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SIMULATION OF VEGETATION CONDITIONS USING DIFFERENCES OF CURRENT NDVI VALUES FROM AVERAGE LONG-TERM INDICATORS

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Abstract

Currently, one of the important tools for increasing crop production is the introduction of precision farming systems. As an obligatory element of such systems, production process control has been successfully used in recent years. Such control is implemented by modeling the responsiveness of the vegetative mass to changes in actual environmental conditions. In domestic and foreign literature, there are many examples of the development of mathematical models of plant growth and development that take into account external influences. It is shown that the predictive models allow us to respond in a timely manner to changing growing conditions. In turn, this helps to quickly make optimal agronomic decisions. In this work, for the first time, the relationship between the difference (anomaly) of the average annual and current seasonal indicators of NDVI (normalized difference vegetation index) and the process of plant growth and development, taking into account the influence of existing conditions, was established for the first time. It is shown that the conditions for the adequacy of approximation, when leveling noisy time series, are completely satisfied by the Gauss-Laplace function. As a mathematical expectation, the average values of the highest NDVI values of the vegetative period of the crop should be used. Mathematical models of the influence of photosynthetic, meteorological, and soil-climatic factors on NDVI anomalies in a particular phase of plant development have been obtained. Our goal was to develop predictive models of the vegetation process of grain crops, based on a comparison of the average long-term indicators of NDVI with its current seasonal values. The influence of actual conditions was taken into account. The research was carried out on the fields of the «Integration» center of the Oryol State Agrarian University (Oryol Procince). In 2021, winter wheat (*Triticum aestivum* L.) cultivar Moskovskaya 39 occupied an area of 48.1 ha, spring barley (*Hordeum vulgare* L. sensu lato) cultivar Raushan — 17.4 ha. Data for calculation of NDVI values were obtained from the CosmosAgro geoportal, as well as using an Agrofly Quadro 4/17 unmanned aerial vehicle (Agrofly International, Russia). Data noise compensation was performed by approximating time series with the Gauss-Laplace function. The adequacy of the regression models for the approximation of NDVI time series was assessed using the Fisher *F*-test and the average error of the approximation coefficient; the accuracy of the predictive models was confirmed by the Mean Absolute Percentage Error (MAPE) indicator. As a result, time series of the average NDVI value for the studied crops were obtained based on long-term observations, and the current NDVI values in the growing season 2021 were calculated. The distribution of time series of the vegetation index has been established. It was close to normal. The maximum (peak) values of NDVI are determined. They amounted to 0.71 for winter wheat and 0.54 for spring barley and fell in June, regardless of the crop. The purpose of leveling the noisy NDVI time series of crops during the growing season is most fully satisfied by the asymmetric Gauss-Laplace function. As a mathematical expectation, the average value of the highest NDVIs for the crop vegetation period was used. Mathematical models were obtained based on the NDVI anomaly index. These models describe the influence of photosynthetic, meteorological, soil, and climatic factors on the crop state during a particular phenophase. The mean absolute error of the proposed models was 9.23 for spring barley and 5.68 for winter wheat. Thus, the proposed characteristic ΔNDVI can be used as an independent variable (optimization criterion) in factorial models for predicting the dynamics of the vegetation process.

Keywords: yield forecast, vegetation index, NDVI, Gaussian function, factor analysis, time series approximation

Agriculture is on the verge of a digital revolution, which becomes the basis for precision farming and contributes to the implementation of the innovative development strategy of the Russian Federation. Site-specific crop management (SSCM) is an important element of precision farming, which is actively implemented to increase crop yields [1-4]. Regulation of the bioproduction process is possible due to timely and prompt response to deviations caused by external influences [5-8]. The latter include the soil-climatic factor, various plant diseases, pests, and weeds.

As tools for assessing the impact of environmental conditions on agricultural crops, the analysis of meteorological data and the values of the vegetation index is successfully used. Taking into account external influences allows not only to quickly respond to emerging deviations [9, 11], but also to increase the efficiency of monitoring the phytosanitary condition of crops [12], create new software products for analyzing incoming information [13, 14], develop and implement automated systems decision-making on plant protection [15], contributing to an increase in the productivity of agrocenoses. The methods of mathematical statistics [16], in particular, multivariate analysis [17) make it possible to carry out forecasting for the management of the vegetation process.

