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SPOT-BASED PROXIMAL SENSING FOR FIELD-SCALE ASSESSMENT OF WINTER WHEAT YIELD AND ECONOMICAL PRODUCTION

SUMMARY

The study was conducted on a test field with an area of 255 ha including four winter wheat varieties (Basmati, Farinelli, Balaton, and NS40S). The objective of this research was to evaluate the suitability of NDVI and soil ECa data in the modeling of selected winter wheat properties. The results in this paper are based on observations of a plant canopy at 40 locations using an NDVI sensor measured at four stages (BBCH65, BBCH75, BBCH83, and BBCH89), as well as soil electromagnetic conductivity using an EC probe before analysis had commenced. The strongest relation between yield components and NDVIs was observed in the milk growth stage (R ranged from 0.30 to 0.67). Poor correlation was determined between soil ECa and wheat traits. Ordinary least squares regression gave models where average NDVI and soil ECa described 75% variation in plant height of the Balaton variety; 74% of Farinelli plant height changes were characterized by NDVIBBCH65 and EC; 73% of Basmati yield was explained by NDVIBBCH75 and EC. Sufficient rainfall during the growing season, high fertility of the soil and appropriate temperature regime lowered the influence of spatial heterogeneity on final crop outcomes due to optimal water and nutrition uptake.

Keywords: geostatistics, NDVI, soil apparent electrical conductivity, wheat, yield prediction.

INTRODUCTION

The efficiency of soil and plant management is strongly dependent on the method of data collection hence data validity and data usability in the decision-making process. Huge scientific resources have been allocated in the

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development of farmer-friendly sensing devices (low price, easy to handle, high efficiency), algorithms and PC software that could be equally efficient in various agro-ecological environments. The most advanced techniques used in temporal studies have been provided from informatics (big data, machine learning, geostatistics, etc.). Some authors have worked on the development of algorithms for distinguishing "good" from "bad" data, on the form and pattern recognition (Moshou et al., 2002; Pantazi et al., 2016), designs of self-driving robots, etc. Optical sensors have become very popular in crop scouting and scientific research. Simple handling and non-destructive measurement make them suitable for wide range of applications on different crops, and instant data can be collected without biomaterials destruction (Raun et al., 2002; Magney et al., 2016; Ljubičić et al, 2017). The results of studies based on remote or proximal optical sensors offer a vast number of vegetative indices which could be used in the prediction of crop maturity, yield potential, plant health estimation, detection of weeds and pests, etc. Spectral analysis of reflected waves from either plant canopy or soil is valuable in recognition of spectral "fingerprints", which help identify some biotic or abiotic processes that are otherwise undetectable by human or machine. Multispectral sensors use natural source of light which highly depends on the sun exposure, cloudiness, architecture and reflective characteristics of scanned objects that could jeopardize recording stability in time, especially if large field area is observed which requires a lot of time (Oberti et al., 2014; Whetton et al., 2017). From empirical point of view, commercial NDVI devices that use artificial source of light are more convenient solution for spectral reflectance sensing. They are more confident in all weather conditions, easy to use, provide instant data, can be hand held, attached to sensor based variable rate applicators or carried by UAVs. NDVI maps ensure insight into crop spatial variability, but single parameter is not sufficient to reveal the real causes of yield variability. Due to the complexity of soil and its influence on plant development, additional examinations in form of standard scientific measurement or proximal sensing increase the quality of spatial modeling and robustness of gained solutions (Huete et al., 2012; Kostić et al., 2016; Magney et al., 2016). Winter wheat is suitable for spectral scanning due to high plant population and early soil coverage. Successive NDVI measurement during the wheat growing period might offer reliable yield prediction modeling (Raun et al., 2002). Also measurements of apparent electrical conductivity (ECa) using electromagnetic induction (EMI) give information related of soil physical properties, and it is broadly used to delineate management zones of yield potential (Bramley, 2001; Rodrigues et al., 2015; Quinta-Nova and Ferreira, 2020).

The objectives of this research were to evaluate the suitability of NDVI data and soil ECa data in the modeling of selected winter wheat properties.

