DIGITAL TECHNOLOGIES IN AGRICULTURE. SCANFIELD-5S SMART SYSTEM WITH INTEGRATED DIGITAL SOIL CUBE FOR INNOVATIVE SOLUTIONS IN AGRICULTURE [1]

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ЦИФРОВИ ТЕХНОЛОГИИ В ЗЕМЕДЕЛИЕТО. SCANFIELD-5S СМАРТ СИСТЕМА С ИНТЕГРИРАН ДИГИТАЛЕН ПОЧВЕН КУБ ЗА ИНОВАТИВНИ РЕШЕНИЯ В ЗЕМЕДЕЛИЕТО

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ABSTRACT

In the conditions of intensively developing digital technologies, agriculture is also an active environment for their application. The article demonstrates some of the capabilities of the intelligent Scanfield-5S system and the integrated DSC - "Digital Soil Cube" for assessing the condition of the soil. The DSC method uses non-contact measurement of electrical conductivity (ECa) up to 0.4m depth in the soil. The study was usually conducted after harvest and before agricultural operations for the next crop. All collected ECa data are georeferenced. An adaptive soil sampling scheme was applied, which is specific for a given field. The number of sampling sites was determined after applying a graph-analytical method. A high confidence probability (over 80%) was obtained from the ECa data, which is a confirmation of the suitability of the method. Analyses were performed for bulk density (BD), relative humidity (dW), clay content (Clay), organic matter (OM) and activated carbon (C_(act.)) in the soil. The presented results characterize the soil as homogeneous with relatively good biological indicators (OM and C_(act.)). The adaptive soil sampling scheme and the obtained regression models for the soil parameters are specific to the studied field. The regression models for the observed parameters are linear and are presented through spatial resolution maps. The Scanfield-5S system provides solutions such as variable rate maps (VRA), soil carbon prediction, and overall soil health assessment. The digital soil model created using the DSC method is specific to the field under study, but has the potential for universality.

РЕЗЮМЕ

В условията на интензивно развиващи се цифрови технологии селското стопанство също е активна среда за тяхното приложение. Статията демонстрира част от възможностите на интелигентната система Scanfield-5S и интегрирания DSC – „Digital Soil Cube” за оценка на състоянието на почвата. DSC методът използва безконтактно измерване на електрическата проводимост (ECa) до 0,4 m дълбочина в почвата. Проучването обикновено се провежда след прибиране на реколтата и преди земеделските операции за следващата реколта. Всички събрани данни от ECa са геореферирани. Приложена е адаптивна схема за вземане на почвени проби, която е специфична за дадено поле. Броят на пробовземните места е определен след прилагане на графо-аналитичен метод. От данните на ECa е получена висока степен на доверие (над 80%), което е потвърждение за пригодността на метода. Извършени са анализи за обемна плътност (BD), относителна влажност (dW), съдържание на глина (Clay), органична материя (OM) и активен въглен (C_(act.)) в почвата. Представените резултати характеризират почвата като хомогенна със сравнително добри биологични показатели (OM и C_(акт.)). Адаптивната схема за вземане на почвени проби и получените регресионни модели за почвените параметри са специфични за изследваното поле. Регресионните модели за наблюдаваните параметри са линейни и са представени чрез карти с пространствена разделителна способност. Системата Scanfield-5S предоставя решения като карти с променлива скорост (VRA), прогнозиране на въглерода в почвата и цялостна оценка на здравето на почвата. Цифровият модел на почвата, създаден по метода DSC, е специфичен за изследваното поле, но има потенциал за универсалност.

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[1] *NOTE: This article was initially published as a pre-print. The current version represents an improved and expanded manuscript that has not been published in any other peer-reviewed journal.*

INTRODUCTION

With the rapid development of digital technologies, agriculture has become a key area for their application. These technologies provide solutions that enable agriculture to strike a balance between protecting natural resources and meeting the growing demand for high-quality food and industrial raw materials, all while ensuring sound management decisions at various levels of government.