Previously, it was shown [18] that taking into account the influence of air temperature, soil moisture, and ultraviolet radiation power on the timing of plant development makes it possible to predict the vegetation process and develop recommendations for agronomic measures. It should be noted that the performance of the proposed method of factor analysis is determined by the choice of a characteristic indicator of the solution of the problem, by the value of which the optimality of the found algorithm is estimated. The implementation of the factor complex, in which the optimization criterion was the period of lagging/advancing the development of plants from the average values calculated from long-term data, made it possible to characterize the course of the process under study, which fully satisfies the task of obtaining an adequate mathematical model, while the predicted harvesting period harvest allowed to reduce the seasonal load of combines. However, this does not allow the assessment to be carried out remotely, which could be used when managing a household based on digital platform solutions.

Thanks to the methods of remote sensing of the Earth (ERS), the amount of information received and the possibilities of its processing are expanding [19-21]. One of the indicators reflecting the assessment of the state and dynamics of plant development is the normalized difference vegetation index (NDVI). To predict the influence of existing conditions on the state of plants, it is advisable to use the method of comparing current values with long-term averages. At the same time, in order to exclude the features of a particular growing season (advance or lag in development), the averaged NDVI time series should be leveled [22-25]. This will make it possible to analyze information on deviations of current values from long-term averages at comparable stages of plant development with a smaller error [26].

In this work, for the first time, the relationship between the difference (anomaly) of the average annual and current seasonal indicators of the normalized vegetative index NDVI and the process of plant growth and development under the influence of existing conditions has been established. It is shown that the use of the average value of the highest NDVI indicators of the growing season of a crop as the mathematical expectation of the Gauss-Laplace function for leveling noisy time series fully satisfies the conditions for the adequacy of their approximation. Mathematical models of the influence of photosynthetic, meteorological and soil-climatic factors on NDVI anomalies during a particular phase of plant development were obtained.

Our goal was to create predictive models of the state of the vegetation process of grain crops under the influence of existing conditions based on a comparison of the average long-term indicators of the NDVI vegetation index with its current seasonal values.

Materials and methods. The research was carried out on the fields of the Scientific and Educational Production Center "Integration" of the Orlov State Agrarian University (Orel Province). In 2016-2020, the average long-term values of the NDVI index were calculated for winter wheat in plots No. 28 (2016), Nos. 23, 26, 31 (2017), No. 36 (2018), Nos. 22, 33 (2019 year), Nos. 23, 24, 26 (2020), for spring barley - in plots Nos. 27, 30 (2016), No. 54 (2017), Nos. 37-39 (2018), No. 27, 34 (2019), No. 13 (2020). In the growing season of 2021, experimental crops of winter wheat (*Triticum aestivum* L.) variety Moskovskaya 39 occupied an area of 48.1 hectares, spring barley (*Hordeum vulgare* L. sensu lato) variety Raushan 17.4 hectares.

Normalized difference vegetation index (NDVI) was calculated by the formula [27]:

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

where *NIR* is the vegetation cover reflection in the near infrared region (0.85-0.88 μm) of the electromagnetic spectrum and *red* in the red region (0.64-0.67 μm).

Satellite data for 2016-2020 were obtained on the CosmosAgro geoportal developed by the ScanEx Engineering and Technology Center (Russia) [28]. We used multi-temporal archival remote sensing data from the Sentinel-2 imaging system (MSI scanner, multichannel), free from clouds (no more than 10%), haze and other adverse factors, with a spatial resolution of 10.2 m/pixel and the frequency of obtaining information once at 5 days For analytical processing, the ScanEx GeoMixer utility [29] was used.

To obtain data on NDVI during the growing season of 2021, an unmanned aerial vehicle Agrofly Quadro 4/17 (Agrofly International, Russia) was used. Compensation for data noise caused by cloudiness, haze, evapotranspiration, precipitation, and other natural-climatic and temperature influences was performed by the approximation method. We used the asymmetric Gauss-Laplace function, which most fully meets the tasks of aligning the NDVI time series during the growing season [30-32]:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2},$$

where σ^2 is distribution variance; μ is mathematical expectation (average value).

