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Remote field monitoring results feasibility assessment for energy crops yield management

Abstract. Most vegetation indices for UAV data analysis are developed for low-resolution satellite platforms, which requires the use of other monitoring methods and agrochemical measures to accurately determine the state of plantations, considering different stages of vegetation and spectral characteristics. The research aims to develop a methodology for assessing the suitability of remote sensing spectral data for energy crop nutrition management. The study was conducted using winter crops, including wheat and rapeseed. The results for winter wheat for the period from 2017 to 2020 were analysed. Stresses associated with nutrient deficiencies were studied in the fields of long-term stationary experiments at the National University of Life and Environmental Sciences of Ukraine. The results obtained from the Slantrange sensor and Slantview software were used. The studies confirmed that the pixel distribution in images of plantations (wheat and winter rape) can be described by a Gaussian distribution. The coefficient of determination for wheat was higher than for rape due to the peculiarities of the plant leaf structure. For rapeseed, a higher coefficient of determination was found for the

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lognormal distribution, which is not convenient for automating fertilisation processes in precision farming technologies. The analysis of the distribution by spectral channels, in particular the presence of several maxima, may indicate the presence of foreign inclusions or transitional stages of vegetation, which makes such data unsuitable for crop management. It has been established that if, after soil filtration, the maximum amplitude of the distribution exceeds the nearest one by more than 3 times, the growing season can be considered stable for a particular area, and the results of spectral monitoring are reliable for further analysis It has been confirmed that the vegetation indices GNDVI and RNDVI are not effective for assessing the reliability of data based on the standard deviation of the distribution. Reference values of the standard deviation of the distribution can be established at research stations with controlled stress factors, which will help in crop management

Keywords: precision agriculture; data suitability; vegetation indices; Gaussian distribution

INTRODUCTION

Unmanned aerial vehicles (UAVs) are an innovative tool for field monitoring that addresses some of the significant drawbacks of satellite systems, such as inaccessibility, high cost, and limited image resolution. However, most vegetation indices used to analyse UAV data have been developed for satellite platforms with low resolution, where a group of plants is displayed in a single pixel. The indices based on the "soil line" concept are mainly aimed at assessing the presence of biomass, but other methodological approaches are needed to monitor crop production. The spectral characteristics of plants also depend on the stages of vegetation, and in such cases, the calculation of the average value for the entire plot, which is typical for satellite monitoring, is not sufficiently accurate.

The problem of determining the conformity of the results of spectral monitoring of plantations with their condition remains unresolved. Unless this issue is resolved, the automation of processes for differentiated fertiliser applications remains unresolved, which critically affects the technical aspect of precision agriculture. Erroneous data on the interpretation of monitoring results fundamentally complicate the selection of plantations for the production of pellets, heat briquettes and biogas. Developing a methodology for assessing the suitability of remote sensing spectral data for nutrition management, and hence crop formation, was the research goal.

Researchers were interested in the presence of crops and their nomenclature, while the issue of crop management was less relevant. The task of obtaining and interpreting information has become fundamentally more complex for precision farming technology, as the spectral characteristics of objects depend significantly on lighting conditions. With this in mind, a set of technical and organisational measures is used to achieve data reproducibility. H. Aasen *et al.* (2015) considered the construction of 3D plant models, where a methodology for combining data from several flights is proposed to achieve high accuracy. Despite interesting results, this approach requires several consecutive flights in different directions, which is not practical on an industrial scale with limited time. F. Liu *et al.* (2021b) consider an approach to determine plant architecture features by mass phenotyping using UAVs and comparing spectral portraits with reference templates. Information on plant size is useful for detecting stress conditions. However, in the early stages of the growing season, high image resolution is required to accurately identify plant conditions, which can only be obtained from low altitudes, making it difficult to use this technology on an industrial scale. Another technical tool for estimating plant size is LiDAR (Light Detection and Ranging), which is described in the review article by H. Dhami *et al.* (2020). However, even this innovative equipment, according to a study by B.P. Banerjee *et al.* (2019), is less effective for small plants with leaves only a few millimetres wide.

R. Lottering & K. Peerbhay (2022) proposed a different approach to identifying the spread of pests in the forest, based on the use of reference values of plant spectral parameters. The authors estimate the deviation of NDVI (Normalised difference vegetation index) from seasonal changes calculated at different stages of the growing season, since satellite imagery is performed at high frequency and data for a specific stage of plant development can be selected. However, in real production conditions, spectral equipment is a valuable resource, and it is necessary to minimise the number of flights.

Y. Cao *et al.* (2020) present an original approach to determining the state of plants by changing their dimensions using sugar beet as an example. The researchers proposed a new vegetation index – WDRVI (Wide-dynamic-range vegetation index), introduced with an additional coefficient for the infrared channel. However, the 5% increase in accuracy achieved requires compensation for the cost of determining dynamically changing coefficients for the infrared channel, which may not be feasible from the point of view of large-scale production. Given this, a more promising approach is to compare the spectral performance with certain reference samples.

The prospects of these innovative indices for crop yield management are described by N. Amarasingam *et al.* (2022). The standard functionality of Slantview is limited to ready-made vegetation indices and does not provide access to the original data adjusted for light and geolocation, so information about the channels was taken according to the method described by S. Shvorov *et al.* (2020).

G. Yan *et al.* (2019) showed that a decrease in the resolution of the images leads to a loss of the ability to distinguish separate bands corresponding to soil and plants. The approach was improved by A. Coy *et al.* (2016), where the identification was refined by assessing the distribution of intensity values of colour components in CIELAB space. The authors used thresholds to determine the area of the plant dome. However, this approach can be effective only in the early stages of the growing season, when the shadow formed on the lower tiers of plant leaves can be neglected.

