

Algorithm of allocation of agricultural land occupied by winter crops

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Abstract. In Russia, many lands legally classified as agricultural land are abandoned. We propose an algorithm for the allocation of agricultural land with winter crops based on the dynamics of normalized relative vegetation index (NDVI) which were verified on the example of the Rostov region, a major producer of agricultural products in Russia. Cereals in Rostov region cover about 70% of the sown areas, most of them are winter wheat. A series of MODIS satellite data for the period March-August 2020 were used for calculations. Crop yields were taken from the Database of Rostov Region Municipalities. NDVI index for the territory of the Rostov region had lowest average value in March, maximum in May with a decrease by August. Pixels with high difference in NDVI values from March to August 2020, were considered agricultural fields. Pixels with NDVI index in range 0.2 - 0.5 in March and April were identified as winter cereal crops. A statistically significant linear relationship with a correlation coefficient of 0.57 between winter wheat yield values according to national statistical data for districts of Rostov region for 2020 and average NDVI values for districts for selected fields occupied by winter wheat in this period was obtained.

1 Introduction

Remote sensing methods are widely used in Russia for applied soil science tasks to control the condition of agricultural lands. Categorization of such lands by the set of grown crops is mainly done by using time series of vegetation indices extracted from satellite data. This method is also relevant for fallow lands detection. Despite the availability of a number of tools for their mapping [1,2,3] so far none of them has been absolutely effective. Analysis of time series data on the reflectance of arable land becomes especially relevant, since in certain phases of plant vegetation the spectral response of fallow lands can be the same as on other lands [4].

Spectral vegetation indices are a key element for analysing vegetation in multispectral space images and reflectance of agricultural fields. The indices can be derived from various satellite images such as MODIS and Landsat. Vegetation indices from MODIS multispectral space imagery, acquired at intervals of every 16 days and with spatial resolutions ranging from 250 to 1000 m, provide consistent temporal comparisons of vegetation greenness, the aggregate property of leaf area, chlorophyll, and phytocenosis structure. The most important and most common index is the normalized relative vegetation index (NDVI). The index varies depending on plant canopy density and plant chlorophyll saturation from 0.18 to 1.0. Index values exceeding the threshold value of 0.33 indicate healthy crops and active

vegetation. Exceeding the threshold value of 0.66 indicates a high closed vegetation cover and the phase of intensive plant growth.

There is an established practice of field categorization based on remote sensing data. Having information on crops in a small number of areas, they approximate the NDVI time series of the remaining fields using space images [5]. Other methods for field identification are also used [6,4,7,8]. However, there are problems related to the quality of the input data. In the study by Rulev et al. [9] on forest cover estimation using the NDVI index, it was found that when using the vegetation index, it is necessary to take into account a number of factors such as the quality of the original image, the scale of the survey, which can lead to errors. The purity of training samples, on the basis of which further classification takes place, has been the subject of research by a number of scientists previously [5]. Despite the above, the application of NDVI allows not only to monitor the dynamics of vegetation growth and degradation, but also to estimate crop yields. There are known works confirming the relationship between crop yield and vegetation NDVI indicator [10,11,12]

The mask of field boundaries, on the basis of which all further calculations are made, should also be close to the real situation. It is noteworthy that land categorization works have a regional scale. For such studies, maps obtained from local authorities are usually used. If the researcher aims to update this information, he/she verifies the data based on the results of fieldwork, which even in

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a small coverage area requires time and material costs [13]. Such costs are especially high for such areas as Rostov Oblast, where arable land occupies more than half of the total area of the region.

Russia, as a partner country of the UN FAO, has committed to compiling a national map of soil carbon sequestration potential, which is part of the global GSOCseq project. It is aimed at practical large-scale implementation of sustainable soil management [14]. The federal scale of the Russian segment of this map precludes the possibility of field verification when compiling the mask of agricultural field boundaries. It became necessary to develop an algorithm for the allocation of agricultural land according to the duration of crop vegetation (spring, winter or no cultivated plants).

Unfortunately, the data on areas of sown crops for Rostov region have a large variation from year to year and have a large element of local subjectivity. Therefore, it was decided to verify the algorithms at the level of individual districts of the region using data on winter grain yields, based on the assumption that if the prediction of yield without knowing the share of fields sown with a crop was accurate, then the predicted share of fields under winter crops was also accurate.

