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MODELING OF THE RELATIONSHIP OF THE COLOR FEATURES AND AGROCHEMICAL SOIL INDICATORS USING DIGITAL IMAGES

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Abstract

In this report, alternative tools for determining agrochemical parameters of soil - content of organic matter (humus), pH, phosphorus, potassium and nitrogen, obtained from colour characteristics of digital images from optical devices by statistical methods are proposed. Regression models were developed using two methods: single factor linear regression analysis LR and multifactor linear regression analysis MLR Stepwise. The models were compared and evaluated using accuracy assessment criteria – coefficient of determination (R2), root mean square error (RMSE) and residual prediction deviation (RPD). With the resulting models from data from the camera device, pH can be determined with an accuracy of 99% and phosphorus P with an accuracy of 90%. With the camera of a mobile phone, the content of organic matter can be determined with the accuracy of 96%. The proposed tools could be used in modern smart agriculture as a proposed method for express monitoring of soil agrochemical indicators, as well as implemented in programming mobile, web-based applications for determining the content of organic matter (humus), phosphorus, pH and potassium. Future work involves using other linkage modelling methods to increase the accuracy rate for nitrogen determination.

Keywords: Agrochemical soil indicators, Prediction, Regression models, Digital Images.

1. Introduction

The express and timely monitoring of the soil implies the determination of a large number of indicators - macro and microelements, pH, humus, humidity at each stage of the phenological development of the cultivated crops. A characteristic feature of the modern farm in the application of sustainable smart agriculture is the expansion of the possibilities for the application of digital and optical measuring devices, based on the extremely rapid development of digital microprocessor and computer technology. The integration of high-speed data processing enables the implementation of algorithms and applications in agricultural production related to obtaining fast and timely information from the field, improving the accuracy of measurements and their transmission from a distance, making them a fast working tool for the modern farmer. The massive use of smart information and communication systems requires the development of mobile, web-based and cloud-based technologies that are accessible and easily applicable [1]. Therefore, it is necessary to develop and implement methods for express monitoring of soil composition and properties, which will contribute to finding the much-needed overall balance between preserving the environment, natural resources and meeting the growing needs of agricultural products.

Maintaining the ecological condition of soils is particularly imperative under the conditions of significant climate changes reported in recent years. With modern smart agronomic technologies for growing agricultural crops, accurate and fast information from the field and transmission on mobile devices is increasingly required.

In traditional laboratory measurements, soil samples are examined with analytical methods that include combustion, oxidation, use of chemical substances and harmful products [2], [6], [9]. This type of laboratory measurement is time consuming and requires trained personnel. These are prerequisites to look for innovative, express methods for measuring soil quality directly in the field [10], [12]. Known diagnostic tools for rapid assessment of soil quality are based on spectral analysis in the UV-VIS-NIR region, satellite imagery, unmanned aerial systems UAV and others [3], [4]. Contact-free, non-destructive methods for soil analysis directly in the field have not been proposed yet.

One of the ways to obtain a fast, reliable and inexpensive evaluation of the parameters of the cultivated soil is by modeling information about the color of the soil obtained from optical devices according to algorithms based on mathematical models through statistical methods. The application of static methods for qualitative analysis and computer technology allows the extraction of information from difficult-to-interpret optical data. In the literature, there are a number of examples of finding relationships between soil color and indicators such as the presence of moisture, soil organic matter, iron impurities, etc. [5], [6], but despite research in this field, there are still aspects not covered and opportunities to search for effective and rational solutions for remote determination of soil quality by its color.

For the conditions in Bulgaria, similar methods for express monitoring of agrochemical indicators of the soil - content of organic matter (humus), phosphorus, pH and potassium, based on computer vision and image analysis techniques have not been applied. All this gives reason to undertake a scientific study on the possibility of modeling the relationship of the color characteristics of digital soil images obtained from optical devices and the agrochemical indicators of the soil as an alternative and rapid measurement method.

The previous research access of the influence of external factors on the measurement of a basic soil quality parameter [16] but the method is based on lab equipment and standardized methods and is time consuming and expensive.