MATERIAL AND METHODS

The study was carried out at the field located in the northern part of the Republic of Serbia (45.563785N, 19.876757E) on calcic chernozem type of soil during the 2015/2016 growing season. It is used in traditional wheat-maize-soybean crop rotation with conventional deep plowing or chiseling as primary tillage. According to Kovačević et al. (2012), Serbia climate conditions could be characterized with higher precipitation sums in autumn and winter, and significantly lower in spring, which is the critical period for wheat development. Table 1 shows significantly higher amount of rainfall in the 2015/2016 growing season compared to an average value obtained from long-term climate data. Field area grown with winter wheat covers 255 ha in total. Four varieties of winter wheat were used in the experiment (Basmati, Farinelli, Balaton and NS40S). The sowing was started on 15th October and finished 12 days later in 2015, with a seeding rate 255 kg/ha and 15 cm row to row distance.

Table 1. Climate parameters for observed field in 2015/2016 growing season

Month	Oct.	Nov.	Dec.	Jan.	Feb.	Mar.	Apr.	May	Jun.	Total
Temp. (ºC)	11.3	7.8	3.2	1.2	7.3	7.9	14.3	16.7	21.6	91.3
Precip. (mm)	74.6	56.1	3.6	51.6	49	65.3	74.2	84.6	143	669.32

Soil sampling was done by a specialized vehicle equipped with a GPS receiver and automatic sampling device (340 samples were taken). Additional observations of soil and plants in the field were conducted at 40 common locations (10 per variety) which were scattered in order to ensure approximately equal coverage considering the irregular subfield shape (Figure 3b). Apparent soil electrical conductivity (ECa) was measured prior to sowing using an EM38-MK2 device (Geonics Ltd., Ontario, Canada). Measurement was done in vertical mode covering the surrounding area of the observed locations as well. Average ECa values for each location were obtained and subsequently compared with other parameters. NDVI measuring was performed with a commercial hand-held sensor (GreenSeeker, Trimble USA) in four growing stages of wheat: full flowering (BBCH65), medium milk (BBCH75), early dough (BBCH83) and fully ripe stage (BBCH89). NDVI measurements were taken by holding GreenSeeker about 60 cm horizontally above the crop canopy and moving in zig-zag pattern including approximately 10x10 m of sensed area. The obtained values were averaged to get a single representative value of the location. Yield components (plant height, spikes/m^2, ear length and grain yield) were assessed from the plant samples collected at full maturity stage from one square meter in five repetitions at the observed area (40 locations, Figure 3a). Also, yield maps were generated using the data collected by the harvester monitors. Since the absolute accuracy of yield monitor varies with different wheat varieties due to uneven grain properties, which cause different response of the embedded sensors, the collected yield values were post-calibrated to reduce possible data discontinuity. Unprocessed yield data could skew the results; the values can be underestimated or overestimated depending on the source of the error. Method for data cleaning was based on statistical data interpretation and minimum and maximum yield thresholds. Yield monitoring was done at 1.2-1.3 m distance according to combine average speed and measurement frequency. In order to compare the data recorded by yield monitors and yield data obtained from samples, certain yield monitor data were manually extracted using GIS. The selection was done on the map by choosing the points-data within 10 m diameter around each location of observation, and the mean value was calculated afterwards (Figure 2a). The obtained linear models given in Table 2 show how well are fitted grain yield data from yield monitor and from samples. The quality of adjusted yield values was evaluated by using the RRMSE parameter which indicates that differences are regular for all varieties, and confirms the confidence of the models.

Table 2. Comparison of wheat yield data collected with yield monitor and standard sampling for postharvest yield monitor data correction.

Variety	$Q_{Ym}(y)$	$Q_{Ob}(x)$	Q_{adjust}	Model	$R^2(x, y)$	RMMSE
Basmati	7246.4^{a}	7672.8^{a}	7673.3	Q_{adjust}=1.05Q_{Ym}+76.8	0.97	2.03
Farinelli	8884.7^{b}	9587.6^{c}	9587.74	Q_{adjust}=0.97Q_{Ym}+945.8	0.86	4.77
Balaton	8149.6^{b}	8464.6^{ab}	8464.76	Q_{Ym}=0.91Q_{Ob}+512.7	0.89	2.01
NS40S	8326.2^{b}	8536.8^{b}	8536.85	Q_{Ym}=0.92Q_{Ob}+502.2	0.74	2.97

Note: ^{a,b,c} different classes obtained by ANOVA (p=0.05); Q_{Ym}(y)-average yield recorded by monitor; Q_{Ob}(x)-average yield calculated from data collected from samples; Q_{adjust}- adjusted yield data.