Soil and plant identification in the study of L. Li *et al.* (2018) were based on the left or right half of the Gaussian distribution. This approach allows for the identification of two components in the presence of three components, but its effectiveness is questionable.

Thus, the analysis of the literature shows that the Gaussian distribution describes the dependence of the number of pixels on the intensity values of colour components for plants and soil. However, the above studies were conducted under stationary conditions with the same plant growing season and air-dry soil conditions. For practical implementation, it is necessary to explore other options, including production fields.

MATERIALS AND METHODS

The study was conducted using winter crops, including wheat and rapeseed. For winter wheat, the results obtained during the period from 2017 to 2020 were analysed. Stresses associated with nutrient deficiencies were investigated in the fields of long-term stationary experiments conducted at the Department of Agrochemistry and Crop Production Quality of the National University of Life and Environmental Sciences of Ukraine, where fertiliser application systems are studied.

This study was conducted under the Convention on Biological Diversity (2022). Multispectral studies in the infrared range were carried out using the Slantrange 3p system (USA) and Slantview software (version 2.13.1.2304), specially developed for this sensor equipment. A feature of Slantview software is the ability to create maps of vegetation index distribution directly quickly and autonomously on the field. It also provides the formation of a general orthophoto plan from the images, and lighting correction and provides the user with ready-made maps of the distribution of vegetation indices, such as various variants of NDVI (Normalised difference vegetation index). Using standard Slantview software tools, the data can be exported in GeoTIFF format. Rapeseed plots with and without signs of technological stress were considered in the study. Data from individual spectral channels and vegetation indices calculated by Slantview were analysed.

To ensure clear identification of pixels in the image, reference points were used, which were implemented in the Slantview software for the image and map windows. These points were present both in the map window and in the images (Fig. 1). Slantview has a distance measurement option in the map window, which is not available in the image window. Therefore, to accurately identify the position of the study plots on the images, it is necessary to have at least two reference points with a known distance between them.

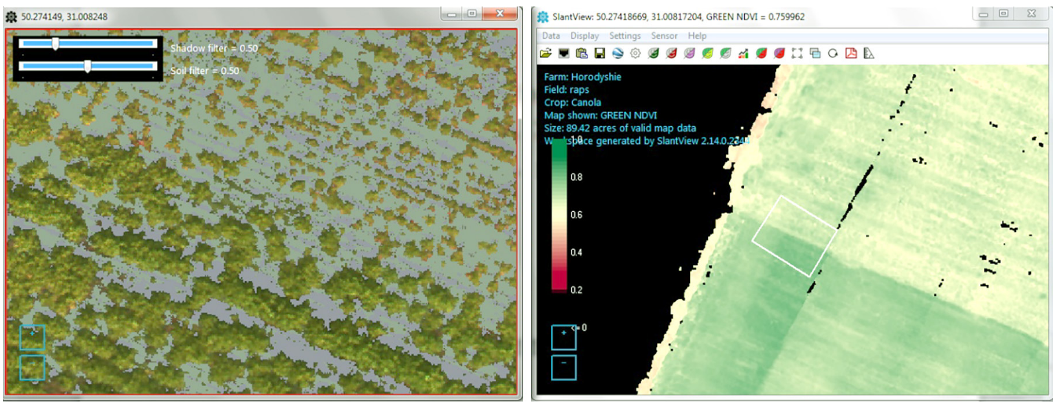

Figure 1. Slantview interfaces, with the "snapshots" and "maps" windows on the left and right, respectively (Green NDVI index)

Note: a white quadrangle in the map window marks the area displayed in the snapshot window

Source: compiled by the authors

The highest detail (GSD of 0.04 m/pixel) was obtained using the snapshot window in Slantview software, which provides access to various NDVI options such as Green, Red and RedEdge. When studying the results for individual spectral channels in the snapshot window, monochrome images were used, which were saved in BMP format to preserve complete information. To do this, Paint (Microsoft Windows 7.0 Sp.1) was used to copy the screen.

Using the map window in Slantview, a smaller-scale map of the index distribution was obtained. In this window, in addition to the standard NDVI indices, indices proposed by Slantview developers, such as Stress, Vegetative fraction and Yield potential, were calculated. The methodology was further improved by using reference points that were also displayed in the image window for individual spectral channels (Pasichnyk *et al.*, 2021). The minimum scale (GSD 0.5 m/pixel) of the index distribution was obtained from the geotiff file, where geospatial data can be stored in Slantview software. Statistical processing of the experimental data on the distribution parameters was carried out using OriginPro v/8.0951 (B951) software developed by OriginLab Corporation.

For the mathematical processing of the spectral data, an approach described by D. Liu *et al.* (2021a), when the distribution was considered as a Gaussian distribution, was used. This particular approach focuses on the early stages of the growing season, when the number of pixels associated with plants and soil is approximately the same, and correctly uses the sum of two Gaussian distributions – one for soil presence and the other for plants, and in the later stages of the growing season, the proportion of the sum attributed to plants will dominate the proportion due to soil, which requires modification of the methodology for assessing the suitability of spectral data for crop management.

In the first stage, using the amplitude version of the modified Gaussian function (GaussAmp) without a shift along the ordinate axis, the parameters of the distribution of the largest peak (Max1) were calculated based on experimental data.

$$N = A \times exp^{\frac{-(X-xc)^2}{2w^2}}, \quad (1)$$

where N – number of measurements (in our case, the number of pixels); X – colour component intensity, A – amplitude; xc – average value; w – standard deviation (according to value A/2).

The amplitude version of the Gaussian function was selected as it better describes peak values compared to the classical Gaussian function and is also easier to adapt to the variable size of the experimental plots, which is important for the industrial implementation of solutions.