Long-term statistical data on the dynamics of changes in the vegetation index NDVI were obtained from archival materials on crops with similar crops located near the plots of the field experiment.

The fairness of using average NDVI values for individual fields to describe the average annual crop indicator was confirmed by the comparison criterion. At the same time, due to the impracticability of the classical conditions for applying the Student's *t*-test in most statistical problems, the assessment of the homogeneity of time series according to the NDVI index was performed using the Cramer-Welch test T for the equality of mathematical expectations based on statistics [33]:

$$T = \frac{\sqrt{mn}(\bar{x}-\bar{y})}{\sqrt{n\sigma_x^2+m\sigma_y^2}},$$

where m, n are sample sizes; $\bar{x}$, $\bar{y}$ are the mean sample values; σ_x^2, σ_y^2 are the variances of sample distributions.

By comparing the T-test with the boundary value $\Phi\left(1-\frac{\alpha}{2}\right)$ where α is a significance level equal to 0.05, a decision was made to accept the hypothesis of homogeneity of the compared samples at the significance level α in accordance with the equality:

$$T \leq \Phi\left(1-\frac{\alpha}{2}\right).$$

The results of biometric calculations were processed in the Microsoft Excel software environment. The arithmetic mean values ($\bar{X}$), standard deviations (σ), coefficients of variation (k_V) and dispersion (σ^2) for the samples were calculated, artifacts were searched for and excluded, and the distribution parameters of the variation series were studied. The error in the calculated values did not exceed 5%.

The adequacy of the regression models for the approximation of the NDVI time series was assessed using the Fisher's F-test and the average error of the approximation coefficient ($\bar{A}$) according to the following formulas.

$$F = \frac{\sigma_x^2}{\sigma_y^2},$$

where σ_x^2, σ_y^2 are variances of compared regression series;

$$\bar{A} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right| \times 100\ \%,$$

where y_i, $\hat{y}_i$ are the actual and theoretical (calculated by the regression equation) values, respectively, of the effective trait.

The accuracy of the predictive models was evaluated using the Mean Absolute Percentage Error (MAPE) model [6] based on the data for each phase of plant development in the growing season of 2021. At the same time, the prediction error was determined by comparing the actual NDVI anomaly index (ΔNDVI) with its theoretical values found for each characteristic segment of the growing season [34]:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_{itheor}-y_{iactual}|}{y_{iфакт}} \times 100,$$

where n is the number of compared pairs of values; $y_{i\text{theor}}$, $y_{i\text{actual}}$ are the values of the indicators of the mathematical model optimization criterion and the actual indicators of the feature obtained during the experiment

Results. Despite some deviations at the end of the growing season, obviously caused by different harvesting times, the calculation of the Cramer-Welch criterion did not reveal significant differences in the compared variation series of the NDVI index for individual plots located near fields with experimental crops in 2021: the calculated values of T did not exceed boundary value $\Phi\left(1-\frac{\alpha}{2}\right)$ at a significance level $\alpha = 0.05$ (Table 1). This confirms the validity of using the values of the vegetation index of the selected plots to calculate the average annual NDVI values.

The seasonal dynamics of the NDVI index change according to long-term data is presented in Table 2. As can be seen, the nature of the change in the values of the time series was similar for the studied crops and, more than other distribution functions, corresponded to the normal law. Regardless of the crop, the lowest values of the vegetation index corresponded to the winter months. The highest

NDVI values were observed between May and June. The maximum average long-term values of the vegetation index were in June and amounted to 0.71 for winter wheat and 0.54 for spring barley.

