UDC 631.8: 629.7

USE OF NEURAL NETWORKS FOR PLANNING THE CORRECT SELECTION OF PLANT AND SOIL SAMPLES IN PRECISION AGRICULTURE TECHNOLOGIES

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https://doi.org/10.31548/dopovidi6(106).2023.005

Abstract. *The article is devoted to the study of the use of neural networks to optimize the selection of plant stands in precision agriculture technologies. The study takes into account the complex aspects of sample selection, such as the speed of image acquisition, the effectiveness of assessing the state of mineral nutrition and soil moisture, etc. This data is a necessary component for precision farming technologies and, in particular, crop management. Research was conducted on production fields in 2019-2020 in Boryspil district of Kyiv region. Spectral studies were performed using the Slantrange 3p complex installed on the UAV. Data processing was performed both with the specialized software for spectral data Slantview and with the mathematical package MathCad. The assessment of the nature of the distribution of both individual spectral channels and their combination in the form of vegetation indices turned out to be unprepared for the identification of uneven water supply of areas. The red channel and its derivatives turned out to be the most promising in the direction of identifying the water supply of wheat. The use of neural networks made it possible to identify probable areas with increased water supply on the maps of the distribution of vegetation indices in the field. The duration of identification using neural networks will not interfere with the sampling procedure, so that such a procedure can be effectively implemented in agronomic practices. Therefore, the use of neural networks allows you to automate and increase the accuracy of selection, improving the quality of the analysis of plant stands, subject to compliance with soil sample evaluation technologies. The obtained results indicate the prospects of implementing this approach in modern agriculture..*

Key words: *selection of plant samples, precision agriculture, remote monitoring, vegetation indices, UAV, neural networks*

Introduction. The conditions of crop production are becoming more and more complex, taking into account climate changes, divergence and instability of the cost of resources, means and products. Precision agriculture, also known as precision agriculture or precision agriculture, is an approach that uses modern technological solutions – remote sensing, sensors, geographic information system (GIS) and others - to collect and analyze data about soil, plants, factors. The main goal is to optimize the use of resources and maximize the harvest, while simultaneously reducing the negative impact on the environment. Implementation of the concept of precision agricultural production requires solving many organizational and methodical issues and fundamentally improving the culture of production in the agricultural sector in general and in crop production in particular. Yes, it is necessary to ensure the accumulation and processing of large data sets, that is, to implement information technologies at a new level within the limits of not a separate field, but an economy or even an industry, as shown in D. Yuniarto et al (2020) in [1]. For Ukraine, it is necessary to increase the number of sensor equipment for monitoring by several orders of magnitude, for which it is advisable to develop universal description languages, an example of which can be Verilog, applied in India by the group of J. Patidar et al (2019) in [2]. The implementation of Internet of Things technologies is promising, the experience of using them specifically for crop production is shown in T. Wiangtong and P. Sirisuk (2018) in [3] and U. A. Bhat et al (2022) in [4]. Significant progress has been made primarily in indoor technologies, as shown by P. Patil et al (2022) in [5], but there the environmental impact is fundamentally lower than in the open air. For the industrial scale of traditional fields, it is necessary to implement fundamentally more complex technologies, which will involve not only obtaining experimental data, but also filtering them for unreliable results, which can be achieved in multi-agent systems, described in M. Zaryouli et al (2020) in [6].

In Ukraine, Smart Farming technologies for plant nutrition are most often implemented according to the following algorithm: survey using UAVs, identification of characteristic areas, ground sampling and their subsequent laboratory analysis to create maps, in particular, of nitrogen nutrition. But the state of plants can be determined not only by the state of mineral nutrition, but also, in particular, by the state of water supply and, accordingly, neglecting this indicator leads to significant errors. The process of sampling is time-consuming and it is impractical to complicate it with additional determinations of soil moisture at different depths. Accordingly, the purpose of the work is to develop methodical approaches to determine the optimal places for sampling plant samples under conditions of different soil moisture conditions.