In the second stage, based on the results of experimental measurements (EHR) and the calculated values of Max1, the difference between them was calculated (EHR – Max1). In the third stage, using expression (1), the results obtained at stage 2 for the second maximum of the distribution (Max2) were calculated. In the fourth stage, the calculated distribution data for (EHR – Max2) were subtracted from the experimental data. In the fifth stage, the parameters of the distribution equation for MAX1 were refined based on the results obtained in stage 4. Stages 2-5 can be performed cyclically to refine the results. The calculations are terminated when the difference in the mean value of the distribution before and after the cycle becomes less than 1.

RESULTS AND DISCUSSION

Following a study by V. Lysenko *et al.* (2018), the state of nitrogen nutrition can be assessed in the optical range. No characteristic colouration was found for technological stresses (Dolia, *et al.*, 2019). However, plants that were damaged by the phytotoxic effect of herbicides or the aftereffects of their application showed typical signs of damage, such as curvature of the leaf blade (Fig. 2). As a result, fragments of the upper and lower sides of the leaf blade were recorded during horizontal scanning.

Technological stresses on winter rape caused abnormal colouration of the 2 lower leaves, the palette of which, depending on the stage of development and the nature of the stress, contained from white to red-yellow-purple colours (Fig. 3).

Figure 2. Winter wheat crops were affected by herbicide residue, which caused leaf curl

Figure 3. Winter oilseed rape crops with the abnormal colouration of the 2 lower leaves, which is a sign of technological stress (2020.10.28)

Stresses associated with technological operations were investigated in the production fields of farms located in the Kyiv region. The presence of technological stress was noted by the farm's employees since, as a result of the unusually warm and snowy winter, herbicides from the previous season were not destroyed, which led to the damage of winter crops.

Figure 4 shows the results of the calculations for the red component for the experimental wheat data obtained in 2017.05.05.

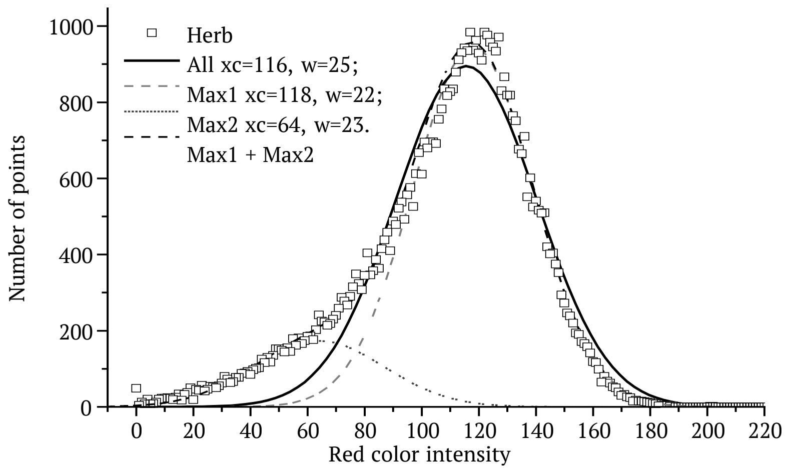

Figure 4. Results of approximation of the dependence of the number of pixels on the intensity of the red colour component (2017.05.05)
Source: compiled by the authors

According to the data presented, the use of the proposed methodology showed that the mean value of the distribution increased by 2 units while the standard deviation w decreased by 3 units. The nature of the distribution corresponds to the data presented in the study by L. Li *et al.* (2018), but it is more correct to consider not one but the sum of 2 distributions, Max1 and Max2, which overlap. This contradicts the results presented in D.-Zh. Liu *et al.* (2021a), but the researchers considered the initial stages of vegetation and the overlap in the results can be explained by possible effects due to the peculiarities of the jpeg data storage format.

The presence of a distribution of Max2 can be explained by the presence of a shadow on the lower leaves that differs from the upper ones, as well as by soil fixation. The proposed approach to processing experimental results will be effective if a condition Max1≫Max2. In practical application, a situation is often encountered when plants of the same crop are simultaneously present in the field at different stages of vegetation or in different physiological states (for example, after the appearance of the flag leaf, which was recorded during the monitoring on 2018.06.08). The analysis of the dependencies presented in Figure 5 shows that Max1≅Max2. This gives grounds to use an approach where, at the first stage, two Gaussian distributions are separately determined, and then 2 separate distributions are considered in parallel.

It is possible to detect the presence of several separate maxima by using expression (1) to describe the experimental results and knowing the value of the standard deviation. For the results obtained, the value of w was 28. However, if we consider the data as the sum of three distributions, Max1, Max2, and Max3, the corresponding w values were between 18 and 23, which is typical for plants and soil (Fig. 5).

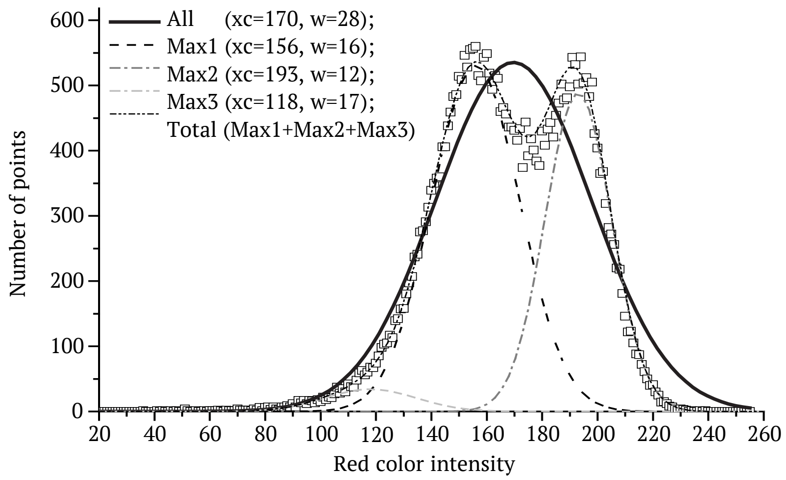

Figure 5. Results of approximation of the dependence of the number of pixels on the intensity of the red colour component for winter wheat (2018.06.08 – there is a flag sheet)
Source: compiled by the authors