1. Evaluation of the homogeneity of time series according to the normalized difference vegetation index (NDVI) **during investigation** (Orel Province)

Test sites	NDVI statistical parameters			
	arithmetic mean, $\overline{X}$	dispersion, σ^2	Cramer-Welch test, T	boundary T-value, $\Phi\left(1-\frac{\alpha}{2}\right)$, $\alpha = 0.05$
	2016			
	Spring barley (*Hordeum vulgare* L. sensu lato)			
No 27	0.47	0.220	$0.45_{27,\ 30}$	1.96
No 30	0.45	0.210		
	2017			
	Winter wheat (*Triticum aestivum* L.)			
No 23	0.48	0.085	$0.23_{31,\ 26}$	1.96
No 26	0.39	0.082	$1.22_{26,\ 23}$	
No 31	0.40	0.052	$1.68_{23,\ 31}$	
	2018			
	Spring barley (*Hordeum vulgare* L. sensu lato)			
No 37	0.34	0.012	$0.11_{37,\ 39}$	1.96
No 38	0.32	0.011	$1.67_{37,\ 38}$	
No 39	0.35	0.016	$1.64_{38,\ 39}$	
	2019			
	Winter wheat (*Triticum aestivum* L.)			
No 22	0.37	0.160	$0.10_{22,\ 33}$	1.96
No 33	0.37	0.220		
	Spring barley (*Hordeum vulgare* L. sensu lato)			
No 27	0.31	0.024	$1.09_{27,\ 34}$	1.96
No 34	0.29	0.026		
	2020			
	Winter wheat (*Triticum aestivum* L.)			
No 23	0.44	0.201	$0.19_{23,\ 24}$	1.96
No 24	0.46	0.223	$1.74_{24,\ 26}$	
No 26	0.42	0.231	$0.51_{23,\ 26}$	

2. Monthly values of the normalized difference vegetation index (NDVI) **across a 5-year study study** (Orel Province)

Year	Month											
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
	Winter wheat (*Triticum aestivum* L.) cv. Moskovskaya 39											
2016	нд	–0,02	0,30	0,26	0,55	0,71	0,44	0,39	0,36	0,28	0,26	nd
2017	–0.03	–0.03	0.19	0.32	0.43	0.74	0.73	0.54	0.55	0.46	0.48	0.20
2018	нд	–0.03	0.35	0.16	0.53	0.70	0.36	0.40	0.39	0.29	0.17	nd
2019	–0.04	нд	0.26	0.29	0.58	0.65	0.39	0.26	0.23	0.20	0.34	nd
2020	нд	нд	0.42	0.42	0.76	0.79	0.39	0.32	0.38	0.35	0.19	0.21
Average	–0.04	–0.03	0.33	0.27	0.54	0.71	0.46	0.38	0.38	0.27	0.28	0.21
	Spring barley (*Hordeum vulgare* L. sensu lato) cv. Raushan											
2016	–0.04	нд	0.18	0.19	0.36	0.55	0.53	0.42	0.32	0.22	0.2	nd
2017	–0.04	–0.03	0.30	0.33	0.50	0.56	0.80	0.54	0.49	0.48	0.23	0.03
2018	нд	–0.04	нд	0.20	0.27	0.48	0.47	0.39	0.33	0.26	0.19	nd
2019	–0.03	нд	0.14	0.14	0.37	0.56	0.52	0.32	0.19	0.19	0.30	nd
2020	–0.01	нд	0.17	0.19	0.27	0.54	0.41	0.37	0.33	0.21	0.13	0.13
Average	–0.04	–0.03	0.19	0.19	0.35	0.54	0.53	0.41	0.33	0.24	0.22	0.11

Note. nd — no data.

We carried out a comparative assessment of the average annual indicators of the vegetation index of the studied crops for 2016-2019; 2020 was not considered due to a clear deviation in NDVI values for compared crops due to lack of rainfall. This anomaly, especially in the spring and early summer periods, predetermined a sharp decrease in the vegetative mass of spring barley. The latter, as is known [35, 36], is more susceptible to lack of moisture compared to winter crops, which make better use of the spring reserves of moisture and nutrients.

A stable ratio of NDVI values for winter wheat to those for spring barley was found, which was 1.16 (16%) on average over the years for the specified period. At the same time, the correlation coefficient (r) between the compared time series turned out to be 0.96.