The regression analysis was used to observe individual contribution of wheat yield components to sensor readings. All statistical analyses were carried out using STATISTICA software (StatSoft Inc., Tulsa, OK, USA). The geostatistical tools were engaged for spatial data analysis. Spatial dependence of the data ware observed and modeled by variogram functions. The kriging interpolation was used for data interpolation, as well as for the mapping. Ordinary least squares (OLS) regression was conducted to determine the relation of NDVIs and soil ECs with yield components. The significance of each explanatory variable was checked with OLS, as well as the normality of distribution of residuals and confidence of the model (Terrón et al., 2011). All geostatistical operations were done in ArcGis software.

RESULTS AND DISCUSSION

Interpretation of 95% confidence intervals was used to assess the difference between mean values given in Figure 1. The results of analysis of the observed parameters revealed that phenotypic divergence of the selected wheat varieties were appropriate for this kind of research in which the reliability of crop and soil scouting technics should be proven. From Figure 1a, it is clear that NDVI reached the highest value (~0.85) around flowering stage when the plant photosynthesis and leaf area were on the top level causing saturation effect and already reported by several authors (Aparicio et al., 2000; Erdle and Schmidhalter, 2013). Afterwards, it gradually decreased until maturity (0.13-0.4) when the reflectance of visible wavelengths increased and reflectance of NIR decreased as a consequence of less absorption of visible light in the leaves (Babar et al., 2006; Naser, 2012; Reynolds et al., 2012b; Sultana et al., 2014).