The results obtained by approximating the data using the general Gaussian relationship (All) are incorrect since the mean value of the general distribution does not correspond to any of the maximums of the distributions. This indicates that the plants were monitored in a transitional state. Thus, the vegetation stage can be considered stable for the site, and the results of its spectral monitoring are reliable if, after soil filtration, the maximum amplitude of the distribution exceeds the closest amplitude by more than 3 times. Therefore, it is recommended to repeat the experiment in a few days when the crop has fully entered the appropriate vegetation phase. To automate the processing of the monitoring results, you can obtain reference values for the pixel distribution by conducting stationary experiments.

For universal optical range digital cameras like the FC200, it is not necessary to observe the selectivity of the filters exactly. Therefore, to verify the results obtained, a study was carried out using the specialised spectral complex Slantrange 3. The results of these studies, showing a lack of mineral nutrition, are shown in Figure 6.

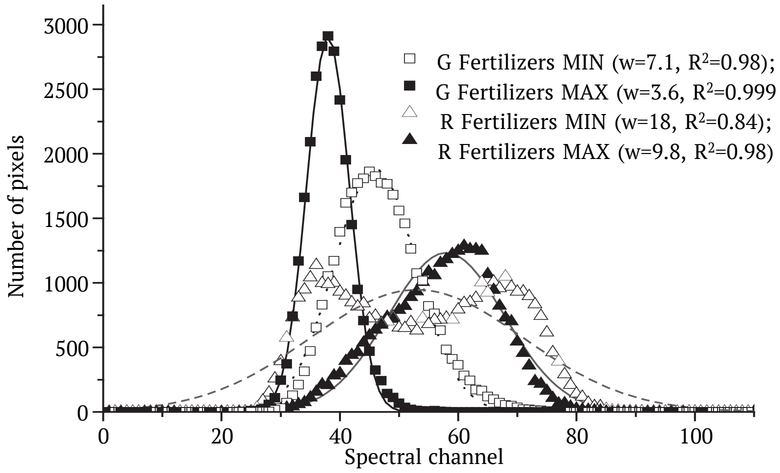

Figure 6. Dependence of the number of pixels on the intensity of green (G) and red (R) colour components (27.04.20)
Note: Fertilisers MAX – 1.5 norms of mineral fertilisers have been applied; Fertilisers MIN – no fertilisers have been applied
Source: compiled by the authors

When the experimental data were approximated using GaussAmp, the standard deviation for the green channel was 7.1 for stressed plants and 3.6 for healthy plants (with a coefficient of determination $R^2 \geqslant 0.98$). Regarding the red component, regardless of the nutritional condition, two maxima were observed, which were more pronounced in conditions of insufficient nutrition. Similarly, to the green channel, for the red channel, the standard deviation for healthy plants was about half that of plants under stress – 9.8 and 18, respectively. The coefficient of determination for the increased rate of mineral fertilisers was 0.98, and for damaged plants – 0.84. Studies on the manifestation of technological stress caused by herbicide aftereffects were conducted on production fields near the village of Hvardiyske with latitude 50.0347 and longitude 30.0286. This is shown in Figure 7.

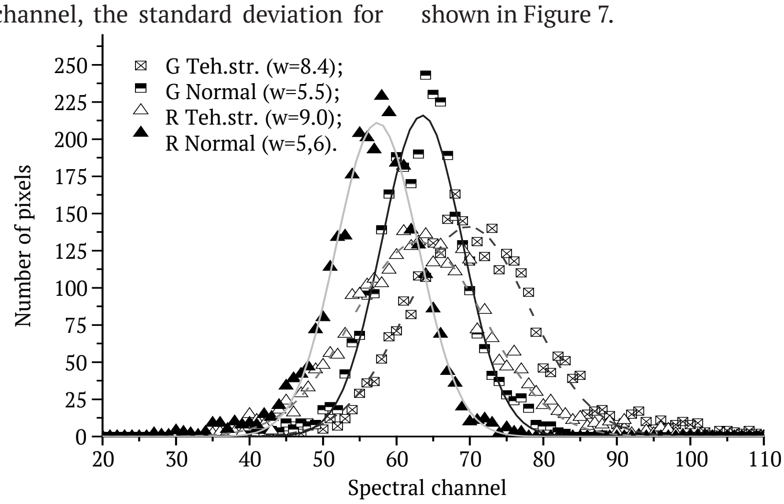

Figure 7. The dependence of the number of pixels on the intensity of the green (G) and red (R) colour components and the presence of technological stresses (The.str). Date of research: 2020.04.27
Source: compiled by the authors

According to the results obtained, the width of the distribution for the green and red channels was 1.5 times larger for plants under stress compared to healthy plants. In the red channel, there were no two distinct maximums of the distribution, regardless of the presence of technological stress, in contrast to the results obtained at the experimental station. The coefficient of determination R2 was ⩾ 0.98 regardless of the channel. The authors assume that the difference in plant development in the production field and the experimental station is due to different sowing dates and wheat varieties. Given that sowing can take several days, the use of unmanned aerial vehicles (UAVs) has an additional advantage over satellite platforms in terms of data reliability.

