INFORMATION SUPPORT OF THE REMOTE NITROGEN MONITORING SYSTEM IN AGRICULTURAL CROPS

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Abstract: The article addresses issues on application of unmanned aerial vehicles (UAV) to monitor nitrogen nutrition through the example of wheat plants. The optical spectral range can be used to monitor exploitation of the UAV. It is recommended to develop specialized spectral indices for such equipment. The article provides calibration curves for nitrogen nutrition monitoring

Keywords: UAV; monitoring; nutrition; fertilizers; drones.

1. INTRODUCTION

Diagnosis of plants nutrition in agricultural production areas today has become extremely necessary in a complex of measures for sustainable development of crop. The high cost of fertilizers, fuel and lubricants, agricultural machinery, motor capacity cause high economic risks of making decisions about plant nutrition on production facilities. Nutrition is most often made by nitrogen fertilizer, so far as grain quality is determined primarily by protein, which is an integral part of nitrogen. Traditional land-based methods of determining the state of plants include colorimetric examination of farm plantations area using chemical reagents and requiring significant expenditure of time, so making immediate decisions on fertilization for each section of the field becomes impossible.

Some of the most promising technologies include non-destructive sensing of crops based on the analysis of reflection spectra that can be remotely fixed by sensors placed in aerial or satellite carriers . Industrial use of satellite monitoring systems for research of vegetation plants condition has been carried out since the early 70s after the launch of Landsat program in the US. Due to the gained experience, implementation of satellite monitoring technologies has been extended and now several tens of satellite platforms are being operated providing data for more than two hundred different Vegetation Indexes (VI) [1]. But along with advantages of satellite platforms for monitoring, there are certain physical limitations on their use, such as the lack of possibility to use them during cloudy weather, restrictions on the frequency band due to "transparency windows" of the atmosphere, and so on. The solution to these problems should be the implementation of a stand-alone in-field remote sensing system (robot plane - RP), which has become affordable for farmers in recent decades.

As such, the aim of our research is to assess the possibilities of RP usage for nitrogen nutrition monitoring through the example of wheat plants.

2. EXISTING SOLUTIONS (STATE OF AFFAIRS)

Placement of sensory equipment on the satellite platform caused certain technological aspects of its usage primarily as to wavelength range and techniques of radio frequency correction, which is required due to the sunlight instability. The direct use of existing techniques for RP is difficult or technologically impossible.

Today, for the nitrogen nutrition assessment such VI as NDVI (Normalized Difference Vegetation Index) [1], and NDNI (Normalized Difference Nitrogen Index) [2] are used, spectral red and near-infrared ranges 1510 nm and 1680 nm channels respectively are exploited. Usage of the infrared or "heat" range of satellite platforms is related to the less sensitive to the light changes. The optical range of 690 – 750 nm is used in multispectral method (Shadchin's method [3]), which is intended for low flying and ground platforms.

For radio frequency correction of satellite data natural optical templates (such as deep reservoirs, etc) are used [4,5]. Regular light source is used for serial equipment, (such as Raptor ACS-225LR) and uses VI NDVI for calibration [6].

The use of a dedicated sensor is shown in [7,8]. But this is acceptable only for uniform illumination [9].

These decisions are difficult to implement for RP because of practical absence of natural optical templates in fields during low flying, and power supply for the test sites lighting is too heavy and big. Proven solution for RP is the use of reflectance panels, which are placed directly on the field and are used to assess light [10,11]. In this document, the automatic control algorithm of multispectral camera parameters, composed of a feed forward back propagation artificial neural network and an adaptive neuro-fuzzy inference system, yielded good reproducibility of results. However, the panel's dimensions must be sufficient for accurate identification and their use on an industrial scale is a significant economic and organizational task. Results of lighting calibration which using the system data from the image (EXIF data), is shown in [12].

However, in this case only incomplete data was displayed and calibration algorithm was not offered because the experiments were conducted during short time of one day.

Thus, the literature analysis suggests that today there are no standard methods of radio frequency calibration of RP that can be used on an industrial scale for the purpose of nitrogen nutrition remote diagnostics.

In real conditions plant nutrition during vegetation is carried out up to 9 times. And that period do not exceed a few days, and therefore the best option is when the data from RP is quickly processed and transferred for being used by the appropriate equipment for making fertilizers. It is necessary to consider that plant diseases, the presence of pests can affect the spectral characteristics of plants. Directly in the field conditions plant state assessment can be made by mobile sensors such as "Floratest", although RP should be adapted to new data.