The purpose of this work is to identify agricultural lands in Rostov region occupied by winter cereals on the basis of MODIS satellite data series for the period March-August 2020 and compare NDVI index values for the month of June with grain yields according to official Russian statistic data (Rosstat) data for the regions of Rostov region.

2 Material and method

The considerable extent of the Rostov region from north to south (470 km) and its location in the middle temperate zone of the Northern Hemisphere creates the specificity of natural landscapes, climate, vegetation, and soil composition. The climate of the territory is temperate continental. The continentality of the climate increases eastward in the region. The average temperature in January is $-6\text{ }^{\circ}\text{C}$, in July $+23\text{ }^{\circ}\text{C}$; the amount of precipitation is 390-480 mm per year. Aridity is one of the zonal seasonal features of the Rostov region territory. Another zonal climatic feature is the predominant western winds.

Steppe landscapes are the main in Rostov region, forests occupy only a small part of land resources, most of the territory is cultivated. Fertile chernozems occupy 64.2% of the total land structure. Favourable agro-climatic conditions predetermined the specialization of the region in agricultural production.

According to the administrative structure, the Rostov region is divided into 43 municipal districts, which, based on the physiographic situation, agro-climatic environment, nature and methods of agriculture of the region, can be divided into six main natural-agricultural zones.

Table 1 shows a comparison of climatic conditions of natural and agricultural zones [15]. According to the sum of t above 10°C , all zones are in favourable conditions in

terms of wheat cultivation, which requires at least 1700°C . The frost-free period is more than 5 months, which further determined our choice of the number of months to delineate field boundaries. In all zones evapotranspiration is about twice as much as precipitation, so the main limiting factor in agricultural production is water. The most unfavourable in this respect is the Eastern zone.

Prevailing types and subtypes of soils by natural and agricultural zones are presented in Table 1. Zones differ in the content of humus in the upper humus-accumulative horizon and its thickness.

Thus, the lowest availability of agro-climatic resources is in the Eastern zone. The best natural-climatic conditions are specific to the Azov and Southern zones.

Agricultural land productivity was assessed using satellite data of Rostov region. MODIS MOD13A2 version 6 (September 2013), which provides two vegetation index values on a pixel-by-pixel basis with a spatial resolution of 250 m 1 km, was used in this work.

This work used a spatial resolution of 1 km and a normalized relative vegetation index (NDVI) that is calculated from data from the National Oceanic and Atmospheric Administration Advanced Very High Resolution Radiometer (NOAA-AVHRR). The algorithm for this product selects the best available pixel value from all the pixel values obtained over a 16-day period. The criteria used are: low cloud cover, small viewing angle, and maximum NDVI / EVI value.

Google Earth Engine (GEE) platform was used for image acquisition and processing. It was used to retrieve average NDVI images from March to August for 2020.

NDVI index for each month of the growing season 2020 from March to August as per pixel average of two satellite images of region available for each month

The main algorithm for agricultural field extraction was implemented in QGIS software (Quantum GIS Desktop with GRASS version 3.8). The map was produced with geographic coordinate system WGS 84, projection code - EPSG: 4326. In this initial projection it is impossible to calculate the area of the fields, so the tasks also included the generation of a random sampling points.

The resource Rostovstat (All-Russian Agricultural Census, 2018), the statistical agency for the All-Russian Agricultural Census, was used to obtain data on crop yields for 2020.

Statistical hypotheses were tested with a significance level of 0.05. Statistical analysis was performed with R Project for Statistical Computing [16].

Table 1. Comparison of natural and agricultural zones climatic parameters.

Zone name	Sum of temperatures higher 10°C	Sum of precipitation per year, mm	Evaporation, mm	Period with positive temperatures, d	Net radiation, MJ m ⁻² y ⁻¹	Dominant soil type (WRB 2006)	Topsoil depth, cm	Topsoil humus content, %
North-West	3200	438	820	160-175	2682	Haplic Chernozems	55-70	3,2-3,8
North-East	3187	394	790	165-180	2679	Haplic Chernozems,	40-50	3,0-3,3
Central	3300	413	710	160-180	2654	Haplic Kastanozem,	40-55	3,7-4,0
The Azov	3252	475	840	160-175	2693	Voronich Chernozems	75-100	3,9-4,7
Southern	3304	480	900	165-180	2685	Voronich Chernozems	75-140	3,7-4,2
Eastern	3300	390	976	175-185	2807	Endosalic Kastanozems	35-60	1.5-3.5

3 Results and discussion

In the first step, for the period from March to August 2020, the minimum and maximum NDVI was found for each pixel. For this purpose, raster files were loaded in R software environment and from 6 rasters for each pixel the difference between the maximum and minimum value for this period was found.