The aim of the research presented in this paper is to find mathematical models that describe the relationship between the agrochemical parameters of the soil, the content of organic carbon-humus H, pH, nitrogen N, phosphorus P, potassium K and the selected color characteristics obtained from the images of soil samples by selected optical devices – document camera (Dd), camera (Df), mobile phone camera (Dt) and colorimeter (Dk), from those presented in press [7].

2. Material and methods

The most frequently applied methods in modeling when looking for a quantitative relationship between the values of the predicted quantity and the input characteristics are the regression methods.

This study seeks to describe the relationship and create mathematical models between the values of the soil parameters organic carbon-humus content H, pH, phosphorus P, potassium K and the selected informative color characteristics in a previous study in press [7] obtained from selected optical devices Dd, Df, Dt and Dk.

The tasks to be solved are related to finding a regression model that describes the relationship between the conditional mean E[Yk] of the soil parameters E[Yk] = E[H, pH, N, P, K], [14] and the selected informative color characteristics listed in Table 1.

Optical devices	Optical drive code	Selected informative color characteristics and indexes
document camera	Dd	R'd, Sd, Sdix, Cdix
camera	Df	R’f, Sf, bf, Sfix
mobile phone camera	Dt	R't, bt, Vt, Btix
colorimeter	Dk	R'k, Skix, Ckix, Ik

Table 1. Selected informative color characteristics and indices obtained from optical devices

The regression models were built using two methods: single-factor linear regression analysis LR and multi-factor linear regression analysis MLR Stepwise [14], [15].

Obtaining linear regression models by the LR method with one regression factor.

The regression factor in this study is the common to all devices color component R' of a model (RGI) [11], which is a normalized red color value. Linear regression models by the LR method were obtained in the MATLAB programming environment with the Curve Fitting Tool function.

Fig. 1 shows a screenshot of the selection of variables involved in the regression equation for determining humus H with the **R'**f color component for a camera.

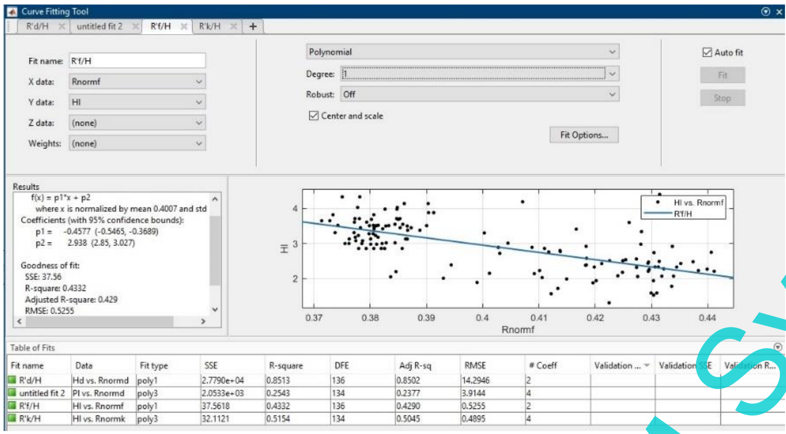


Fig. 1. Screen of obtaining linear regression models with the Curve Fitting Tool function in MATLAB R2021a.

The general form of the regression equation has the form:

$$Y = b_0 + b_1 \mathrm{R}'n$$

where: n is the type of optical device; b_0 and b_1 are regression coefficients, [13].

The correlations were obtained between the values of R' from a model (RGI) of the soil samples obtained by the optical devices Df, Dt, Dd, Dk and the values of the soil indicators presented in Table 2.