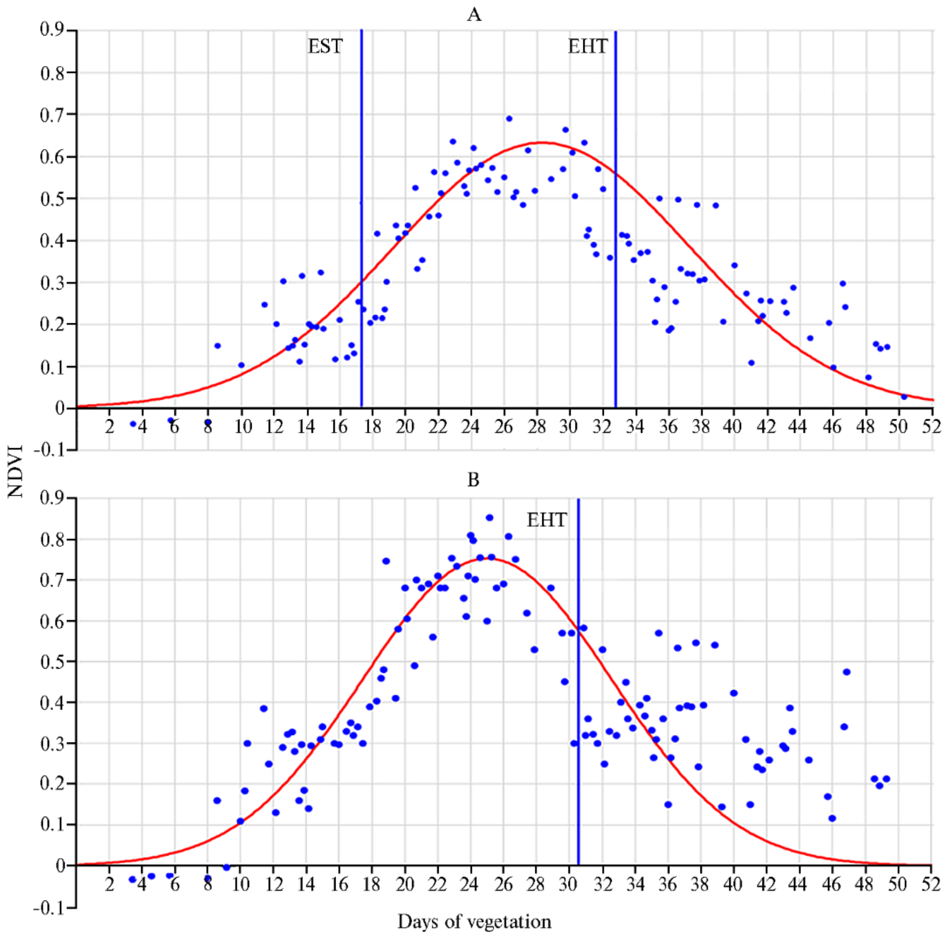

Fig. 1. The alignment of the average long-term time series of the normalized difference vegetation index (NDVI) **using the Gauss-Laplace function for spring barley (*Hordeum vulgare* L. sensu lato) cv. Raushan** (A) **and winter wheat (*Triticum aestivum* L.) cv. Moskovskaya 39** (B)**:** blue dots — actual values, graph — calculated values, EST — estimated sowing time, EHT — estimated harvest time (Orel Province).

Based on the use of the Gauss-Laplace function, an approximation of the actual NDVI time series was performed based on long-term average data and plots of regression models with a variable structure were plotted (Fig. 1). It is known [26] that one of the main conditions for the approximation of empirical series is the minimization of the sum of squared deviations of the theoretical points $\bar{y}_x{}'$ of the regression line from the points y_i of empirical (experimental) observations: $Q = \sum(y_i - \bar{y}_x{}')^2 \Rightarrow \min$. When using the Gauss-Laplace function, this requirement was provided by the values of the parameters σ and μ. Thus, the mathematical expectation μ was taken equal to the average value for the five highest NDVI indicators of the growing season for the crop. To equalize the time series of the vegetation index for winter wheat and spring barley, μ was 181 and 198, respectively. In both cases, the shift in the position of the mathematical expectation relative to the centers allows us to classify the obtained approximations as functions of an asymmetric left-hand distribution.