Status of the issue. Sampling should be carried out using robots, since accurate positioning means are necessary in any case, because visual positioning by landmarks in the field is not always possible, as confirmed by O. M. Vechera et al (2018) in [7]. For the European market, which has fields with an area of up to several tens of hectares, it is possible to use special multispectral sensors capable of immediately issuing maps of the distribution of vegetation indices. Such sensors as Mapir Survey3W, as shown by Z. Zhang et al (2022) in [8] or Sentera Double 4K, shown by N. u. Sabah et al (2022) in [9], developed for small UAVs of the mini class and require constant radio communication with the operator, which is not always possible for the fields of Ukraine with an area of 50-100 hectares. Based on the experience of using experimental hospitals (V. Lysenko et al., 2019 in [10]), the order of 6 gradations and the corresponding number of repetitions are required to study the fertilizer application system. Therefore, the amount of ground work is considerable and the use of robots is quite appropriate. The expediency and effectiveness of such an unconventional tool was studied in the work of M. Edmonds and J. Yi (2021) in [11], where the problems and prospects of such solutions are shown.

In general, considerable attention has been paid to the use of robots in agricultural production. Thus, the methods of choosing routes according to various optimality criteria were developed in the works of Y. Gunchenko et al (2019) in [12], A. N. Voronin et al (2003) in [13] in the presence of obstacles, J. Pak et al (2022) in [14] and A.N. Voronin et al (2002) in [15] for minimal mileage. These tools can be effectively used in crop production, taking into account the topography of the area, the presence of known obstacles, and the energy efficiency of the devices. With regard to operational data, the work of S. A. Shvorov et al (2019) in [16] describes the experience of choosing the optimal route on the basis of data obtained from UAVs with the Slantrange complex. The work shows that with the Slantrange multispectral complex and the SlantView software, maps of the distribution of vegetation indices, on the basis of which the state of vegetation is determined, can be obtained for a field of 60-70 hectares within one to two hours. Calculations do not require cloud services and, accordingly, access to the Internet, and therefore, it is appropriate for conditions of changes in the state of vegetation.

For the most common unmanned aerial vehicles with electric motors, which are easier to control due to the absence of electromagnetic interference generated by internal combustion engines, the issue of power supply is also well studied. These are the optimal routes in the conditions of limited storage batteries, described in the work of D. S. Komarchuk et al (2021) in [17], and alternative energy supply from solar galvanic cells, shown in R. S. Krishnan (2022) in [18]. That is, the main methodological issues regarding the selection of samples are not in the technical side regarding the possibility of selection or the organizational area regarding the availability of such places, but in the identification of areas with different plant conditions.

The issue of remote soil moisture assessment is extremely important for crop production, and a review by M. J. Pandian and D. Karthik (2022) in [18] describes the existing experience with UAVs, which involves the use of thermal imagers. When taking samples, it is technically possible to measure soil moisture, but reliable consideration of the dynamics of changes in the moisture supply of plants, especially in drought conditions, has doubtful prospects. A possible option for remote establishment of the state of plants is the assessment of the parameters of the distribution of indices on the site, shown in the work of N. Pasichnyk et al (2021) [20].

Organization of research.

Research was carried out on production fields in 2019-2020 in Boryspil district of Kyiv region with coordinates 50º16' N, 30º58'E 50.0347. The Slantrane 3p system mounted on the base of the DJI Matrice 600 Pro UAV was used for spectral research. Data on separate spectral channels and vegetation indices calculated by the SlantView program were considered. Maximum detail (GSD 0.04 m/pixel) is possible from the SlantView image window (available NDVI options - Green, Red and RedEdge). Monochrome images were used in the studies of results for individual spectral channels (picture windows), which were stored in bmp format to ensure completeness of information (Fig. 1).