Soil index	**Correlation matrix**			
	R'f	**R't**	**R'd**	**R'k**
Content of organic carbon - humus H, measured by the Turin method	-0,77	0,87	-0,84	-0,80
Mobile forms of phosphorus P_2O_5 – P, determined spectrophotometrically, by the Egner-Riem acetate-lactate method	0.62	-0.56	0.60	0.59
Mobile forms of potassium K_2O – K determined by Egner-Riem acetate-lactate method with flame photometer	-	0.44	-0.49	-0.32
Values of Soil reaction pH, determined potentiometrically in a soil suspension, with the soil : water (e. H_2O) ratio being 1 : 2.5	0,43	-0.26	0.34	0.32
The mobile forms of nitrogen N-NH3+N-NH4, determined by the Kjeldahl method	-	-	-	0,21

Table 2. Correlation coefficients for determining the relationship between soil indicators and color component R' from a model (RGI) for individual optical devices

Correlation coefficients with values from -0.77 to 0.87 indicate that there is a strong relationship between soil indicator humus H and color component R' from all optical devices. The relationship with the correlation coefficients between the indicator mobile forms of phosphorus P2O5 – P and color components R' from all optical devices with values in the range from -0.56 to 0.62 is significant. Indicators pH and potassium K2O – K have a moderate dependence with color components R = 0.34 R'f from the camera R = 0.43 and R'd from the document-camera device R = 0.49 respectively. For an indicator of absorbable forms of nitrogen, there is a weak dependence only with the color component R'k. Regression models were built on data from the strong and significant correlations.

Obtaining MLR Linear Regression Models with Multivariate Linear Regression Analysis and Stepwise Technique

In order to check the possibility of predicting the soil indicators with more color components included, besides the common to all devices color component R', the data of the already determined color components with the greatest informativeness were applied (Table 1).

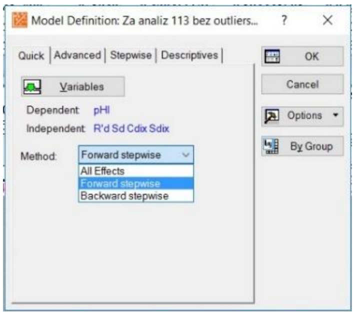
The method of multivariate linear regression analysis and stepwise regression technique (MLR Stepwise) which is applied when multicollinearity must be avoided without losing information about the input color data. The general form of the required regression model is:

$$Y_k f = b_0 + \sum_{1}^{n} b_l\, f(X_n)$$

where Y_k are the values of the required soil parameters; b_o , b_l – regression coefficients, $f(X_n)$ is the color data for n number of color variables for individual f devices. The regression equation has the form:

$$Y_k f = b_0 + f b_1 x_1 + f b_2 x_2 + \cdots + f b_k x_n,$$

A multivariate linear regression analysis was performed for the soil parameters organic carbon-humus H content, pH, nitrogen N, phosphorus P, potassium K and the selected color characteristics obtained from the images of soil samples from the selected optical devices Dd, Df, Dt and Dk (Table 1). Regression models were obtained with the STATISTICA StatSoft package and Stepwise method selection shown in Fig. 2.



a)

	Regression Summary for Dependent Variable: K R= 0,32 R^2= 0,10 Adjusted R^2= 0,08 F(3,108)=4,0191 p					
	b*	Std.Err. of b*	b	Std.Err. of b	t(108)	p-value
Intercept			196,95	75,29	2,62	0,01
I'k	-0,42	0,21	-0,44	0,21	-2,06	0,04
Ckix	4,45	2,64	160,44	95,34	1,68	0,10
R'k	-4,25	2,67	-320,95	201,92	-1,59	0,12

b)

Fig. 2. a) Stepwise method selection from STATISTICA StatSoft package
b) regression analysis results

Obtaining regression models for determining the content of organic carbon-humus H by the LR and MLR method with the Stepwise technique

The study involved soil samples from three investigated arable fields with different organic carbon content from 1.31% low stocked to 4.40% very high stocked [8] (Table 3).

Soil index	Organic carbon, %			
	Mean	**Minimum**	**Maximum**	**Std.Dev.**
Content of organic carbon - humus, measured by the Turin method	2,94	1,31	4,40	0,69

Table 3. Descriptive statistics for organic carbon content

The average content of organic carbon in the samples of the three soil types was 2.94%. The larger range of organic carbon content in the calibration group is an important factor in obtaining a calibration equation, which with proven high accuracy of determining this parameter, could be successfully applied in determining organic carbon of new soil samples, characterized with a wide range of organic carbon content.