As can be seen, the description of the NDVI time series using the Gauss-

Laplace function made it possible to get rid of the noise caused by the difference in the conditions for obtaining the initial data.

Checking the adequacy of the accepted mathematical models using the Fisher's F-test and the average error of the approximation coefficient $\bar{A}$ in the areas characterizing the timing of the vegetation process of crops showed satisfactory convergence of the actual and theoretical series:

winter wheat — $F_{0.05}^{calc} = 1.20 < F_{0.05}^{test}(76) = 1.47$; $\bar{A} = 23.4\%$;

spring barley — $F_{0.05}^{calc} = 1.22 < F_{0.05}^{test}(50) = 1.6$; $\bar{A} = 19.9\%$.

A fairly high value of $\bar{A}$ was due to a large variation in the actual long-term average NDVI indicators (coefficients of variation $k_v = 0.50$ for winter wheat, $k_v = 0.51$ for spring barley). Nevertheless, based on the comparative assessment of the F-test, we believe that the result obtained gives the right to recommend these mathematical models for a comparative analysis of the deviations of the current values of the NDVI index of a crop from the long-term average data.

The average long-term values of the NDVI index for the studied crops differed somewhat from the dynamics in the growing season of 2021 (Fig. 2, A, B). In June 2021, NDVI values turned out to be higher; in July, they were lower than the average long-term observations. For both crops, the NDVI values were higher than the long-term average in the heading phase. Thus, with the maximum long-term average NDVI for winter wheat and spring barley of 0.75 and 0.63, respectively, the highest values of this indicator in 2021 for these crops were 0.80 and 0.74.

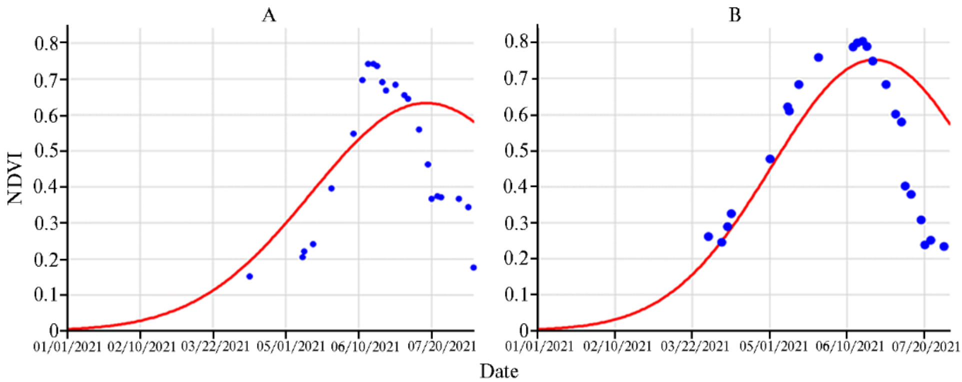

Fig. 2. Deviations of the normalized difference vegetation index (NDVI) **from the average long-term indicators in 2021 for spring barley (*Hordeum vulgare* L. sensu lato) cv. Raushan** (A) **and winter wheat (*Triticum aestivum* L.) cv. Moskovskaya 39** (B)**:** blue dots — actual values, graph — long-term averages (Orel Province).

The peak of the increase in NDVI in 2021 fell on June 15-20, which is 7-9 days earlier than the long-term average. Accordingly, an earlier decrease in the vegetation index associated with the completion of growth processes was observed compared to the average long-term norm. It was established that the optimal value of NDVI, equal to 0.30-0.35 and characterizing the readiness of the field for harvesting, was achieved for spring barley on August 11, for winter wheat on July 15. This is 2-2.5 weeks earlier than the average long-term deadlines for the end of the vegetation process. That is, for the growing season of 2021, we should state an advance relative to the long-term average normal values.

A diagram showing NDVI anomalies in 2021 (deviation of NDVI values from the average) (Fig. 3) can be used as a basis for assessing the influence of certain external factors on the change in the vegetation index. This will allow timely adjustment of agronomic measures, creating conditions favorable for the crop growth and developemt.