3. MATERIALS AND METHODS

3.1 STATIONARY EXPERIMENT

Research was carried out during 2016 in the long-term stationary experiment of Agricultural Chemistry and Quality of Plant Products Dept. of National University of Life and Environmental Sciences of Ukraine (certificate of NAAS # 080 of 2006 year).

Long term experimental field was founded in 1956 and is designed for studying the fertilization of field crops. Geographically it is located in village Pshenychne Vasylkiv district, Kyiv region (GPS Position 50º 4 '29.00 "N, 30º 13' 21.00" E).

Within the stationary field, in addition to the basic options of the experiment the micro-field experiment for creating various backgrounds of plant nitrogen nutrition was held. Land area of main experiment is 100 m^2, areas of micro-field experiments - 10 m^2, three-fold repetition (Fig. 1). The studies were conducted with winter wheat varieties Tsentylivka.

To study the effect of different fertilizer standards such experiment options were selected for winter wheat: 1) no fertilizer (control); 2) P80; 3) R80K80; 4) N60R80K80; 5) N90R120K120 (normal N60R80K80 is recommended for this type of ground). Fertilizers were made in the form of ammonium nitrate, ammophos and potassium chloride.

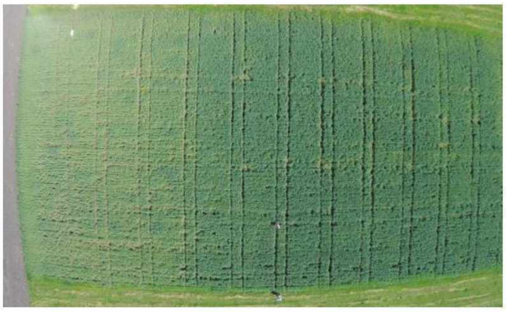

Fig. 1. – Stationary experiment "Agronomic Research Station".

3.2 ANALYTICAL STUDIES OF PLANT NITROGEN NUTRITION

Plants (aerial parts) were taken from each repetition option, washed under running water for cleaning dust and other dirt, dried on paper decks at room temperature to air-dry state. After air drying the material was crushed by scissors and dried in the oven at the temperature of 60 ºC. The dried material was milled. After wet ashing the nitrogen content in plants was determined using photometric method with Nessler reagent.

3.3 REMOTE SENSING SYSTEM

Remote monitoring was performed with the help of RP DJI Phantom 3+. Camera Model - PHANTOM VISION FC200. Radio frequency calibration was performed on the basis of official data from exiff photo file jpeg format, and adjusting camera settings - by the method described in [13, 14, 15]. Setting parameters of a digital camera are the following: Exposure Time - 1/1205; Aperture Value - 2.8; Light Source - Fine Weather; Color Space - sRGB, ISO - 100. RP flight height was 100 meters above the surface.

Analysis of image data was carried out in the following sequence.

Output image file format was re-formatted from jpeg format to bmp, where the value of each color component was determined for each point of the image. The meaning of each color component was taken out for each point individually. The average value of each area on the micro-field experiments was calculated. Then areas whose values differed by more than 15% from the average were excluded "Fig. 2".

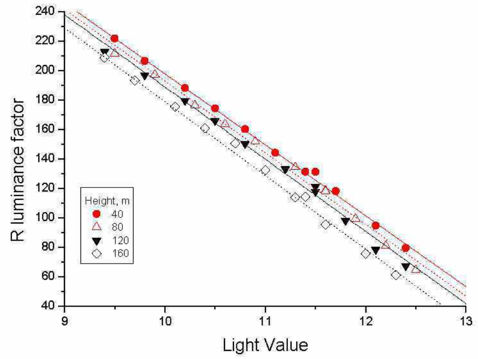

Fig. 2. – Relationship between red color component and light values at different monitoring altitude.

The procedure feasibility is due to the ground and the shadows of leaves that is at the image. Such areas availability on the image leads to errors which impact decreases with increasing distance from the field, i.e a decrease in resolution (in the phase of wheat growth - out of the tube). In experiments on selecting a mode of flight it was found that starting from the height of 100 meters numbers of "rejection" areas of the field is rise.

4. RESEARCH RESULTS

Analysis of the relationship between the values of the color components intensity and nitrogen content in the dry matter (Fig. 3) allows concluding such relationship for the red and green components. Relationship between existing VI [1,12], which use optical channels R, G, B, and nitrogen content in upper leaves of wheat (dry matter) were calculated basing on the experimental data (Table 1).

The calculations results show that the maximum coefficient of determination (Adj.R^2) was obtained for the green and red color component, confirming the assumption [12] on the feasibility of development of specialized VI for RP.