Vegetation index distribution maps for wheat

To conduct research using remote sensing with the help of unmanned aerial vehicles (UAVs), the width of the study areas of the hospital was relatively small. Therefore, the results from the Slantview software map window were used to obtain data for the studies. The results of the research on stresses related to power shortages and technological stresses are shown in Figure 8.

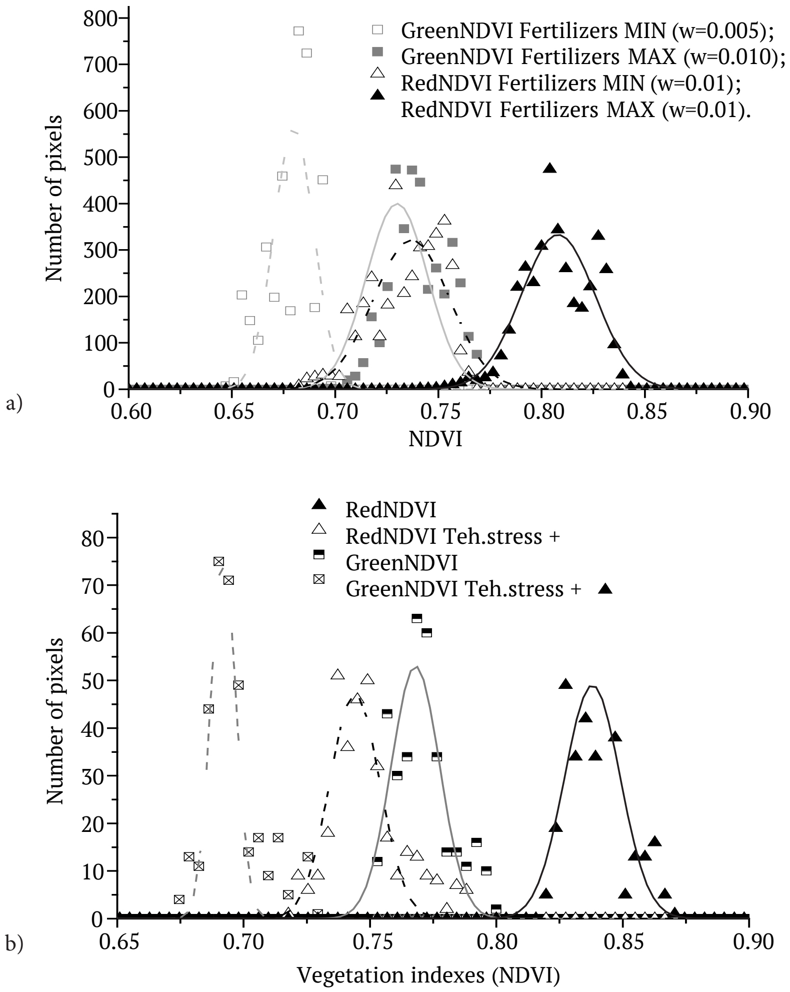

Figure 8. Dependence of the number of pixels on the value of the vegetation index GreenNDVI (GNDVI) and RedNDVI (RNDVI)

Note: a – stress caused by nutrient deficiency – fertilisers; b – stress caused by inadequate performance of technological operations – stress

Source: compiled by the authors

Considering the obtained experimental results, it is possible to conclude that the characteristics of the Gaussian distribution for pixels of the NDVI vegetation index map differ significantly from those obtained directly using spectral channels. For example, for NDVI, the standard deviation of the distribution in damaged plants was equal to or even smaller than in healthy plants (in contrast to the results obtained using spectral channels). The coefficient of determination for the NDVI distribution was 0.85-0.95, which is significantly lower than the distribution obtained using the green and red spectral channels. This implies that the use of standard NDVI indices does not allow for a sufficient assessment of the suitability of spectral monitoring results for further analysis.

Winter rape (separate spectral channels)

In the early stages of plant growth, it is not enough to completely cover the soil. Slantview software is not capable of filtering out soil and shadows in images acquired using spectral channels. Therefore, to identify plants, we used the infrared channel (NIR 800-900 nm) to filter the soil. The monitoring was carried out under uniform cloud cover, so shadows from the leaves were not considered during the filtration. It was found that, in comparison with wheat, the experimental data for rape are better described by a lognormal dependence, considering the value of the coefficient of determination:

$$N = \frac{A1}{\sqrt{2\pi}w1X} e^{\frac{-\left[\ln\frac{X}{xc}\right]}{2w1^2}}, \tag{2}$$

where N – number of measurements (in our case, the number of pixels); X – intensity of the colour component (8-bit model), $A1$ – area; xc – mean; $w1$ – standard deviation (correlates with A1/2).

Based on the analysis of the distribution for rapeseed in the G channel (Fig. 9), it was found that the lognormal relationship is slightly better than the Gaussian relationship in explaining the left part of the distribution. This applies to the plots with healthy plants (40-50) and those showing technological stress (60-80). These results confirm the conclusions about the nature of the relationship given in W. Song *et al.* (2015), where the authors also considered the shadow from the upper leaves on the lower ones, which is probably relevant for plants with wide leaves such as rape.