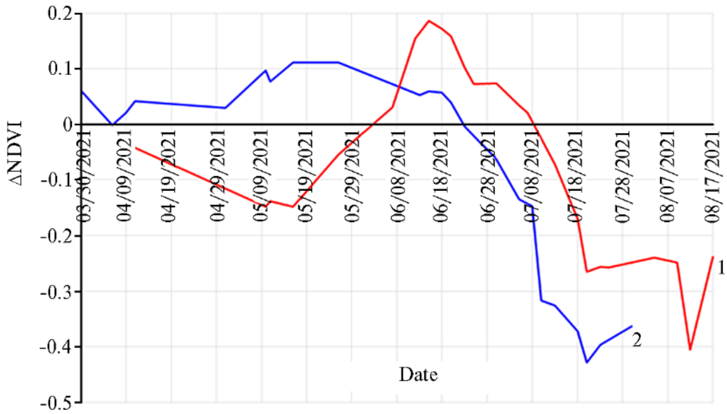

Fig. 3. Deviation of the the normalized difference vegetation index (ΔNDVI) **from the average long-term indicators during the growing season of 2021 for spring barley (*Hordeum vulgare* L. sensu lato) cv. Raushan** (1) **and winter wheat (*Triticum aestivum* L.) cv. Moskovskaya 39** (2) (Orel Province).

An assessment of the possibility of using deviations (anomalies) of the current values of the NDVI vegetation index from the long-term average made it possible to apply the previously obtained mathematical models that describe the influence of photosynthetic, meteorological, and soil-climatic factors on NDVI anomalies during a specific phase of plant development:

$$\Delta y_{\text{sp}} = -0.022 + 0.136x_2 - 0.184x_3 - 0.006x_5 - 0.002x_6 + 0.002x_8,$$

$$\Delta y_{\text{wn}} = -0.296 + 0.144x_1 + 0.004x_4 + 0,.021x_7 - 0.005x_8,$$

where x_1 is the content of chlorophyll a (mg · g^{-1}), x_2 is the content of chlorophylls a + b (mg · g^{-1}), x_3 is the content of carotenoids (mg · g^{-1}), x_4 is the soil temperature (T, °C), x_5 is the soil moisture (W, %), x_6 is the ambient air temperature (t, °C), x_7 is the accumulated amount of precipitation (ΣRN, mm), x_8 is the level of ultraviolet radiation (UV, W · m^{-2}).

Figure 4 shows the actual and modeled regression curves of the influence of acting factors on the NDVI anomalies of the 2021 growing season.

The assessment of accuracy by the MAPE indicator revealed a satisfactory average absolute error of the models: for spring barley 9.23, for winter wheat 5.68. Some decrease in the estimate of the accuracy of the predictive model for spring barley was probably due to the greater variability in seasonal NDVI values. So, if the variance of the vegetation index series for barley was 0.026, then for winter wheat it was 0.016. However, in general, the accuracy of the proposed models allows us to recommend them for practical use in production conditions. Regular assessment of current anomalies (for example, before the onset of the next crop phenophase and especially during the earing period) provides a real opportunity for operational management of the vegetation process to form maximum yields under specific conditions.

The results of numerous studies [37-39] demonstrate the practical applicability of the indicators of the normalized difference vegetation index for predicting the yield of cereals and other crops. At the same time, there is a higher correlation between the actual productivity of crops and the maximum (peak) NDVI values during the beginning of the heading phase [40, 41]. Some reports [42-44] discuss in detail the possibilities of using predictive models to assess the state of the vegetative mass, as a tool for managing the production process. Particular attention is paid to the processes of formation of yield, growth of the root system, changes in the composition of dry matter in plants, etc. This takes into account photosynthesis, respiration, transpiration and soil hydraulics, autotrophic processes and stomatal control. The results of studies are given for a number of crops - corn [41], cotton [43], soybeans [37], sugar beets and potatoes [38], forage grasses [40]. However, the characteristics of the relationship between the vegetation process and the dynamics of NDVI during individual phenophases are not studied, and attention is not focused on the influence of weather and climate impacts.