Then a threshold value of the difference between the maximum and minimum NDVI values was determined by brute force, at which the majority of pixels with values above the threshold value would be inside the boundaries of the vector mask of agricultural fields taken from the Russian Federal Service for State Registration, Cadastre and Cartography (Fig .1).

Based on the weather conditions at the beginning of 2020, March and April have approximately the same positive temperature. Therefore, the beginning of the growing season can be considered as March.

Based on Fig. 2, March and April practically do not differ in NDVI values, biomass increases maximally until May (highest NDVI values), vegetative productivity declines in June: growth of cereal crops ends as they reach the first stage of maturity

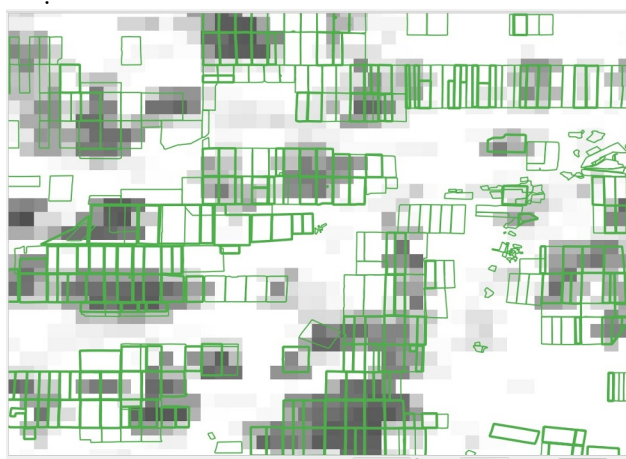


Fig. 1. Matching field mask and threshold value 0.31 for min and max NDVI difference layer.

Further, in July and August NDVI index values were significantly lower than in the previous months, as agricultural crops reached full maturity and harvesting took place. This is especially evident in the Eastern Natural-Agricultural Zone, arid in climate and consisting of saline chestnut and light chestnut soils, where grassy steppe vegetation appears to have dried up.

Thus, monthly NDVI images for the growing season of 2020 reflect the overall productivity of agricultural land in Rostov Oblast, and thus the fertility of arable land.

The second step of the algorithm proposed in this paper involved the selection of those agricultural lands where grain crops (winter wheat) turned out to be in March and April. The boundary for NDVI was set from 0.2 to 0.5, because if NDVI index is too large at the beginning of the growing season, it means abnormal values. In this way, the sites where winter cereals were grown were obtained.

In the third step of the algorithm, the NDVI values were averaged in the R software environment for each municipal district, and the median, lower and upper quantiles, and maximum were calculated.

The last step of the algorithm was to find relationships between vegetation index values and yield. The maximum correlation was found to be with the mean NDVI value. The corresponding graph is shown in Fig. 3. A statistically significant linear relation was detected in spite of dropping out 2 points.

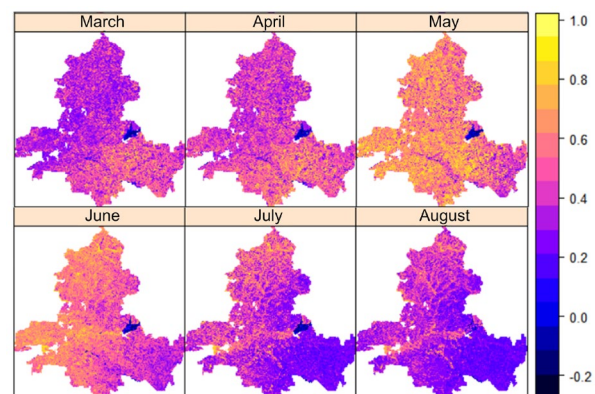


Fig. 2. NDVI index for the growing season 2020 (monthly).