The basis of the predominant part of digital technologies in agriculture is the use of mathematical models proven by science and practice, describing separately or in combination various physical, mechanical, biological and other processes occurring during the cultivation of agricultural crops. In this way, technologies in agriculture can acquire adaptive, can become adaptive and even proactive - capable of responding promptly to changing conditions and adjusting the expected outcomes accordingly. The sustainability of such technologies largely depends on maintaining a constant connection with the environment in which they are implemented. By developing adequate mathematical models, it is possible to predict and adapt processes and phenomena manifested at a later stage as a result of changes in the factors influencing the object of impact.

Advances in understanding plant growth and development, as well as improvements in instrumentation, lead to better analysis and interpretation methods.

In the past and even today, many farms treat the entire cultivated area as a uniform unit—irrigating the whole field when it's time to water, or applying the same fertilizer rate across the entire area when needed. In reality, however, the needs of different parts of the field vary due to soil heterogeneity.

Acquiring, analyzing and applying accurate information through analytics is essential for making the right decisions. Soil testing is an important tool related to the application of technologies for growing crop plants. The adequacy of soil analysis largely depends on the methodology's ability to determine the non-uniform nature of the soil in a given field.

The basis of the existing methods for soil analysis is the classical methodology with its three main stages, which include:

Stage 1. Building the soil sampling – the surveyed field is divided into modular units (plots) of certain sizes, with the number and locations for drilling marked along a pre-defined trajectory. Generally, the "W-scheme" is suitable for most plot shapes and sizes, but "Z-scheme" or "X-scheme" also apply. Thus, one soil sample should be formed from each modular unit, obtained after mixing the samples from the drilling sites. The goal in drawing up a drilling scheme is to capture the soil diversity in the surveyed field. The number of drilling sites in a modular unit varies from 10 to 40, and the size of a modular unit from 0.5 ha to 10-12 ha (*FAO soil bulletin 18; https://sites.google.com/site/poushkarov/home/vzemane-na-pocveni-probi; The LaMotte soil handbook*);

Stage 2. Soil sampling – it is done either manually or mechanically using special tools that extract samples from soil layers with a depth of 0-30 cm; 30-60 cm and 60-90 cm, according to the purpose of the surveyed field and the goals of the analysis;

Stage 3. Laboratory analysis – soil samples collected from the field are subjected to laboratory tests according to established procedures and standards (*Benton, 2001*). The analysis of the results compares the reported with the reference values of the observed indicators and on this basis a generalized assessment of the soil condition is formed and relevant recommendations can be prepared.

A mandatory requirement for the classic method is soil sampling, and the reliability of the results depends on the sampling density (*https://bds-bg.org/bg/project/show/bds:proj:109684*). This determines the representativeness of the soil material collected. Due to the complexity of ensuring the representativeness of soil samples in Stage 1 of the conventional method, modern specific developments such as global navigation satellite system (GNSS), global positioning system (GPS), geographic information systems (GIS) are being used. According to a set algorithm, these systems can divide the field into modular units of a certain shape and size, which forms a network of drilling points on the field. The network density, resp. the density of sounding points is set by the size of the modular unit.

Conventional soil analysis methods typically rely on a set of samples to ensure representativeness and reliability of the analysis results. These samples are often combined into a composite sample, the analyses of which are assigned to the soil in the entire field. This makes their application difficult in modern digital technologies.

In the sense of the digital transformation in agriculture, classical soil analysis cannot provide a high enough degree of precision. It also takes a lot of time and resources, which is why farmers often neglect it.

The idea of the DSC method is related to digitalization of soil analysis. A key point in it is the replacement of the soil sample from the so-called "Digital soil cube" which, by means of mathematical models, provides timely information on the condition of the soil.

To develop the method, a cybernetic approach known from science is applied. The approach is based on the principle of the black box, according to which any object can be studied and managed only by its reactions caused by one or other external influences, without knowing the processes and phenomena that take place inside the object (*Mitkov, 2011; Mitkov and Bratoev, 2023*). The application of this approach is also related to the use of probabilistic statistical methods (*Kardashevski and Mitkov, 1977; Mitkov, 2011; Mitkov and Minkov, 1989, 1993; Mitkov and Bratoev, 2023*), in which the reactions shown by the object are viewed as a random event, a random variable or a random process. At the so-called poorly organized systems (objects) including soil, these methods are a means of obtaining objective information. The DSC methodology uses the elements of mathematical statistics, correlation analysis, dispersion analysis and regression analysis (*Kardashevski and Mitkov, 1977; Mitkov, 2011; Mitkov and Bratoev, 2023*).