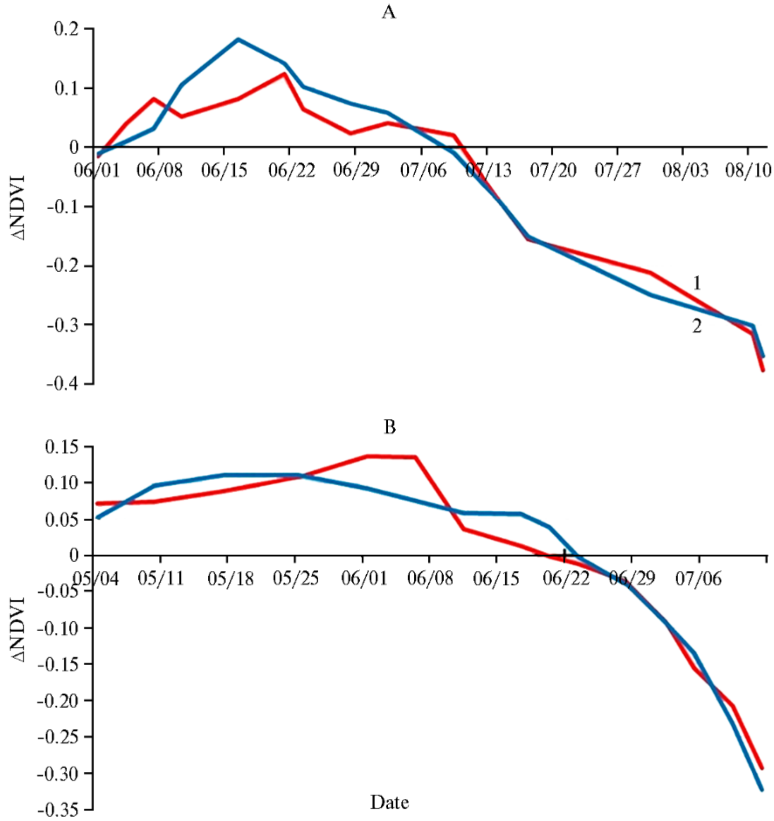

Fig. 4. Actual and simulated deviations of normalized difference vegetation index (ΔNDVI) **from the average long-term values during the growing season of 2021 for spring barley (*Hordeum vulgare* L. sensu lato) cv. Raushan** (A) **and winter wheat (*Triticum aestivum* L.) cv. Moskovskaya 39** (B): **1 — calculated anomaly 2 — actual anomaly** (Orel Province).

The approach proposed in this paper to the construction of a predictive model of the growing conditions of grain crops shares the goals formulated in the above works, but adds new aspects to them. A qualitative indicator of the process of growth and development of plants is a comparative assessment of the vegetation index, calculated from the results of the average annual and current seasonal values of NDVI. A short-term forecast of the state of plants is built on the basis of operational information about external influences. This approach is very important for a timely and reliable assessment of the current conditions and making an adequate decision on agrotechnical measures. In addition, unlike the known models with a daily step, the new model is based on the use of a complex indicator that takes into account the input parameters observed in real time. In addition to NDVI indicators, these are atmospheric and soil-climatic characteristics. In practice, the use of the proposed forecast algorithm and the corresponding set of monitoring tools will allow you to quickly respond to changing external influences and make the right agronomic decisions.

Thus, the task of managing the vegetation process of agricultural crops can be implemented on the basis of predictive models obtained through factor analysis of influencing external conditions. We considered the possibility of using deviations (anomalies) of the current seasonal values of the NDVI vegetation index from the long-term average as a dependent variable for a multivariate regression model. The purpose of leveling the noisy time series of NDVI of agricultural crops during the growing season is most fully satisfied by the asymmetric Gauss-Laplace function, where the average value of the highest NDVI indicators of the crop growing season is used as a mathematical expectation. As a result of a comparative analysis of the long-term average and the current (vegetation season 2021) NDVI indices for the studied crops, a diagram of NDVI anomalies (ΔNDVI) of the current growing season was obtained, which is recommended for assessing the influence of external factors on the vegetation process. The characteristic ΔNDVI can be used as an independent variable (optimization criterion) in factorial models for predicting the dynamics of the vegetation process.

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