Soil moisture, presence of cavity and hills also influence optical properties of plants. Standard tester type GreenSeeker takes into account these random factors [16], but appropriate adjustments to the calibration curves should be made quickly. Such mathematical tool as neural networks was suggested for solving this problem.

The resulting image was divided into parts with area of 10x10 meters for construction of a neural network. The size of the area was defined by technological dimensions of fertilization machine and may be adjusted depending on the type and brand of equipment.

Application package STATISTICA, developed by StatSoft was used for statistical data analysis. Variables Var1, Var2 and Var3 meet the numerical value of additive color model in RGB format under: Var1 - R, Var2 - G and Var3 - B.

After analyzing the input data distribution the three measures of central tendency are the same, i.e average is almost equal to the median and mode (Var1- 106,8; 106; 102; Var2-129,1; 129; 121; Var3-75,6; 74 ; 73), and thus all incoming data is normally distributed [17]. That is, the average of statistical characteristics for additive RGB color model can be used as the input of the neural network and fully describe the nature of the image, that is being analyzed.

Classical models of statistical data analysis can be implemented using neural networks (NN) [18] because a definite relationship with continuous nonlinear function may be reproduced by layered network. That is, instead of the input display surface (phase) space, the resulting data with a hyper (AR), several hyper (TAR), or more hyperplane connected one another (STAR), NN can make it arbitrary nonlinear display.

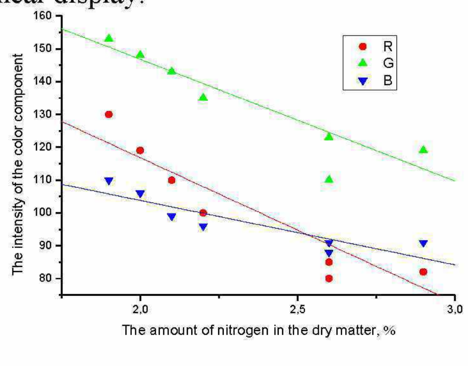

Fig. 3. – Relationship between red color component and light values at different monitoring altitudes.

TABLE 1. RELATIONSHIP BETWEEN NITROGEN AND VI

№	Name	Formula	Adj.R^2
1	VARIgreen	VARIgreen = (G-R)/(G+R-B)	0,85
2	RGR	RGR=R/G	0,79
3	RI	RI=(R-G)/(R+G)	0,81
4	NGRDI	NGRDI=(G-R)/(G+R)	0,81
5	IO	IO=R/B	0,84
6	IF	IF=(2*R-G-B)/(G-B)	0,88
7	I	I=(R+G+B)/30,5	0,82
8	H	H=atan((2R-G-B)(G-B)/30,5)	0,20
9	GLI	GLI=(2*G-R-B)/(2*G+R+B)	0,58
10	IPCA	IPCA =0.994(R-B)+0.961(G-B)+0.914(G-R)	0,83
11	R intensity	-	0,89
12	G intensity	-	0,94
13	B intensity	-	0,82

To synthesize and study appropriate NN the application package STATISTICA was used. Criterion - minimization of NN errors [17,19,21]. The advantage over similar developments is the implementation of the functional optimization unit of NN architecture that uses a linear approach and method for simulating "annealing" based on the probability distribution of Gibbs:

$$P(\overline{x^*} \to \overline{x_{i+1}} | \overline{x_i}) = \left\{ \begin{array}{l} 1, F(\overline{x^*}) - F(\overline{x_i}) < 0 \\ \exp\left(-\dfrac{F(\overline{x^*}) - F(\overline{x_i})}{Q_i}\right), F(\overline{x^*}) - F(\overline{x_i}) \ge 0 \end{array} \right\} \qquad (1)$$

where $Q_i > 0$ — elements random descending down to zero sequence.

The developed neural network is a mathematical model of parallel computing, which includes interacting simple processor elements - artificial neurons; it was implemented to analyse optical images of plantations objects. The research aim is to develope, test and design artificial neural network for the plant state assessment.

For effective operation of the “Statistica Neural Networks” program, input data was divided into three blocks: studying, control, test. The presence of three blocks is not obligatory, however, the "test" blocks improves the quality of further work of NN, since it makes it possible to verify that there has been no "overfitting " of the network.

In terms approximation, the simplest model will be a linear [13,14,15,20,22], in which the approximating function is determined by a hyperplane. In the classification problem, the hyperplane is placed in such a way that it divides itself into two classes (linear discriminant function); in the regression problem, the hyperplane must pass through given points. The linear model is usually accepted by the equation:

$$Y = XW + B \qquad (2)$$

where: W – matrix of weight of the network; B – displacement vector.