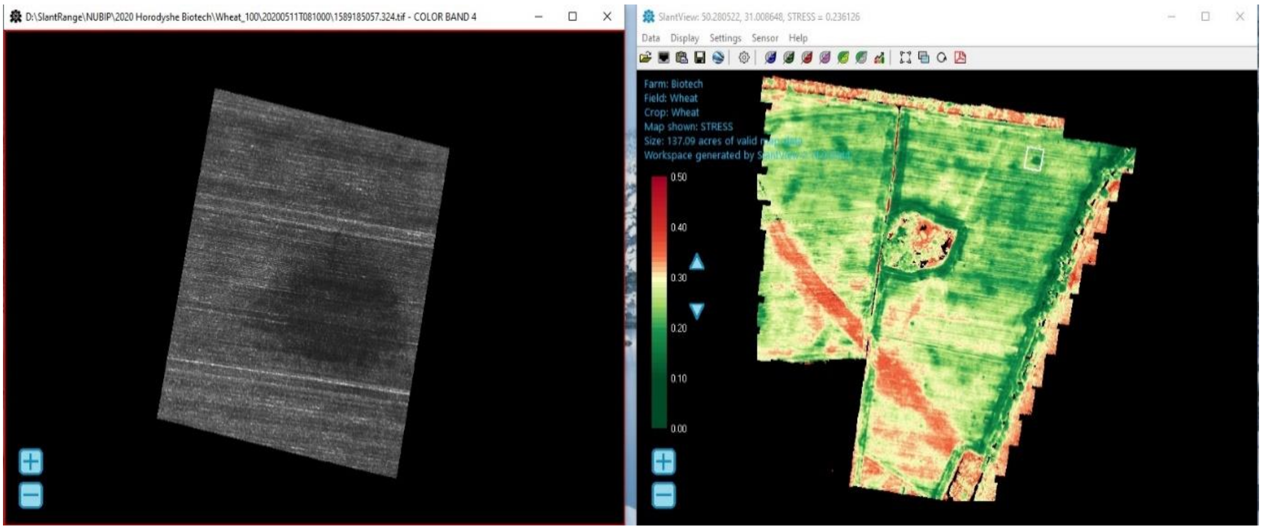

Figure 1. A picture in the IR spectrum of a field with a lowland (left) and the Stress map in the SlantView software (right)

Obtained results and discussion.

Assessment of the nature of the distribution. To approximate the experimental data, the amplitude version of the modified Gaussian function (hereinafter GaussAmp) was adopted, without a shift along the ordinate axis. The choice of the Amplitude version of Gaussian peak function is due to the fact that, compared to the classical Gaussian function, it better describes the peak values and. as a result, it is easier to adapt it to the variable size of the experimental area, which is important for the industrial implementation of solutions (1):

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

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

The results obtained for individual spectral channels are shown in Table 1, where 1 is a normal wheat plot, and water is an improved state of water supply due to the accumulation of water in the lowlands.

1. Results of approximation of experimental data using GaussAmp distribution for plots of winter wheat. Research date 2020.04.27

	Green		Red		RedEDGE		NIR	
	1	water	1	water	1	water	1	water
xc	98	88	89	79	65,3	65	42	48,5
w	22	23	22,2	18,6	15	15,7	10,7	11,3
A	107	105	101	121	153	149	217	202

For individual spectral channels, the use of a promising parameter - the standard deviation, shown in N.Pasichnyk et al (2021) in [20] for identifying the best state of water supply turned out to be ineffective. The difference in this parameter was recorded only in the red channel. With regard to the average value, the difference was recorded in the Red Green and NIR channels, while in the visible range the areas in the lowlands are darker, and for the infrared channel - the opposite. This is probably explained by the difference in the dimensions of the plants, which was also recorded visually during ground observations. Therefore, it was not possible to find a convincing identification of uneven wetting, based on the values and indicators of the distribution, so the issue needs additional study. Identification by source channels is probably possible, but its practical implementation in relation to sampling needs raises some doubts, based on the required time for calculations. Available serial Slantrange software and hardware provides rapid retrieval of distribution maps within an hour, but does not include a vegetation index calculator. The data can be calculated with other software, but it takes time. According to the available experience, more than 5 hours were spent using the alternative Agisoft software installed on the graphics station (Core_i5-9400F_2.90GHz_16.0GB_ 250SSD_2T_GeForce GTX1050Ti). Given the amount of raw data of 9 GB and the bandwidth of the mobile Internet, the time to build the maps is too long for production use. In our opinion, it is advisable to use the possibility of the Slantrange complex and its standard vegetation indices, since for them the calculations with the Slantview proprietary software for a field of 60 hectares took 40-50 minutes. The Slantview program interface provides access to standard vegetation indices, such as various variations of the most common NDVI index, as well as several proprietary indices such as Stress, Veg. fraction, etc., whose calculation formulas are not disclosed by the manufacturing company. The GreenNDVI and RedNDVI indices were selected for research. The results are presented in Figure 2.