A regression model for the determination of humus in soil	R	R^2	RMSE	F	p-value
Hd =5,70-6,77. R'd	-0.83	0.68	0.34	F(1,136)=155,17	p < 0,05
Hk =3,97-3,04. R'k	-0.70	0.49	0.50	F(1,136)=128,86	p < 0,05
Hf =11,24-20,71. R'f	-0.66	0.43	0.53	F(1,136)=103,92	p < 0,05
Ht = 25,92. R't -6,89	0.85	0.75	0.32	F(1,136)=101,39	p < 0,05

Table 4. Values of the criteria for determining the adequacy of the obtained models

Table 4 shows the regression models with the adequate regression coefficients for predicting the content of organic carbon-humus in the soil by the individual optical devices. The significant coefficients of the models were calculated and analyzed for adequacy depending on the value of the Fisher coefficient and p-value. Nonsignificant coefficients, those for which p values > 0.05 were not included in the models. From the given example in figure 2 b) it is clear that the coefficients in front of the color parameters Ckix and R'k are insignificant and will not be applied in the model.

The significance of the regression coefficients and the adequacy of the entire model were assessed. The correlation coefficient R, coefficient of determination R2, Fisher's criterion, the probability p-value at the significance level $\alpha=0.05$ and the value of the root mean square error of the models RMSE were determined, which are criteria for determining the adequacy of the obtained models. In the obtained models for humus determination, the p-value is below 0.05, which indicates their adequacy. The RMSE values are relatively low, in the normal range of 0.32 to 0.53. The coefficient of determination R^2 indicates that 73% of the humus variation is due to the color parameter R't obtained from a mobile phone camera and described by the linear model. Highest values of coefficient of determination 0.85, correlation coefficient 0.73 and lowest value of RMSE=0.32 shows the model obtained for mobile phone camera. A model was also built for this device using the MLR Stepwise method.

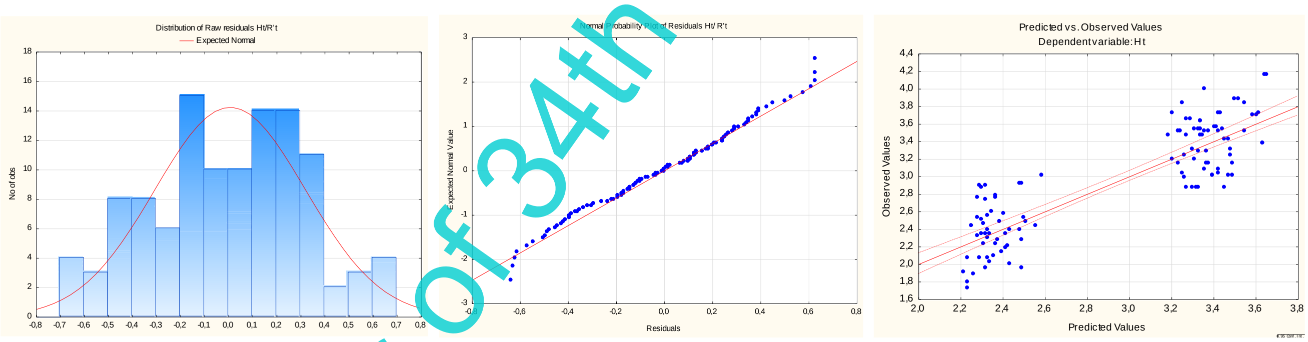
The regression models for soil humus index obtained from the color data by the mobile phone camera using linear regression LR and multivariate linear regression analysis MLR Stepwise and their characteristics are summarized in Table 5.

linear regression method LR	**Model evaluation criteria**			**linear regression with method MLR Stepwise**	**Model evaluation criteria**		
Organic carbon - humus	R	R^2	RMSE	Organic carbon - humus	R	R^2	RMSE
Ht = 30,41. R't - 8,63	0.85	0.73	0.32	Ht = 1,99+0,04.bt	0.87	0.75	0.31

