVI to assess the state of vegetation cover. It was decided to develop a geoinformation system for remote monitoring of the state of vegetation for applying the results of experiments and comparing the derived indicators with NDVI. The availability of promptly received reliable information about the state of crops (or farmland) will help to make timely decisions on optimizing the timing of harvesting, the necessary fertilizing of plants and other current activities.

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