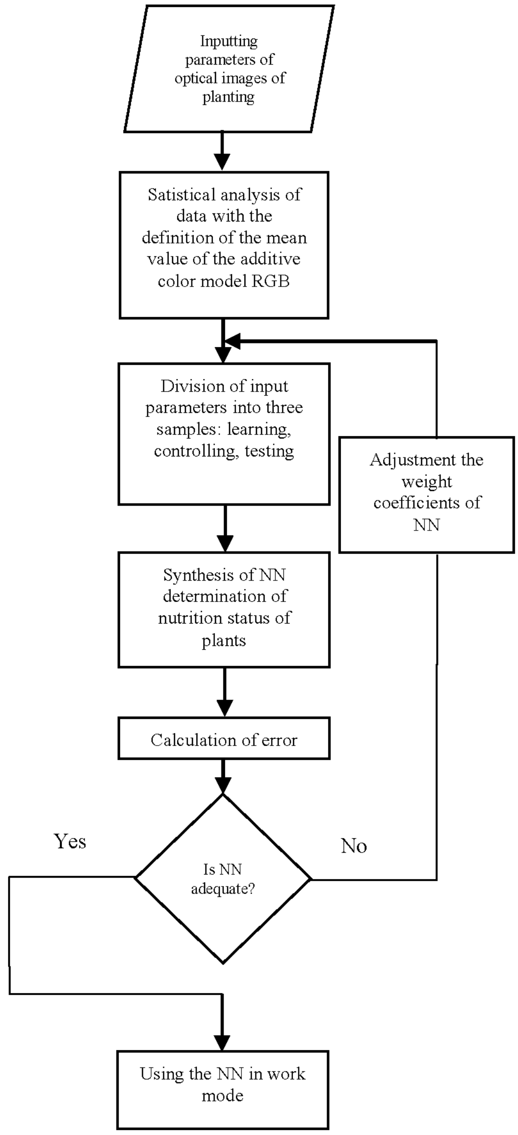

Fig. 4. – NN synthesis algorithm for determination of plant nutrition state.

In the neural networks, the linear model is represented as a network without intermediate layers, which in the output layer contains only linear elements (elements with a linear activation function). The weight corresponds to the elements of the matrix, and the thresholds are the components of the shear vector. During the operation, the network actually multiplies the vector of inputs into the matrix of scales, and then adds a vector of displacement to the resulting vector. In accordance with the algorithm (Fig. 5), a linear NN determination of the state of nutrition of planting plants is synthesized:

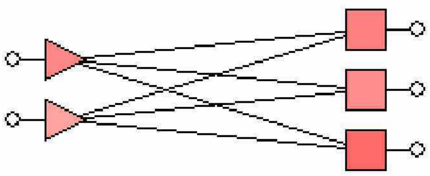

Fig. 5. – The architecture of the linear neural network.

Learning outcomes of the linear neural network:

• productivity: learning - 0,549; control - 0,559; test - 0,492;

• errors: learning - 0,152, control - 0,153, test - 0,154

In NN based on a multilayered perceptron, input signals passing through the synapses into three neurons are input to the inputs, creating a single layer of this network and generating three output signals:

$$y_i = f(\sum_{i=1}^{n} x_i w_{ij}), j = 1,\ldots,3, \quad (3)$$

It is obvious that all weight coefficients of synapses of a single layer of neurons can be reduced to a matrix W, in which each element Wij sets the magnitude of the i-th synaptic relation of the j-ne of the neuron.

Thus, the process occurring in a neural network can be written in a matrix form:

$$Y = f(XW) \quad (4)$$

where: X i Y – respectively, the input and output signal vectors (here and below under the vector is understood vector-string), f (S) - the activation function.

In accordance with the algorithm (Fig. 6) two networks of the type of multilayer perceptron are synthesized for determining the state of plant nutrition:

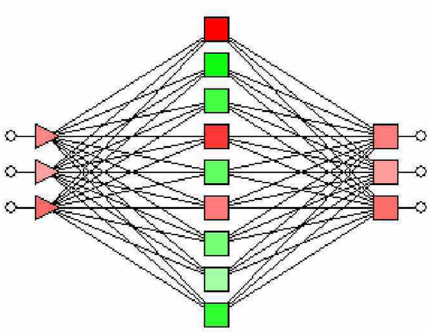

Fig. 6. – Architecture of networks based on multilayer perceptron.

Analyzing the results and schedules of the educational determination of the nutrition status of plants (Fig. 7 - Fig. 9), the use of neural networks to assess the nutritional status of agricultural plantings is sufficiently precise and can be used in the developed system of remote monitoring of agricultural crops.