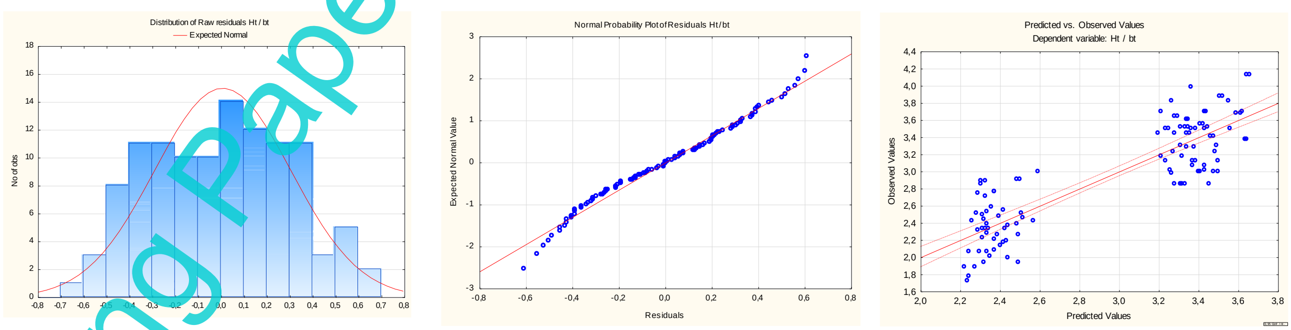
Table 5. Regression models and characteristics for humus soil indicator obtained from the color data from mobile phone camera device by two methods: LR and MLR Stepwise

From the higher value of the coefficient of determination R=0.87 and the coefficient of determination R^2 and the lower value of RMSE, it is evident that the model built by the MLR Stepwise method improves the model built by the LR method.

The distributions of the residuals for these models were estimated, thus verifying that the prerequisites for regression analysis were met. The normal probability plot of the residuals of the obtained models for humus H from a mobile phone camera by the two methods are shown in Fig. 3 a) and b).



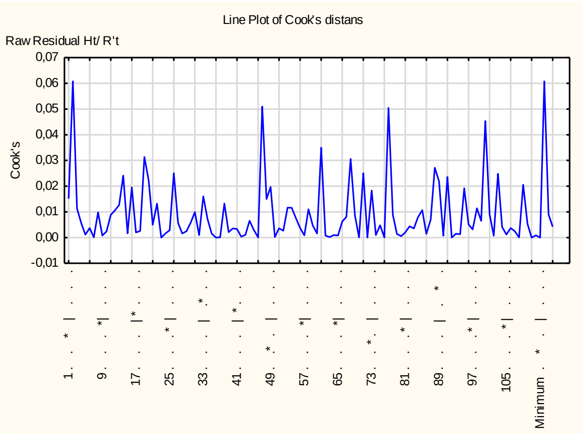
a)

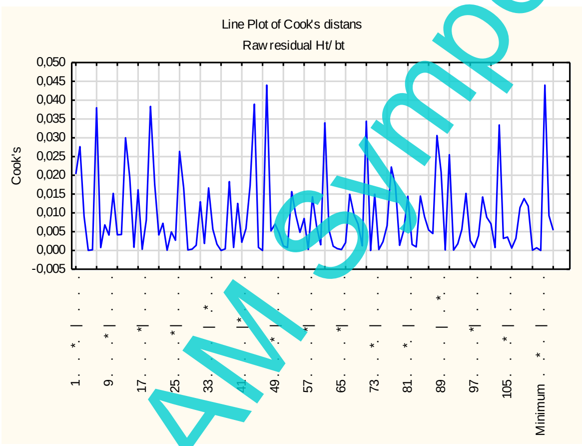


b)

Fig. 3. Distribution of residuals, normal probability plot and graphical representation of the models for determination of humus H a) linear regression method LR; b) linear regression with method MLR Stepwise

From the graphs in Fig. 3 it can be concluded that the distribution of the residuals follows a normal law and their location is close to the regression line. The confidence region for the predicted value of H from data by the MLR Stepwise model is narrower, suggesting a higher accuracy of the model. This is evident from the Cook's method inspection graphically presented in Fig. 4. In the LR method, the systematic deviations of the measured data by the Cook method are reaching 0.06 in samples 1, 49 and 80 and are 40% greater than those in the MLR Stepwise method, which are within 0.04 (Fig. 4).