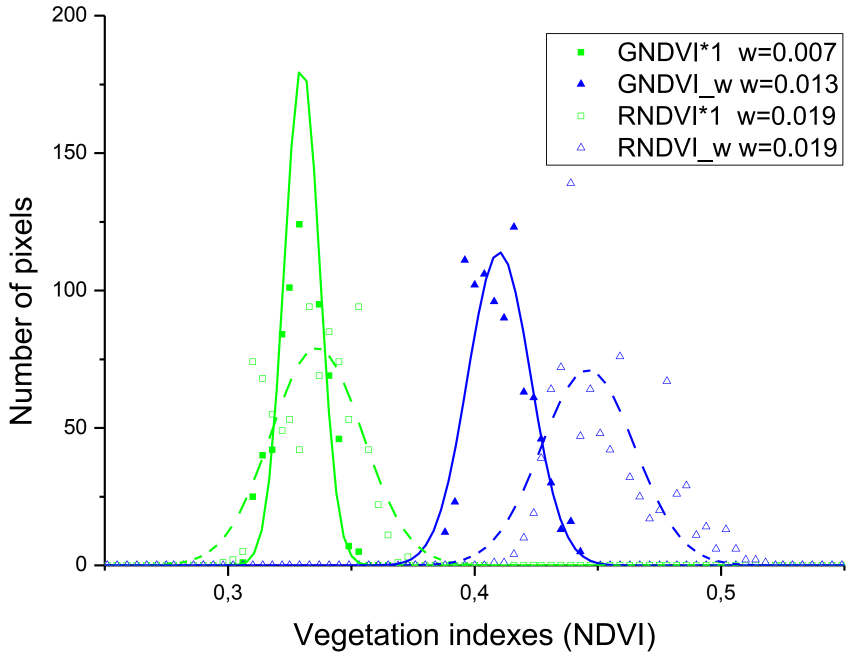

Figure 2. Dependence of the number of pixels on the value of the vegetation index GNDVI and RNDVI: where _1 is a normal state, _w is an increased state of water supply

Based on the results of the research, it can be stated that the characteristics of the Gaussian distribution for the pixels of the map of the distribution of the NDVI vegetation index are significantly different from those obtained directly from the spectral channels. Thus, for NDVI indices, the standard deviation of the distribution in normal plants was equal to or even smaller than in those with a better water supply regime, in contrast to the results obtained directly based on the use of spectral channels. At the same time, the coefficient of determination for the distribution of NDVI indices was 0.85-0.95, which is significantly less than the distribution based on the results of using green and red spectral channels, where this indicator was 0.98 and higher. The red spectral channel and its derivatives in the form of indices turned out to be the most promising for identifying increased water supply. In our opinion, consideration of individual spectral channels or their combination in vegetation indices is insufficient for confident and correct identification of areas for sampling for laboratory analysis.

To solve this problem, we proposed the use of neural networks to analyze the distribution of plots on the field. For example, relief depressions in the form of puddles are mostly round in shape, which can be recognized on the field. In this case, there are no restrictions on the nomenclature of available indexes that can be used for analysis.

Neural networks. Convolutional Neural Networks (CNNs) are a powerful class of deep neural networks specially designed for processing grid-structured data such as images and videos. They are capable of automatically learning various levels of abstraction in data and are used with great success in computer vision tasks, image processing, object recognition, and other applications related to the perception of visual information.

Convolutional neural networks are based on two main concepts: convolutions and pooling. Convolution is a linear mixed sum operation between the input data and a small filter (called a kernel) to produce a new processed output value. This operation allows you to detect various features in the data, such as boundaries, textures, and other local details. Sampling is the process of reducing the dimensionality of data by taking the maximum, mean, or other statistical value from a certain area.

Mathematically, convolution for 2D data can be defined as follows:

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(i-m, j-n) * K(m,n), \qquad (2)$$

where: I is the input data, K is the kernel (filter), S is the output data.

To achieve greater instability to various displacements in images, convolutional neural networks often use stride and padding operations. Print defines the step at which the filter moves over the input data, while padding adds extra pixels around the input data to help preserve dimensionality after convolution.

Convolutional neural networks are often combined with fully connected layers to perform classification, regression, and other tasks. The results of the convolutional layers are concatenated and fed to the input of the fully connected layer.

Convolutional neural networks have shown significant achievements in many areas where it is important to analyze large volumes of visual data. Their success is due not only to the power of the model, but also to the ability to learn abstract levels of representation of the hierarchical structure of input data, which makes them an indispensable tool for many tasks of analyzing and processing objects in large data sets, which allows considering this tool in the question of determining the optimal sampling point soil samples.

Learning convolutional neural networks includes two main processes: forward propagation and backpropagation. These processes help the network learn the optimal weights and parameters to solve a particular task.

The forward propagation process occurs from the input data to the output layer of the network. The data passes through successive layers, which include convolutional layers, activation functions, and possibly pooling layers. In each convolutional layer, the kernel performs a convolution with the input data that learns various features in the data.