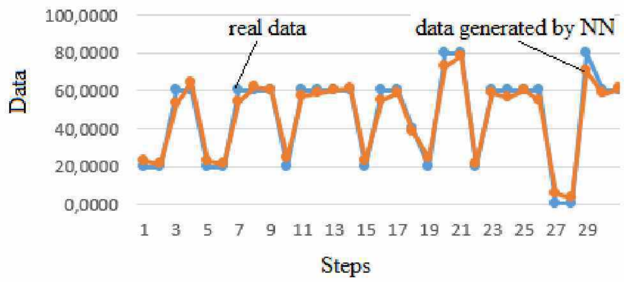

Fig. 7. – Schedule of educational determination of nitrogen supply state of plants by MLP 3:3-9-3:3

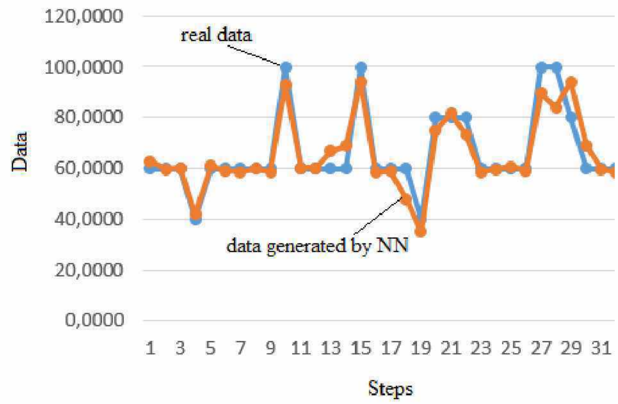

Fig. 8. – Schedule for the educational determination of potash plant nutrition by MLP 3:3-9-3:3

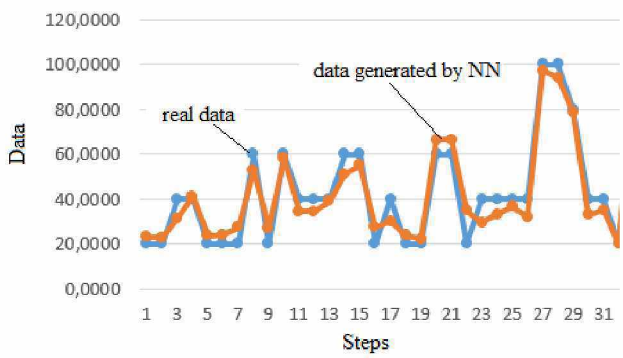

Fig. 9. – Schedule of educational determination of phosphorus plant nutrition by MLP 3:3-9-3:3

As a result of solving an optimization problem the folloing NN were selected as the best: linear with three neurons in the input layer (mistakes: learning - 0.12, control - 0.13, test - 0.127), multilayer perceptron with three neurons in the hidden layer (mistakes: learning: - 0.07, control - 0,076, test - 0.07), generalized regression network has 1,498 neurons in the hidden layer (mistakes: learning - 0.03, control - 0.03, test - 0.03), Radial Basis Function (RBF) with 102 neurons in the hidden layer (mistakes: learning - 0,011, control - 0,013, test - 0.011), RBF with 154 neurons in the hidden layer (mistakes: learning - 0.0109, control - 0 0127, test - 0.0115).

Neural network type RBF showed the best results. RBF network with fewer neurons in the hidden layer was chosen for further research. Code in C ++ was used to develop the crop conditions remote monitoring system with RBF NN. The program code was compiled with the help of a standard compiler for free Unix-like GCC operating systems and implemented in the web-interface of the server, which allowed the use of the created NN remotely, directly in the production environment without high demand of the computing power of a personal computer. Consequently, the neural networks should be used for analysis and image processing of agricultural crops to evaluate the plants nitrogen nutrition. This is a sufficiently accurate method to be used in remote monitoring system.

5. CONCLUSION

It has been experimentally proved that in the optical range the color components intensity of the wheat upper leaves depends on nitrogen content in plants, due to the nutrition level.

The closest relationship between color intensity of wheat upper leaves and nitrogen content in plants is observed for green (coefficient of determination Adj. R2 - 0,94) and red (Adj. R2 - 0,89) components.

Results of the research show how to create the specialized RPVI adapted to technological capabilities of UAVs. It has been experimentally proved that input parameters that describe the state of agricultural plantations are regularly distributed. The average statistical characteristics for additive color RGB model is advisable to be the neural network input instead of large sample data volume.

As result neural network type RBF was synthesized as code in C ++ what can be used in the developed remote web monitoring system of agricultural plants condition.

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