а) б)

Fig. 4. Systematic deviations of measured data by Cook's method for a) linear regression method LR; б) linear regression method MLR Stepwise.

Obtained regression models for determining the content of pH, nitrogen N, phosphorus P, potassium K by methods LR and MLR Stepwise

Table 6 summarizes the characteristics of the built regression models for soil indicators humus, phosphorus, pH, potassium and nitrogen by methods LR and MLR Stepwise.

linear regression method LR	**Model evaluation criteria**			**linear regression with method MLR Stepwise**	**Model evaluation criteria**		
organic carbon - humus	**R**	**R²**	**RMSE**	**organic carbon - humus**	**R**	**R²**	**RMSE**
Ht = 30,41. R't - 8,63	0.85	0.73	0.32	Ht = 1,99+0,04.bt	0.87	0.75	0.31
Phosphorus				**Phosphorus**			
Pf = -29,89+107,59. R'f	0.60	0.36	3.58	Pf =0,63.bf	0.62	0.38	3.58
Pk = 7,80+16,69. R'k	0.58	0.34	3.64	Pk =13,07 + 5,83.Skix	0.59	0.34	3.64
Pd = 29.11. R'd	0.49	0.24	3.93	Pd =11.24 +15.8.Cdix	0.58	0.33	3.67
Pt = 60.06 -123.56. R't	-0.48	0.23	3.94	Pt = 16,39 - 0,26.bt	-0.50	0.25	3.90
pH				**pH**			
pHd = 5,33+2,88R'd	0.34	0.12	0.75	pHd=104,45+11,28Sd-297,22R'd + 66,91Cdix + 65,09Sdix	0.44	0.20	0.72
pHk =6,08+1,26R'k	0.25	0.06	0.80	pHk =6,06+0,02Ik	0.35	0.13	0.74
pHf =3,11+8,57.R'f	0.43	0.18	0.72	pHf =77,29-206,61R'f+41,66Sfix	0.48	0.23	0.71
pHt = 10,09-9,45R't	-0.20	0.04	0.81	pHt =7,07-1,16Vt	-0.26	0.08	0.80
Potassium				**Potassium**			
Kt = 17,43+127,29R't	0.24	0.06	11.50	Kt =-5,4B**tix**-4,73bt+1374,75Rt	0.44	0.20	10.80
Kd = 80,695169-36,83R'd	0.30	0.09	11.28	Kd =69.49-12.95.Sd	0.49	0,24	10.60
Kk = 71,29-16,59R'k	0.22	0.05	12.69	Kf= -585,25-585,25R'f-376,40. Sfix	0,32	0.10	12.46
Nitrogen				**Nitrogen**			
There is no adequate model		-	-	Nk=67,99 -135,87R'k+ 1,72I'k	0.21	0.05	41,83

Table 6. Summary characteristics of the built regression models for soil indicators humus, phosphorus, pH, potassium and nitrogen by two methods LR and MLR Stepwise for the individual optical devices

For the obtained models, the level of significance and adequacy was assessed by determining the correlation coefficient R, determination coefficient R^2 and the value of the root mean square error RMSE. RMSE values were lowest for humus and pH models for both methods, but with MLR Stepwise errors being 5% lower. For phosphorus determination models, the RMSE values were 3.8% lower with the MLR Stepwise method. The coefficient of determination R^2 shows a significant increase in the MLR Stepwise models for pH and K parameters.

A cross-validation procedure was conducted, which aims to test how well the resulting models predict soil parameters by comparing the actual measured laboratory values of humus, phosphorus, potassium, and pH with the model-derived values. If the model results with the test set are close to those with the calibration subset, the output model is assumed to be valid and its accuracy can be determined.

When creating the models, the option was chosen to work with the values of the soil indicators for all 138 soil samples, and the test sample was formed with 30% of them using the Monte Carlo method [13], [15]. The method is implemented in the package Statistica StatSoft and in Fig. 5 a screen of selection is shown.