After forward propagation, the output of the network is compared with the desired results, and the error backpropagation phase occurs. The basic idea is to estimate how much the weights and parameters affect the error, and then adjust them to reduce that error.

Error backpropagation is based on gradient descent, where the loss gradient (a function that measures the difference between predicted and actual results) is calculated with respect to the network weights and parameters. This gradient shows how the weights and parameters should be changed to reduce the error.

After calculating the gradient, the network applies an optimization algorithm (eg, stochastic gradient descent) to make corrective changes to the weights and parameters. This process is repeated for many data packages (mini-batches) during several training epochs.

An important component of training convolutional neural networks is the use of a loss function, which measures the amount of error between predicted and actual results.

In summary, training convolutional neural networks involves passing data through the network, calculating the error, calculating the gradient, and adjusting the weights and parameters to minimize the error during training.

Training of a convolutional neural network in Python for recognizing circles (puddles) in images was carried out on the fields obtained as a result of UAV surveying (Fig. 4).

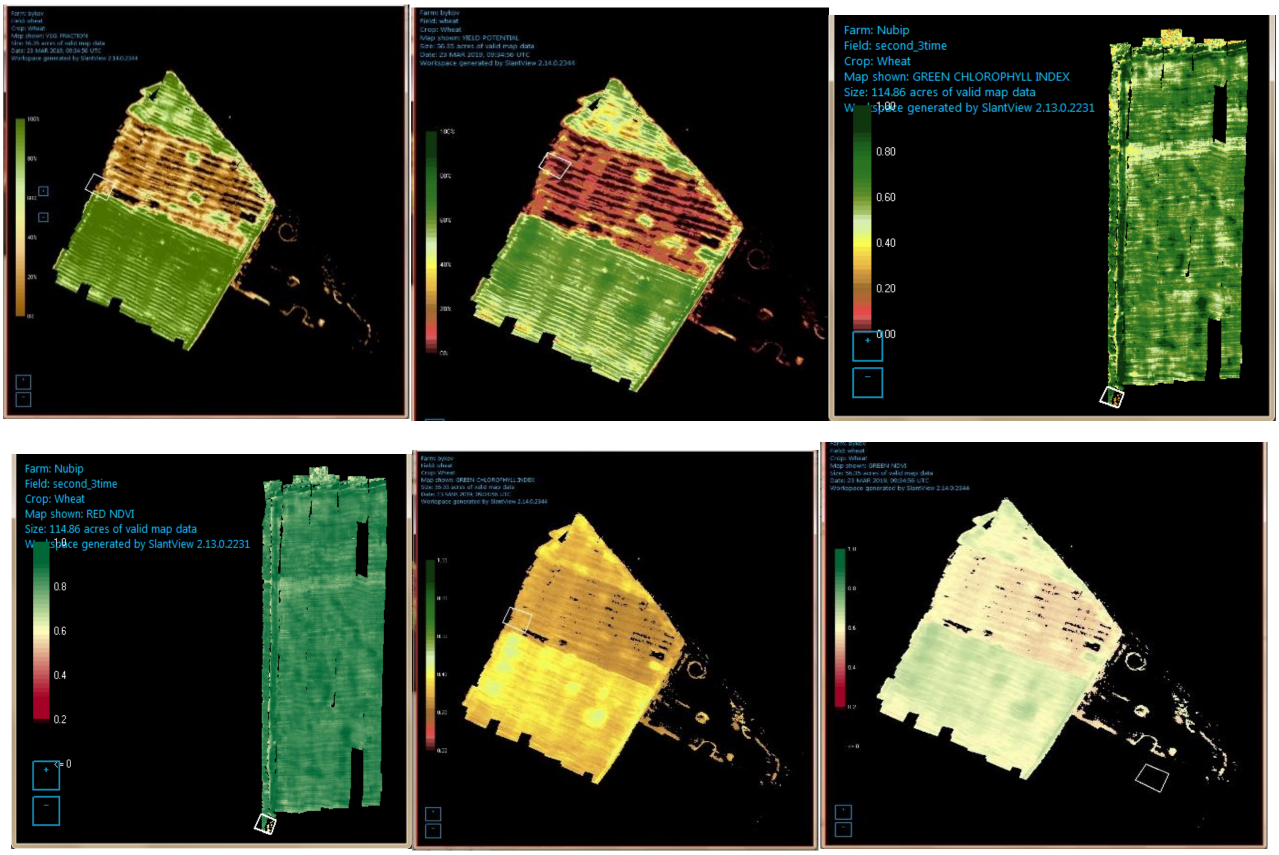

Figure 4. Field images obtained by the Slantrane 3p system (DJI Matrice 600 Pro UAV platform, calculated by the SlantView program)

For this, the TensorFlow library was used, which allows you to easily build and train neural networks. Part of the network training code is shown in Figer 5.