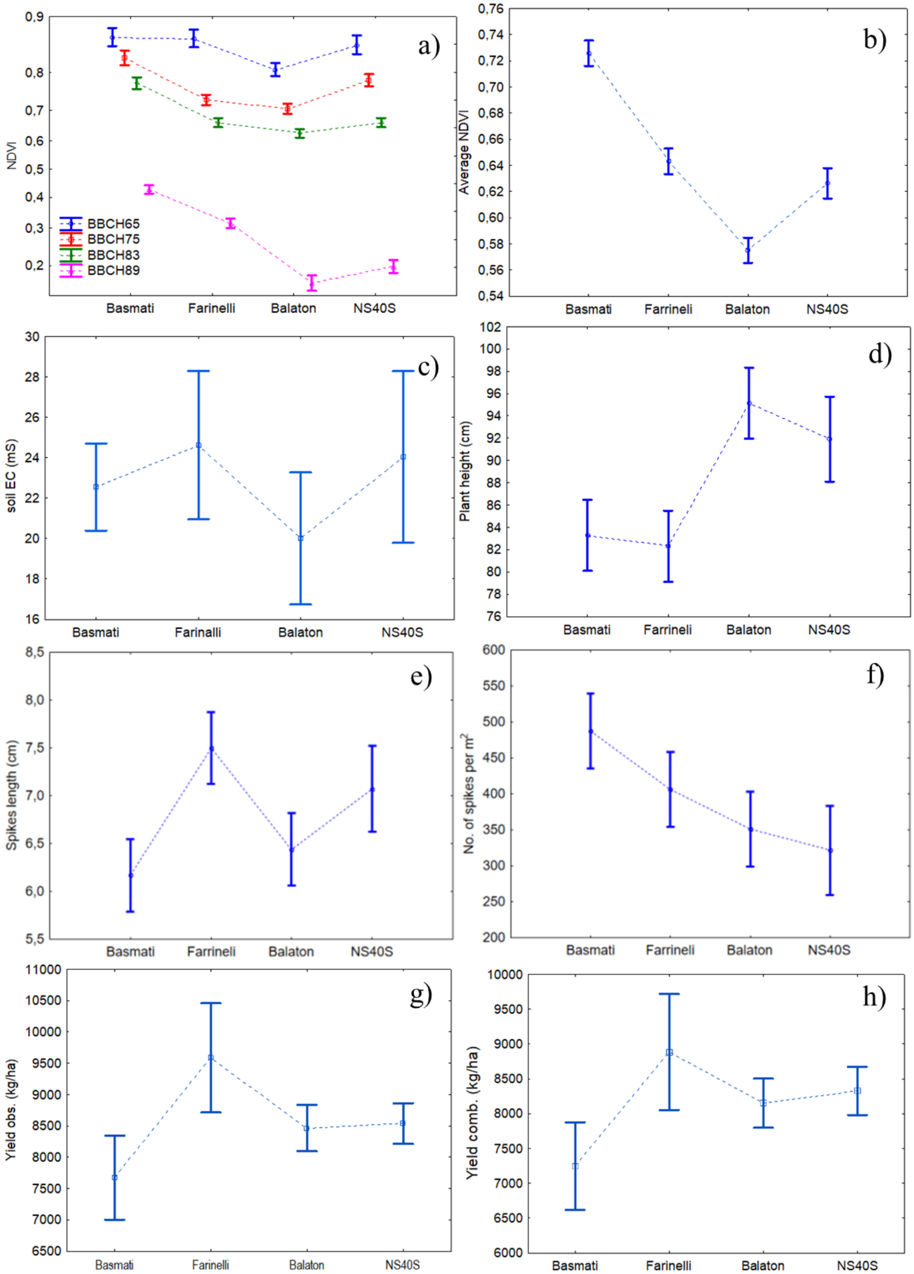

Figure 1. The overall mean values of the observed crop parameters, soil apparent electrical conductivity (ECa) and normalized difference vegetation index (NDVI)

In general, NDVI for all genotypes was slightly decreasing from BBCH65 stage to BBCH83 stage; thereafter, NDVI decrease was more rapid. Slower reduction of NDVI index of Basmati plot (Figure 1a) can be explained by the fact that during maturation period, volume reduction of vegetative parts did not uncover the soil surface as much as in case of other varieties which had less plant density. Hence, the spectral characteristics of reflected light from Basmati plot include more NIR lights and higher average NDVI at all. The Basmati variety had the highest average value of NDVI and spike/m^2 (Figure 1b,f), likewise the lowest grain yield of all included varieties (Figure 1g,h). It could be stated that high average NDVI readings of Basmati plants are induced by higher plant density (spike/m^2) which caused the lower reflection from soil surface (in comparison to other three varieties). According to range of NDVI downtrend of each variety as shown in Figure 1a and their yield performance (Figure 1f,g), the NDVI declining characteristics could be good indicator of tillering and yield potential. Farinelly plants had the longest spikes hence the highest yield. Also, Farinelli had smaller reduction of NDVI index during maturation than Basmati and NS40S.

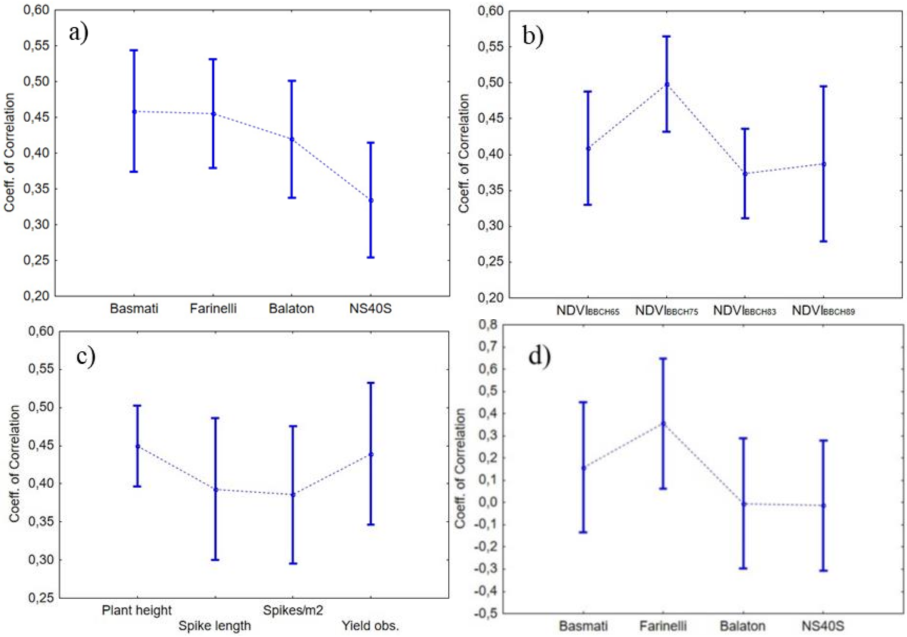

Figure 2. Comparison of R coefficient calculated between selected wheat traits and sensors recordings