The reactions of the object (the soil) and the external influences are considered as random quantities that describe a given feature (property) of the general population (the soil in the entire field). A given property of the soil is seen as a reaction of the soil, and the soil itself as an object with an external influence. The entire soil survey process is passive in terms of the statistical data collected (*Kardashevski and Mitkov, 1977; Mitkov, 2011; Mitkov and Bratoev, 2023*). The methodology for implementing the DSC is distinguished by a dynamic functional scheme. In its entirety, this functional scheme consists of five stages that must be followed to obtain the final digital soil model. Once created, the digital soil model allows the functional scheme to be reduced to two stages - the first and the last, and the soil analysis itself takes on a proactive nature.

<u>Stage 1. Measurement of the electrical conductivity of the soil</u> - one of the significant measurements that can be used as an indicator of soil fertility and digitized is its electrical conductivity (*Corwin et al.,1996, 2005; Drommerhausen et al. 1995; Greenhouse et al.,1983; Hanson et al., 1997; Kitchen et al., 1999*). Soil electrical conductivity (ECa) is a measurement that correlates with soil properties that affect crop productivity. Such properties include soil texture, cation exchange capacity (CEC), organic matter, salinity, nutrient availability, etc. The nature of the current flow in soil has been described in detail in numerous studies (*Corwin et al.,1999; Ellsbury et al., 1999; Fitterman et al., 1986; Halvorson et al., 1976; Rhoades et al., 1990, 1991, 1992, 1999*). Some studies have reported the effects of soil salinity, CEC, water content, and bulk density on ECa (*Bohn et al.,1979; Bratoev et al., 2020; Corwin et al.,2005; Hanson et al., 1997; Slavich et al., 1990*). Others have analyzed the effects of clay, organic matter, soil temperature, texture, and cation availability (*Brevik et al., 2002; Cook et al., 1992; Corwin, 1996; Corwin et al.,1999; Drommerhausen et al., 1995; Stroh et al., 2001; Triantafilis et al., 2001*). ECa measurements should be interpreted with these factors in mind. Studies have shown that the optimal ECa values for fertile soils should be in the range of 110 – 570 mS/m (*Cook et al., 1992; Triantafilis et al., 2001*). The level of soil moisture and the nutrients dissolved in it play a decisive role in the measured ECa in the soil. In order to use it as an indicator of soil health and therefore to make informed decisions, it is necessary to understand the relationship of ECa with soil properties. The complex nature of the relationships between individual soil parameters is also transferred to their relationship with ECa (*Bohn et al., 1979; Brevik et al., 2002; McDaniel et al., 2014*). Such complex relationships are difficult to describe with traditional functional mathematical relationships. By measuring the ECa, the information contained in the soil about its main characteristics is recorded as a numerical series that provides an opportunity to describe the complex interrelationships. In the DSC method, non-contact measurement of ECa is used, based on the principle of electromagnetic induction. Soil ECa screening is performed for 100% of the surveyed field area, with the location of each record being marked with geographic coordinates.

<u>Stage 2. Building the soil sampling</u> - the collected data on ECa of the soil in the surveyed field are subjected to statistical processing. The aim is to identify areas of the field in which the ECa can be assumed to be the same from a statistical point of view. In general, zones with strong, medium and weak electrical conductivity of the soil are formed, but in detail the number of zones depends on the observed soil diversity in the field. Statistical processing consists of determining the estimates of numerical characteristics and testing statistical hypotheses. The information from the received assessments is used to find the so-called the maximum relative error, which is accepted in the DSC method, should not exceed 10%. Such an error value determines the number of soil samples that must be taken from an area in order to guarantee the results obtained at a 95% confidence level. By performing a statistical hypothesis test for equality of a series of means it can be

determined at how many zones within the field the hypothesis will be rejected. Thus, zones will be formed on the field, which will be significantly different from each other by the measured ECa of the soil in them.
The outlines of each of the zones are determined by the geographic coordinates of the individual records during the scan. The field locations where soil samples will be taken are also set with their geographic coordinates, their location being adjusted to avoid autocorrelation with respect to ECa.