A convolutional architecture with three convolutional layers and pooling followed by a fully connected layer for classification was used. To train the model on the task of binary classification, the binary loss function binary_crossentropy was used.

The testing of the network was carried out in order to identify areas with increased moisture supply, which were located in the fields and had a shape close to circles and differed in color.

Accuracy metrics: The worst and most important metric is accuracy. The created network demonstrated high accuracy on test data: acc: 0.91422765.

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# Data loading and preparation
train_datagen = ImageDataGenerator(rescale=1.0/255.0) # Normalization of pixel values
train_generator = train_datagen.flow_from_directory(
    'path/to/training_data',
    target_size=(1270, 840),  # Image size
    batch_size=32,
    class_mode='binary')   #Binary classification

# building a convolutional neural network
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(1270, 840, 3)),
    MaxPooling2D((2, 2)),
    Conv2D(1270, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Conv2D(2540, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(2540, activation='relu'),
    Dense(1, activation='sigmoid')
])

# Compilation
model.compile(optimizer=Adam(learning_rate=0.001),
              loss='binary_crossentropy',
              metrics=['accuracy'])
```

Figure 5. Convolutional neural network learning code listing

Conclusions.

1. The assessment of the nature of the distribution of both individual spectral channels and their combination in the form of vegetation indices turned out to be unprepared for the identification of uneven water supply of areas.

2. The red channel and its derivatives turned out to be the most promising in the direction of identifying the water supply of wheat.

3. The use of neural networks made it possible to identify probable areas with increased water supply on the maps of the distribution of vegetation indices in the field.

4. The duration of the identification using neural networks will not interfere with the sampling procedure, thanks to which such a procedure can be effectively implemented in agronomic practices.

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ВИКОРИСТАННЯ НЕЙРОННИХ МЕРЕЖ ДЛЯ ПЛАНУВАННЯ КОРЕКТНОГО ВІДБОРУ ЗРАЗКІВ РОСЛИННИХ НАСАДЖЕНЬ В ТЕХНОЛОГІЯХ ТОЧНОГО ЗЕМЛЕРОБСТВА

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Анотація. *Стаття присвячена дослідженню використання нейронних мереж для оптимізації вибору насаджень у технологіях точного землеробства. Дослідження враховує такі комплексні аспекти відбору зразків, як швидкість отримання зображення, ефективність оцінки стану мінерального живлення та вологості ґрунту тощо. Ці дані є необхідною складовою для технологій точного землеробства і, зокрема, управління посівами. Дослідження проводили на виробничих полях у 2019-2020 роках у Бориспільському районі Київської області. Спектральні дослідження проводились за допомогою встановленого на БПЛА комплексу Slantrange 3p. Обробку даних проводили як за допомогою спеціалізованого програмного забезпечення для спектральних даних Slantview, так і за допомогою математичного пакету MathCad.*

Оцінка характеру розподілу як окремих спектральних каналів, так і їх поєднання у вигляді вегетаційних індексів виявилася непідготовленою для виявлення нерівномірного водозабезпечення територій. Червоний канал та його похідні виявилися найперспективнішими у напрямку виявлення водозабезпеченості пшениці. Застосування нейронних мереж дозволило виявити на картах розподілу вегетаційних індексів на місцях ймовірні ділянки підвищеної водності. Тривалість ідентифікації за допомогою нейронних мереж не заважатиме процедурі відбору проб, тому така процедура може бути ефективно реалізована в агрономічній практиці. Отже, використання нейронних мереж дозволяє автоматизувати та підвищити точність відбору, підвищити якість аналізу рослинних насаджень за умови дотримання технологій оцінки проб ґрунту. Отримані результати свідчать про перспективність впровадження даного підходу в сучасному сільському господарстві.

Ключові слова: *відбір зразків рослин, точне землеробство, дистанційний моніторинг, вегетаційні індекси, БПЛА, нейронні мережі*