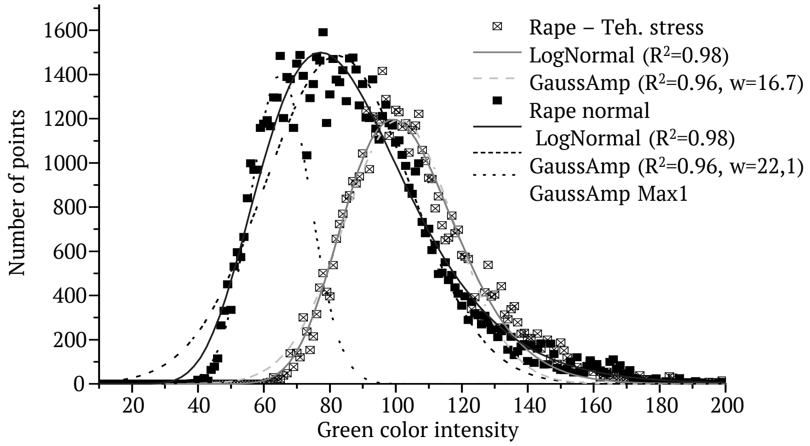

Figure 9. Results of approximation of the dependence of the number of pixels on the intensity of the green component of colour for winter rape (2019.10.30)

Source: compiled by the authors

Reducing errors can be achieved by considering the experimental results as a sum of Gaussian distributions, for example, using the Max1 function. This can be attributed to the fact that not only the length/width ratio is different, but also the dimensions of rapeseed leaves are much larger than those of wheat, and the camera can capture individual plant parts, such as "petiole", "leaf veins", etc., from the same height, and these parts create their distributions. The ratio of such parts can vary significantly, which will affect the distribution parameters and fundamentally complicate the interpretation of the data. The presence of a shadow additionally increases the number of factors that affect the results of spectral studies. As a solution to this problem, which is necessary for crop management in crop production practices, Z.Y. Niu *et al.* (2021) and Z. Wang *et al.* (2023) proposed the use of machine learning technologies. However, the problems of neural network training, which are indicated in these papers when classifying plant images, may include the following aspects:

- Insufficient training data: for successful training of neural networks, a sufficient number of diverse plant images is required. However, collecting a large amount of high-quality data can be a time-consuming and resource-intensive process, especially when it comes to classifying a wide range of numerous plant varieties and hybrids, the number of which is growing every year.
- Unbalanced classes: an uneven distribution of images between different plant classes can sometimes occur in the training data. This can lead to incorrect weighting of certain classes during training, and the model may be more inclined to classify more represented classes.
- Influence of external factors: When capturing photos of plants, various factors can affect the image, such as lighting, angle, noise, and image resolution. These factors can create additional noise or change the appearance of plants, which makes it difficult to classify them, including by neural networks.
- Processing large amounts of data: classification of plant images can be computationally intensive and time-consuming, especially when deep learning and complex models are used. Processing large amounts of data can be burdensome for systems that are limited by computing power.

Q. Yuan & Z. Zuo (2022) tried to limit the number of training images to 800, but even this number can be problematic in terms of research organisation.

To overcome these problems approaches such as data augmentation, training set augmentation, the use of pretrained models, transfer learning techniques, and neural network architecture optimisation can be used. However, the issues remain controversial and require additional research, as shown in the study by H. Li & L. Zhang (2021). Thus, it is premature to consider the focus on machine learning technologies as the most promising approach.

Y. Liu *et al.* (2012) suggested using combinations of Gaussian distributions to obtain the average value of plant spectral parameters. This required capturing the bands belonging to plants and soil separately in the image. Although positive results were achieved, the high resolution of the images taken from a height of 3 metres made it difficult to apply on a large scale in industry.

As for the R channel, the nature of the distribution remained unchanged – the coefficient of determination was higher for the lognormal dependence than for the GaussAmp dependence (Fig. 10).

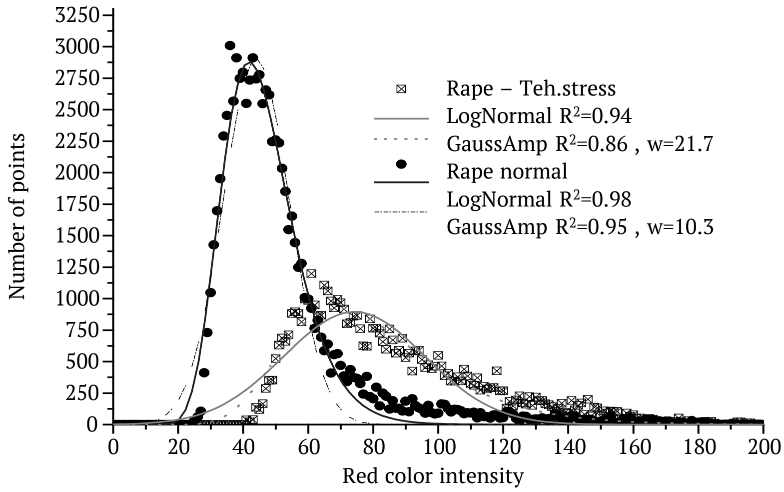

Figure 10. Results of approximation of the relationship between the number of pixels and the value of red colour intensity for winter rape (2019.10.30)

Source: compiled by the authors

When the experimental data were approximated by the Gaussian equation, the standard deviation for healthy plants was half that of plants showing technological stress (as opposed to the G channel). This is probably due to the abnormal colour of the two lower leaves of rapeseed affected by technological stress, which have a palette of yellow to red colours. The results obtained for the RedEdge spectral channel are similar to those for the green channel (Fig. 11). The use of a lognormal relationship instead of GaussAmp to approximate the experimental data did not bring a significant improvement – the R^2 value increased by only 0.006.