Stage 3. Soil sampling - it is carried out either manually or mechanically using special tools that extract samples from four soil layers with a depth of 0.2 m; 0.4 m; 0.7 m and 1.0 m, according to the purpose of the surveyed field and the goals of the analysis. Each soil sample is marked with its geographic coordinates and recorded ECa value.

Stage 4. Laboratory analyses - the soil samples collected from the field are subjected to laboratory tests according to established procedures and standards (*Benton, 2001*). The obtained results of the laboratory analyses are used in the next stage to compile mathematical models.

Stage 5. Creating digital soil models - a digital soil model is a collection of separate regression models expressing the relationship between a given soil parameter and the measured soil ECa. To obtain a specific regression model, the ECa data at the drilling (sampling) site and the results obtained from the laboratory analysis for the selected soil indicator are used. With these data, a regression analysis is carried out to quantitatively describe the relationship between the soil parameter and ECa. The statistical analysis of the obtained regression models shows that the change of the soil index can be described by ECa and the obtained regression model. Another aspect of the statistical analysis is determining the adequacy of the model, which in the case of individual digital models is confirmed by Fisher's criterion (*Kardashevski and Mitkov, 1977; Mitkov, 2011; Mitkov and Minkov, 1989; ; Mitkov and Minkov, 1993; Mitkov and Bratoev, 2023*). This gives reason to assume that the error of the model does not exceed the error of the experimental data. By including a given regression model to the coordinates of the field, georeferenced data is obtained, with which the values of the observed soil indicator in the given field can be presented visually (through spatial resolution maps) or digitally.

MATERIALS AND METHODS

The digital nature of the DSC method allows it to be integrated with other modern digital technologies. Such a digital technology is the Scanfield-5S system, which offers innovative services and solutions for agriculture. The Scanfield-5S system platform is built on several main pillars of a digital nature: 3D scanner, Data processing and analyses.

3D scanner – a patented scanner is used for non-contact measurement of soil electrical conductivity (*https://geoprospectors.com/en/*). Raw data from the ECa scanner is converted into information on several baseline metrics: soil zones, depth to compaction, relative soil moisture and tillage maps. The scanner mounts directly on a vehicle, which can be a tractor, ATV, pickup truck, or similar field vehicle. The sensor can be used on any soil, even when it is covered with vegetation. There is also no restriction on minimum or maximum soil moisture content. The scanner works on the principle of electromagnetic induction. A magnetic field is induced through a transmission coil (Fig. 1). Four receiving coils then measure electrical conductivity at four cumulative depths, up to 1.0 m. The device also permanently records spatial information. No contact with the ground is required to obtain soil electrical conductivity data, making it suitable for scanning dry soils. The data is collected and can be processed in real time to be immediately used on the tractor (for example for managing agricultural equipment).

Data processing - raw data is processed with filters and sophisticated algorithms to produce a series of files. Some of these files can be used directly from the agricultural machine's ISOBUS terminal for further use. With the filtered data, spatial resolution maps of the observed indicators are prepared. From the spatial resolution maps for the soil zones, the locations of the soil sampling sites are determined.

Analysis – physical soil samples are sent to a soil analysis laboratory. The obtained results are processed and analyzed using specialized software and the DSC method, after which the data are transformed into soil maps. The soil maps are spatial resolution maps for each soil parameter for which a digital model was obtained using the DSC method. Each map is made by specialized software. The data from the maps can also be transformed into a tabular form. The detail in the soil map can be changed according to the needs of the user.