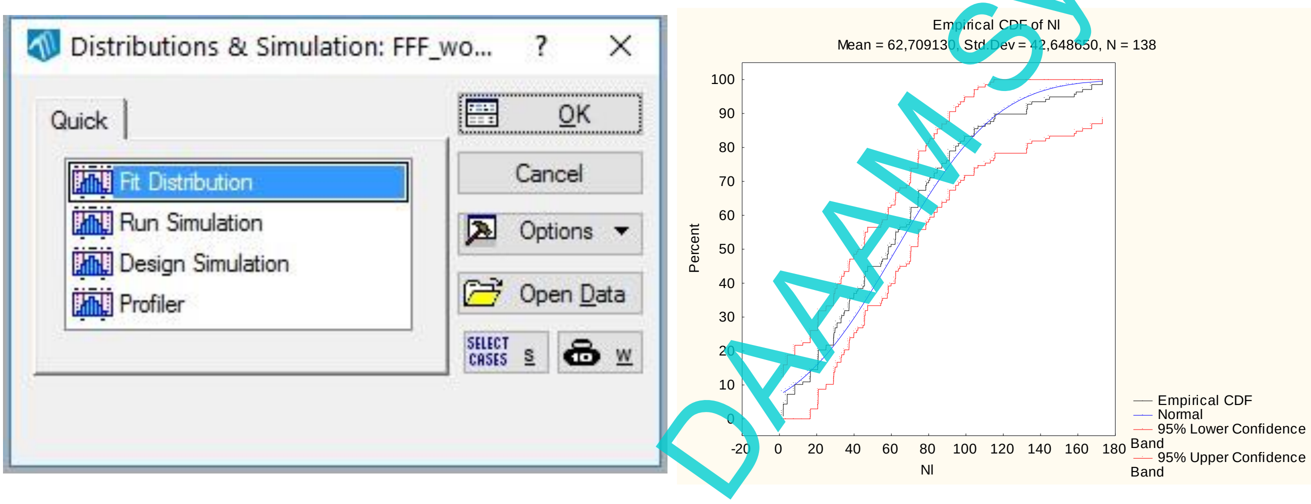


Fig. 5. Monte Carlo method selection settings

For this purpose, all adequate models obtained by both methods were checked for 40 observations from the test set.

As criteria for evaluating the calibration predictive models, root mean square error (RMSE) obtained was calculated by the formula (1):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{i\,izm} - y_{ipred})^2} \tag{1}$$

and residual prediction deviation ***RPD***, which is obtained by the formula (2):

$$RPD = \frac{SD}{RMSE} \tag{2}$$

where ***SD*** is the standard deviation of the values (3):

$$SD = \sqrt{\frac{\sum |Yi\ izm - \bar{Y}|^2}{N}} \tag{3}$$

The results of the calculated model evaluation criteria are summarized in Table 7. Post-validation statistical parameters describing the calibration equations obtained with MLR analysis indicate the highest accuracy in determining soil response pHH with data from the camera device, with correlation coefficient values $R^2 = 0.99$ and the lowest accuracy in determining nitrogen with $R^2 = 0.65$ (Fig. 6).

Criteria calibration model				**Post-validation criteria**		
soil index	**R**	**R^2**	**RMSE model**	**Accuracy model R^2**	**RMSE model**	**RPD**
pH						
pHf	0.43	0.18	0.72	0.99	0.80	4.84
pHdSw	0.35	0.12	0.75	0.99	0.83	4.65
Potassium						
KtSw	0.44	0.20	10.80	0.97	11.97	4.95
KdSw	0.49	0.24	10.60	0.97	11.69	5.07
organic carbon - humus						
HtSw	0.87	0.75	0.31	0.96	0.56	5.02
HdSw	0.84	0.70	0.33	0.77	1.83	1.64
Phosphorus						
PfSw	0.62	0.38	3.58	0.90	4.69	4.59
PkSw	0.59	0.34	3.64	0.90	4.73	4.56
Nitrogen						
Nk	0.21	0.04	43.11	0.65	41.52	4.83

Table 7. Criteria for evaluating the accuracy of models after validation.