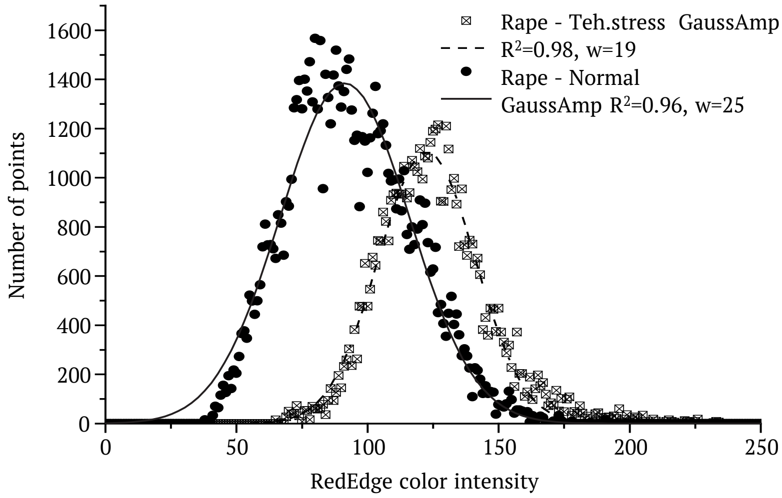

Figure 11. Results of approximation of the dependence of the number of pixels on the intensity of the green component of colour for winter rape (2019.10.30)

Source: compiled by the authors

Winter rape (maps of the distribution of vegetation indices)
For vegetation indices, the possibility of soil and shadow filtering is provided, but the manufacturer does not disclose the algorithms, so the parameters recommended by the developers were used (Soil filter = 0.5, Shadow filter = 0.5). The results are presented in Table 1.

Table 1. Results of approximation of experimental data using GaussAmp distribution for winter rape plots

No.	Index	GSD m/pixel	Plot sample	xc	*w*	R^2	$w_p/w_{r.t.str}$
1	2	3	4	5	6	7	8
1	Green NDVI	0.04	Rapeseed + technical stress	0.671	0.039	0.972	***1.05***
2			Rapeseed	0.767	0.041	0.921	
3		0.25	Rapeseed + technical stress	0.675	0.016	0.932	0.5
4			Rapeseed	0.772	0.008	0.915	
5		0.5	Rapeseed + technical stress	0.671	0.015	0.961	0.53
6			Rapeseed	0.767	0.008	0.967	
7	RedNDVI	0.04	Rapeseed + technical stress	0.716	0.06	0.945	*0.067*
8			Rapeseed	0.830	0.004	0.848	
9		0.25	Rapeseed + technical stress	0.72	0.016	0.966	0.56
10			Rapeseed	0.83	0.009	0.958	
11		0.5	Rapeseed + technical stress	0.717	0.012	0.971	0.75
12			Rapeseed	0.823	0.009	0.961	
13	RedEdgeNDVI	0.04	Rapeseed + technical stress	0.39	0.117	**0.792**	***0.812***
14			Rapeseed	0.578	0.095	**0.711**	
15		0.25	Rapeseed + technical stress	0.406	0.026	0.898	0.46
16			Rapeseed	0.567	0.012	0.921	
17		0.5	Rapeseed + technical stress	0.384	0.034	0.899	0.59
18			Rapeseed	0.560	0.020	0.877	
19	Stress	0.5	Rapeseed + technical stress	0.305	0.215	0.02	0.037
20			Rapeseed	0.372	0.008	0.902	
21	Veg. Fract.	0.5	Rapeseed + technical stress	0.068	0.029	0.732	0.65
22			Rapeseed	0.439	0.019	0.258	
23	Yield pot.	0.5	Rapeseed + technical stress	0.068	0.029	0.732	3.1
24			Rapeseed	0.49	0.09	0.65	

Source: compiled by the authors

Table 1 of the results shows that the lowest coefficient of determination was obtained for the RedEdge spectral channel at the maximum resolution. According to Figure 12, regardless of the presence of technological stress, two separate distributions with different amplitudes are observed for winter rape in the RedEdge channel.

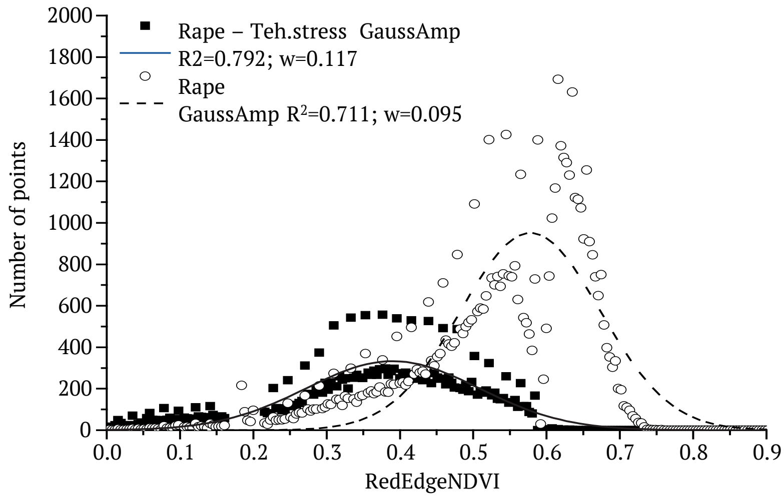

Figure 12. Results of approximation of the dependence of the number of pixels on the value of the RedEdgeNDVI index at GSD=0.04 for winter rape (2019.10.30)
Source: compiled by the authors

One of the possible reasons for this phenomenon is the difference in the fixation of individual components of the leaves and stem of rape in this range. This is confirmed by the fact that when the resolution decreases (GSD⩾0.25), this phenomenon is no longer observed. This phenomenon was not observed for other variants of the NDVI index. In the future, a specific study of this phenomenon for the RedEdge channel could be useful for foliar diagnosis of rapeseed.

The presence of a significant difference in the NDVI index between healthy and damaged rape plants, in our opinion, is explained by the abnormal colouration characteristic of technological stresses, which is not recorded in the considered spectral ranges for wheat. For all variants of the NDVI index with a resolution of GSD⩾0.25, the standard deviation (w) for plots with rapeseed damaged by technological factors was larger than for healthy plants. With the high resolution of Slantview software, recording organic residues from the previous crop as separate objects, the following manifestations are observed (Fig. 13).