According to the range of confidence intervals of soil ECa (Figure 1c), certain data dissipation is evident which implies absence of data normality. Various ECa values of subfield could be the result of elevation impact, hence water and clay distribution over soil layer. The Farinelli subfield had the highest value of soil ECa with very wide 95% confidence intervals. Due to a range of intervals, no meaningful difference was recorded between soil ECa data groups. Concerning plant height feature, the highest average value was obtained for Balaton variety (95 cm), which were similar to NS40S variety (92 cm, Figure 1d). There were no differences between Basmati (83 cm) and Farinelli (82 cm), although these two varieties statistically differed from Balaton and NS40S. The mean values of spike lengths ranged from 6.2 cm for Basmati to 7.5 cm for Farineli, as shown in Figure 1e. It could be noted that similar average values were obtained for Basmati (6.2 cm) and Balaton (6.4 cm) varieties, also between Farinelli (7.5 cm) and NS40S (7.1 cm) varieties. The greatest spikes/m^2 were observed on Basmati plot (480), followed by Farinelli (420), Balaton (350) and NS40S (310) varieties. The last two graphs in Figure 1 are presented to show how well the data on wheat yield from observed locations is matched comparing manual collection with data from harvester yield monitor. For better understanding of relationship between selected parameters and sensors data, the R values are presented as 95% confidence intervals of mean values (Figure 2). The Figure 2a shows that the highest average correlation between NDVI and wheat traits was achieved on Basmati plot (R=0.46) while the weakest correlation was observed between NDVI and wheat traits of NS40S (R=0.33).

If consider the average correlation among NDVI index and phenotypic parameters (Figure 2b), it is clear that stage from full flowering to medium milk appears as the best for the early assessment of wheat outcomes (Hansen et al., 2002, Magney et al., 2016). Based on the width of the confidence interval of the coefficient R (Figure 2c), it can be noted that the parameter plant height was best recognized (R=0.45) considering all varieties and time of measurement. Almost the same value was obtained in case of yield parameter but with lower confidence due to wider confidence intervals. Soil ECa didn’t reach any meaningful correlation with tested varieties or their components (Figure 2d), although the yield of Farinelli could be distinguished from others (R=0.35).

Spatial analysis

The thematic maps are generated to enable additional inspection of spatial arrangement of measured parameters (Figure 3). The map of humus shows that the zones with similar values are randomly grouped in the field without any relation to a particular plot or direction of the field. Certain zones with slightly higher humus content were formed on a subplot with Farinelli variety and they matched with higher grain yield zones. The maps of potassium and phosphorus show certain regularity in spatial distribution. The zone with highest content of P_2O_5 and K_2O in soil is located in the south-west part and changes gradually to opposite direction. This fact is contradictory to the yield map since the greatest yields were achieved in the south-east part. The yield maps visualize spatial variability of gathered yield, which was ranged at most from 6.5 to 10.5 t ha^{-1} (Table 3). The low value zone is concentrated along the right-bottom side of the field and its position coincides with the position of Basmati subplot. Higher yield associated with dark green color overlaps the area where Farinelli variety was grown. On NS40S and Balaton subplots, there is erratic distribution of raster grid with sporadic changes of high and low yield. Field elevation map comprises higher altitude in the bottom zone (Basmati field) and lower in the middle of Farinelli subplot. Spatial structure of altitudes describes a relief, which is one of the greatest contributing factors for crop yield. It is indicative that water availability in soil, and consequently the nutrients, has a significant impact on wheat yield. Considering the results given in Figure 1, it could be concluded that Farinelli and Basmati varieties have the widest confident intervals, which matches the presented spatial pattern of yield map (Figure 3). The results of OLS analysis of the sensor data as the indicator of yield components are presented in Table 3.

Table 3. Characteristics of OLS analysis of selected wheat features and sensed parameters

Yield (Basmati)						
Variables	Coeff.	StdError	t-Stat.	p	VIF	R^2
Model intercept	-1548.69	480.95	-3.22	0.015*	--------	0.73
$NDVI_{BBCH75}$	2268.47	555.52	4.08	0.005*	1.10	
ECa	6.77	2.46	2.76	0.03*	1.10	
Plant height (Farinelli)						
Variables	Coeff.	StdError	t-Stat.	p	VIF	R^2
Model intercept	70.76	9.24	7.66	0.00005*	--------	0.74
$NDVI_{BBCH65}$	10.90	10.78	1.01	0.35	1.05	
ECa	0.09	0.03	2.75	0.03*	1.05	
Plant height (Balaton)						
Variables	Coeff.	StdError	t-Stat.	p	VIF	R^2
Model intercept	-67.88	37.02	-1.83	0.11	--------	0.75
$NDVI_{AV}$	275.24	62.33	4.42	0.003*	1.04	
ECa	0.349	0.21	1.62	0.15	1.04	

VIF greater than 7.5 indicates redundancy in the explanatory variable
*Statistically significant at 0.05 level.