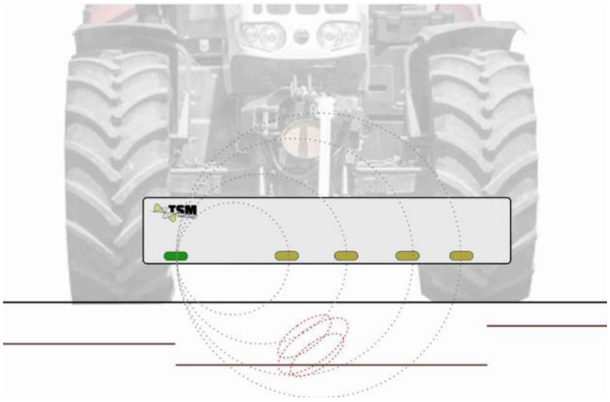

Fig. 1 - Top Soil Mapper (Geoprospectors GmbH)

1) Description of the study site

The studied field is located in the territory of the village of Boychinovtsi, Montana region in Bulgaria. The soil in this field is loam (*Gyurov and Artinova, 2001*). The field has an area of 207.7 ha, on which cereals and cereal crops are grown. The research was conducted after the wheat harvest. Up to the time of the study, no soil treatments were carried out.

2) Soil condition

In order to assess the soil condition, the following steps were taken: (a) ECa measurement across the field, (b) formation of markers for soil sampling, (c) analysis of soil properties, and (d) compilation of georeferenced spatial resolution maps for visual presentation of results.

a) ECa measurement across the field

The measurement of the ECa was carried out on 01.09.2023 with a mobile electromagnetic scanner TSM (Top Soil Mapper) of Geoprospectors GmbH. Successively, the measurements were taken about 1 m apart, collecting almost 20000 soil ECa data in four layers at the depth of 0.2 m; 0.4 m; 0.7 m and 1.0 m. All collected data are georeferenced with a GLONASS system (GNSS) receiver.

b) Formation of markers for soil sampling

Using the ECa data and the methodology of the Scanfield-5S system, six characteristic zones were formed within the field (Fig. 2). The resulting zones are distinguished by the average ECa in them, covering a different proportion of the field area, and in general characterize the spatial variability in ECa of the whole field. The marker in a given zone provides a statistical representation of the most frequently measured ECa in the zone. The location of the marker is georeferenced and a soil sample should be taken from it.

The soil samples were taken on the ECa measurement day (September 1, 2023). Soil cores were taken consecutively from the top two soil layers with a depth of 0.2 m to a depth of 0.4 m. Extraction of soil cores from the soil was carried out with a Royal Eijkelkamp hand probe. Duplicate soil samples were taken within each zone to ascertain variability at the zonal level. A total of 12 markers (stars on Fig. 4) were formed, from which a total of 24 soil samples were taken (12 from both soil layers).

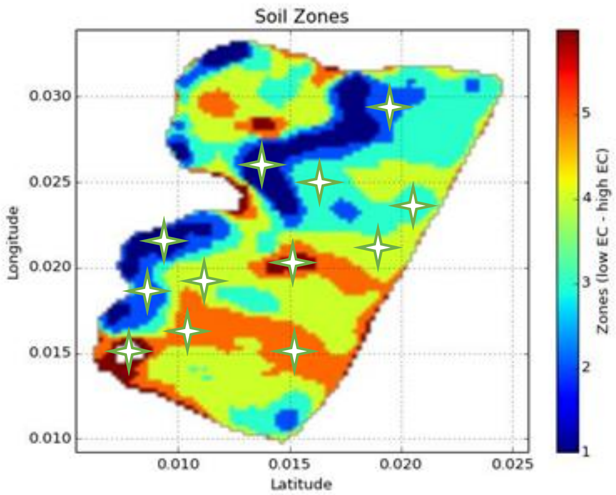

Fig. 2 - Zones and field markers (from TSM Client Cloud & Scanfield-5S) *

*Note: * full field coordinates not presented* *c)* Analysis of soil properties

Relative humidity dW, bulk density BD and clay content were analyzed for the 24 soil samples from soil physical properties, and organic matter OM and active carbon $C_{act.}$ in the soil were analyzed as biological indicators. The choice on these indicators is dictated by the fact that the physical and biological properties of the soil are often not a focus when performing soil analyses. Validated methods were used to analyze these indicators (*Trendafilov and Popova, 2007; Moebius-Clune et al., 2017*). The relative humidity is expressed as a percentage of the maximum field moisture content of the soil, the value of which is 31.5%. Statistical processing was performed with TIBCO's “Statistica” software product.

d) Compilation of georeferenced spatial resolution maps for visual presentation of results

All spatial data for the ECa, as well as those from soil analyses, are entered into the Scanfield-5S system. Georeferenced spatial resolution maps are created for each of the observed soil indicators, for which a digital model was obtained using the DSC method. The data from the maps can also be transformed into a tabular form. The detail in the soil map can be changed according to the needs of the user.