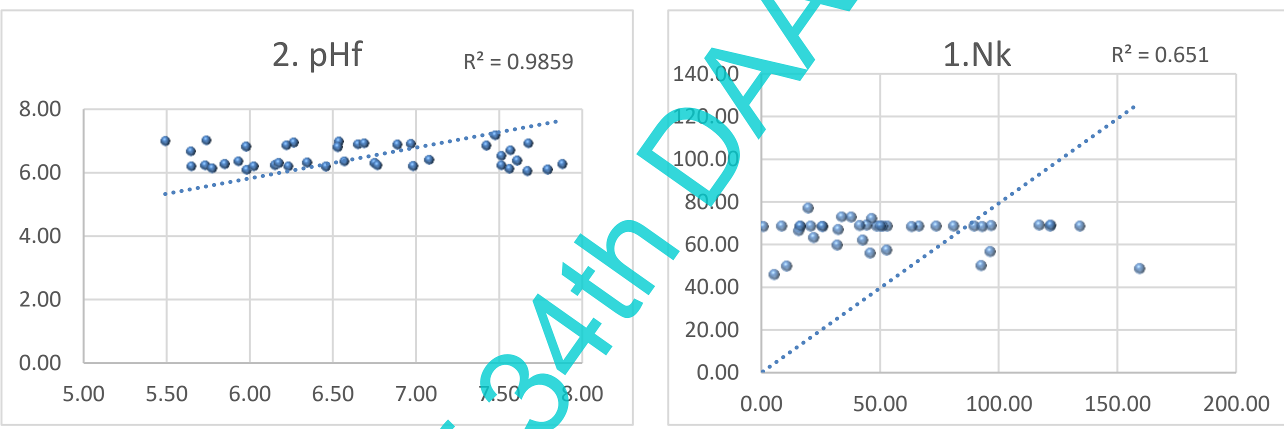


Fig 6. Graphical representation of the correlation coefficient pHf, R2 = 0.99 and nitrogen Nk with R2 = 0.65.

The high values of the relation to the measured and obtained by model indicators of soil pH and phosphorus, R2=0.99, 0.90 according to data of the camera device and for indicators, potassium K, R2=0.97, and organic carbon - humus, measured with a camera of mobile phone with strong and moderate dependence on color data shows an excellent possibility of mobile phone camera and camera to be applied as an alternative measuring device for measuring agrochemical parameters of soil directly in the field or farm.

High values of RPD, which are above 3 [10] in the interval 4.56-5.07, classify the obtained models as models with very high - excellent accuracy.

From the accuracy results of the models, it was found that the color data from the camera device could be used to determine potassium phosphorus and pH. To determine humus and potassium, device camera on a mobile phone. The colorimeter device shows the ability to measure phosphorus and available forms of nitrogen with high error.

The document-camera device shows a high accuracy of 0.99, 0.97 for the determination of pH, potassium and humus with linear regression models, which is most likely due to the local homogeneous illumination.

According to the coefficient of determination R2, the Stepwise regression method supported the models by an average of 13.5% when determining K and pH with a device camera and a mobile phone camera, and showed a weak or weak relationship with absorbable forms of nitrogen by color data from a colorimeter device . The (RMSE) values of the humus and pH models are within normal limits in the range 0.56 – 0.80. For the indicators, phosphorus has a value of 4.69 and potassium 11.69, which leads to errors.

3. Conclusion

The experimental results shows that linear regression models using two regression methods (LR, MLR- Stepwise) could describe the relation between soil agrochemical indicators H, pH, P, K, N and color characteristics obtained from images of soil samples from optical devices.

The values of error (RMSE) of the models created by the Stepwise method for the parameters potassium and pH are up to 10% lower than those created by the linear regression LR method.

Absorbable forms of nitrogen can be modelled with the stepwise regression method only with color characteristics obtained using colormeter device.

Analysis of agrochemical parameters of the soil in the field or on the farm using a camera and a mobile phone camera can allow obtaining stand-alone results in real time. The application of mobile devices as a measuring instrument in agriculture would facilitate the work of the farmer as a complementary method to chemical laboratory measurements to determine soil quality for on-site analysis.

4. Acknowledgments

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