Models with other combinations of explanatory variables (sensor data) in which variables did not reach significant level of contribution were omitted from further analysis. The best correlation, R^2=0.73, was determined between yield and sensor data for Basmati variety which implies that the explanatory variables in their joint interaction have a relatively good potential for wheat yield prediction. The values given in the Coefficient column indicate the degree and type of correlation that exists between the explanatory variable and dependable variable. Statistically significant variables are marked with an asterisk ($p<0.05$). It can be concluded that $NDVI_{BBCH75}$ variable was most influenced by wheat yield, and not so significant relation can be observed between yield and soil EC. This statement supports the R analysis presented in Table 2.

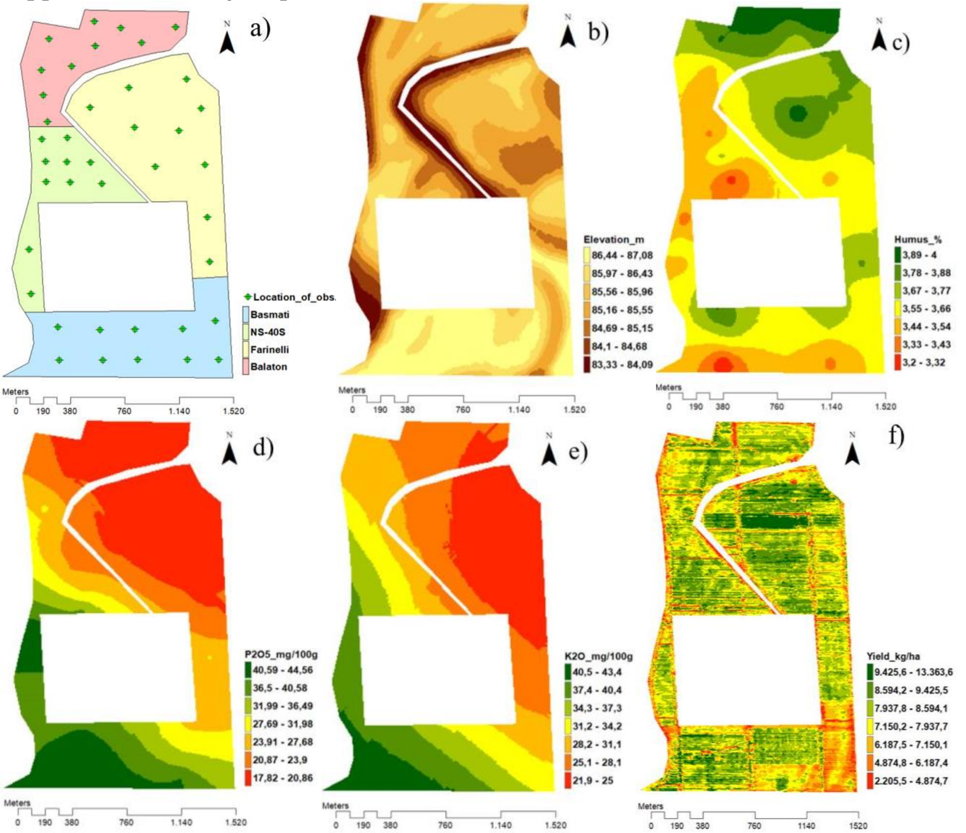

Figure 3. The maps of wheat variety plots, soil properties and wheat yield presented over real geographical proportions

The OLS model found that ECa could be a good predictor of wheat height when considered jointly with NDVIBBCH65. Yield model for Balaton was best explained (75%) with soil ECa and NDVIAV variables, although NDVIAV proved to be equally meaningful in modeling. With OLS analysis, model fitting showed better results compared to the comparison of single parameters. In order to make more confident conclusions, regardless of geographic location and period of observation, more elements need to be taken into consideration followed by various data analysis methods. Without that, the given conclusions could be relevant but only for the specific moment of measurement and the constellation of natural factors that are highly changeable over time and space.

CONCLUSIONS

The presented results of multivariable analysis confirmed that the combined measurements of NDVI and soil apparent electrical conductivity have the potential to identify the differences in soil conditions, crop stand and wheat traits. The best associations between yield components and NDVIs were achieved in milk growth stage with R2 ranged from 30% to 67%. Soil EC didn't match certain correlation with wheat traits and in this case couldn't be characterized as meaningful parameter. Geostatistics partly confirmed the correlations obtained by standard statistics. The quantity of dominant factors and complexity of its interrelations impose constraints in terms of robustness of given models. Uncommon climate condition manifested with sufficient rainfall during growing season diminish the influence of observed spatial heterogeneity on final crop outcomes hence uncovering of certain relationships.

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