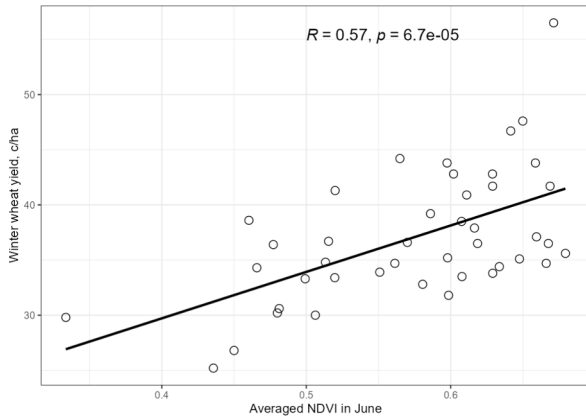


Fig. 3. Relation of averaged winter wheat yield to NDVI index for June 2020.

The correlation coefficient was $R=0.569$. The regression equation can be described in the form:

$$y = 42.086x + 12.88 \quad (1)$$

where y is the winter wheat yield in $c\ ha^{-1}$ and x is the averaged NDVI index values in June.

Thus, based on a series of MODIS satellite data for the period March-August 2020, the agricultural lands occupied by winter cereals were identified, for which a regression relationship was obtained between grain yields according to Rosstat data for the regions of Rostov region and the average values of NDVI index for the month of June ($R=0.57$).

4 Conclusion

The popularity of remote sensing techniques for monitoring the current state of agricultural land and forecasting its productivity is easy to explain. Satellite data are accessible, easy to understand and relatively simple to use. Their use does not require extensive field surveys, which significantly reduces user costs.

Vegetation productivity can explain the spatial distribution and change in vegetation cover, so turning to vegetation indices seems to be the most reasonable way to assess this key characteristic of ecosystem condition. The results of this work confirmed the existence of a relationship between NDVI index and winter wheat yield in Rostov region. The author's algorithm for identifying lands occupied by winter crops based on this index was proposed, which is very valuable both for the purposes of agricultural land control and objective identification of fallow areas.

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References

1. E.A. Terekhin. *Computer Optics*, **5** (2017) (in Russian)
2. A.V. Prishchepov, V.C. Radeloff, M. Dubinin, C. Alcantara. *Remote Sensing of Environment*, **126**, (2012)
3. E.A. Baldina. *Geomatics*, **4** (in Russian) (2012)
4. E.A. Terekhin. Current problems in remote sensing of the Earth from space, **9**, 4 (in Russian) (2012)
5. N.S. Vorobyova, A.V. Chernov, *Approximation of NDVI time series in the problem of early recognition of crop species from satellite images* In: Proceedings of the III International Conference and Youth School "Information Technologies and Nanotechnology" (ITNT-2017) - Samara: New Technology, (2017)
6. I.N. Chursin, D.V. Philippov, I. Gorokhova. *Herald of computer and information technologies*, **11** (in Russian) (2018)
7. I.Y. Savin, E.R. Tanov, S. Kharzinov. *Bulletin of the Soil Science Institute*, **77** (in Russian) (2015)
8. T.A. Adamovich, G.Ya. Kantor., T.Ya. Ashikhmina., V.P. Savinykh. *Theoretical and Applied Ecology*, **1** (in Russian) (2018)
9. A.S. Rulev, O.Yu. Kosheleva, S.S. Shinkarenko. *Izvestiya Nizhnevolzhskogo agrouniversitetskogo kompleksa: nauka i vy'sshee professional'noe obrazovanie*, **4** (in Russian) (2016)
10. I.G. Storchak, F.V. Eroshenko. *Zemledelie*, **7**, (in Russian) (2014)
11. L.V. Berezin, M.R. Shayakhmetov, A.M. Gindemit, A.Y. Bulletin of the Omsk State Agrarian University, **2**, 18 (in Russian) (2015)
12. I.G. Storchak, E.O. Shestakova, F.V. Eroshenko. *Agrarian Bulletin of the Urals*, **6**, 173 (in Russian) (2018)
13. I. N. Gorokhova, E. I. Pankova, E. A. Shishkonakova. *Bulletin of the Soil Institute*, **89** (in Russian) (2017)
14. V.I. Belyaev, A.V. Varlagin, V.K. Dridiger, I.N. Kurganova, L.V. Orlova, S.V. Orlov, A.I. Popov, A.A. Romanovskaya, A.L. Toigildin, N.M. Trots, A.A. Fomin, D.M. Khomyakov. *IACJ*, **1** (in Russian) (2022)
15. O. S. Bezuglova, M. M. Khyrkyrova, *Soils of the Rostov region: a textbook (Rostov-on-Don Publishing House of the Southern Federal University)* (2008)
16. R Core Team. *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. <https://www.R-project.org/> (2023)