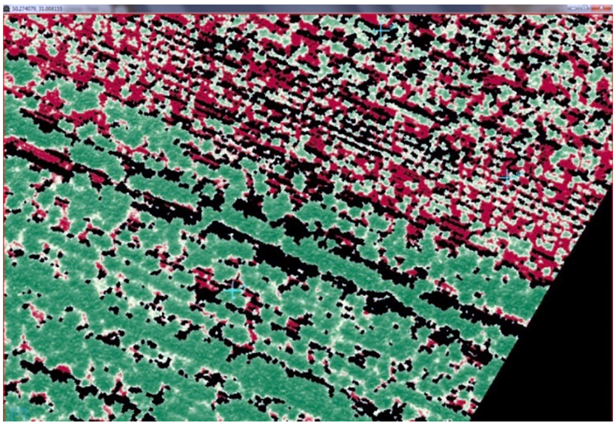

Figure 13. Image of the Slantview software image window with the distribution of the RedNDVI index for the boundary between healthy rapeseed plants (bottom) and those with technological stress (top)
Note: blue crosses indicate reference points for pixel positioning in different spectral channels
Source: compiled by the authors

The study considers the Slantrange system to capture maps of vegetation index distribution only at maximum resolution. This software operation mode and the use of the snapshot window interface allow the agronomist to assess the quality of tillage and the number of organic residues in the fields. High-resolution maps of vegetation index distribution can be useful for estimating not the total plant area, but separately for determining the area of photosynthetically active leaves. For example, leaf borders have lower vegetation index values in the images, and damaged plants with underdeveloped leaves have a higher percentage of the area covered by leaf mass.

CONCLUSIONS

The study experimentally confirmed the statement that the distribution of pixels in images of plantations (wheat and winter rape) can be described by a Gaussian distribution. The coefficient of determination in the approximation of experimental data for wheat is higher than for rape, which can be explained by the peculiarities of the plant leaf structure. For rapeseed, the highest coefficient of determination was obtained for a lognormal distribution. Such a distribution is inconvenient given the automation of fertilisation processes in precision farming technologies.

Analysis of the distribution by spectral channels, in particular the presence of several maxima, may indicate the presence of foreign inclusions or transitional stages of vegetation, which means that such data may not be suitable for crop management.

The vegetation stage can be considered stable for a particular site, and the results of spectral monitoring are reliable for further analysis if, after soil filtration, the maximum distribution amplitude exceeds the nearest value by more than 3 times, based on agronomic crop management rules.

The reliability of the data can be assessed based on the calculated standard deviation of the colour component distribution for pixels, rather than the average value used for traditional vegetation indices. The reference values of the standard deviation for the proposed GaussAmp equation for approximating experimental data should be established at research stations with controlled stress factors.

The GNDVI and RNDVI vegetation indices proved to be ineffective for assessing data reliability based on the standard deviation of the distribution. This highlights the need to introduce additional packages in GIS that separately describe the green and red spectral channels for inclusion in the standard set of vegetation indices.

The issue of shadowing from the upper leaves to the lower leaves significantly affects the distribution results and, accordingly, the assessment of the suitability of the data for crop management, machine learning technologies are a possible option, which, despite their effectiveness, will have to be adjusted for all varieties and hybrids separately. In further research, the use of alternative colour formation models is a possible solution to this issue.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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Оцінка придатності результатів дистанційного моніторингу полів для управління врожаєм енергетичних культур

Анотація. Більшість вегетаційних індексів для аналізу даних БПЛА розроблені для супутникових платформ низької роздільної здатності, що вимагає використання інших методів моніторингу та агрохімічних заходів для точного визначення стану рослинних насаджень, враховуючи різні стадії вегетації і спектральні характеристики. Тому головна мета дослідження – розробка методики оцінки придатності спектральних даних дистанційного моніторингу для управління живленням енергетичних культур. Дослідження проведено з використанням озимих культур, зокрема пшениці і ріпаку. Аналізувалися результати для пшениці озимої за період з 2017 по 2020 рік. Дослідження стресів, пов'язаних з нестачею елементів живлення, проводилися на полях багаторічних стаціонарних дослідів Національного університету біоресурсів і природокористування України. Використовувались результати отримані від сенсору Slantrange та програмного забезпечення Slantview. У проведених дослідженнях підтверджено, що розподіл пікселів на зображеннях рослинних насаджень (пшениці та ріпаку озимих) може бути описаний розподілом Гауса. Коефіцієнт детермінації для пшениці був вищим, ніж для ріпаку, через особливості будови листів рослин. Для ріпаку було виявлено вищий коефіцієнт детермінації для логнормального розподілу, який не є зручним для автоматизації процесів підживлення в технологіях точного землеробства. Аналіз розподілу за спектральними каналами, зокрема наявність кількох максимумів, може свідчити про наявність сторонніх включень або перехідних етапів вегетації, що робить такі дані непридатними для керування врожаєм. Встановлено, що якщо після фільтрації ґрунту максимальна амплітуда розподілу перевищує найближчу більш ніж в 3 рази, етап вегетації може вважатися стабільним для певної ділянки, а результати спектрального моніторингу є надійними для подальшого аналізу Підтверджено, що вегетаційні індекси GNDVI та RNDVI не є ефективними для оцінки надійності даних на основі стандартного відхилення розподілу. Еталонні значення стандартного відхилення розподілу можуть бути встановлені на дослідницьких станціях з контрольованими стресовими чинниками, що допоможе в керуванні врожаєм

Ключові слова: точне землеробство; придатність даних; вегетаційні індекси; розподіл Гауса