RESULTS

After statistical processing of the ECa values measured by TSM for the soil layer with a depth of 0.2 m, an overall average value $\overline{ECa}_{20cm} = 27.95\ mS/m$ and a coefficient of variation $V_{20cm} = 14.9\ \%$ are obtained. For the layer with a depth of 0.4 m, these estimates are respectively $\overline{ECa}_{40cm} = 34.71\ mS/m$ and $V_{40cm} = 15.4\ \%$.

All data for ECa_{20cm} and ECa_{40cm} are divided into six groups (classes), which are a prerequisite for the formation of georeferenced areas in the field. The number of classes was determined after applying a graph-analytical method (*Mitkov and Bratoev, 2023*). Its result shows that over 80 % is the confidence probability that the average value obtained from the six groups does not differ by more than 10 % from the ECa average for the corresponding layer, i.e., $\overline{ECa}_{20cm}$ and $\overline{ECa}_{40cm}$. The high confidence probability justifies the spatial variation of the ECa to be represented by six georeferenced zones along the field.

After grouping the data for ECa_{20cm}, the average coefficient of variation in individual groups is $\bar{V}_{20cm} = 5.3\%$. For the groups of data referring to ECa_{40cm}, the average coefficient of variation is obtained $\bar{V}_{40cm} = 5.4\%$. The nearly identical values of the two coefficients of variation, along with the previously mentioned graph-analytical method, indicate that two measurements within a group or field zone are sufficient to guarantee 90% accuracy of the ECa group average. This confirms the necessity of collecting duplicate soil samples in each zone.

This is how the 12 markers for this field are formed, and their locations are determined by the georeferenced data associated with the most common ECa in a given group. The number and locations of markers, i.e., the soil sampling scheme depends on the spatial variability of soil ECa in the field being studied. Therefore, such a soil sampling scheme is adaptive in nature. The need to change existing soil sampling schemes when using the ECa is noted in research by D.L. Corwin and S.M. Lesch (*Corwin et al., 2005*).

From the correlation matrix (Table 1) it can be seen that ECa_{20cm} stands out as the most influential and most powerful indicator. As expected, this indicator has the strongest linear correlation with ECa_{40cm} ($\hat{r} = 0.94$), which is positive. The correlation of ECa_{20cm} are significant and with the other indicators, such as with BD_{20cm}, it is negative - $\hat{r} = -0.74$. A negative correlation is also observed between ECa_{40cm} and BD_{40cm} - $\hat{r} = -0.61$. Therefore, in areas of the field where the observed ECa decreases, the bulk density BD of the soil in these areas is expected to increase. An increase in soil stiffness is likely to occur as BD increases, but this was not included in this study.

A similar but positive correlation of ECa_{20cm} is observed with $Clay_{20cm}$ and the included biological indicators - OM_{20cm} and $C_{act.20cm}$, respectively $\hat{r} = 0.7$; $\hat{r} = 0.77$ and $\hat{r} = 0.74$. The correlation of the indicators OM_{40cm} and $C_{act.40cm}$ with ECa_{40cm} is also significant ($\hat{r} = 0.6$; $\hat{r} = 0.74$). The absence of a significant correlation of ECa_{40cm} with $Clay_{40cm}$ ($\hat{r} = 0.4$) as well as with dW_{40cm} ($\hat{r} = 0.51$) may be due to unforeseen circumstances, since sees that they are highly correlated with the conductivity ECa_{20cm}.

The significant correlation of ECa_{20cm} and ECa_{40cm} with biological indicators (OM_{20cm}, $C_{act.20cm}$, OM_{40cm} and $C_{act.40cm}$) makes the measurement of soil ECa a suitable tool for determining the amounts of organic carbon (OC) in the soil.

Table 1

Correlation matrix- Marked correlations are significant at $p < 0.05$. N=12

Variable	Means	Std.Dev.	ECa_{20cm} (mS/m)	ECa_{40cm} (mS/m)
ECa_{20cm} (mS/m)	26.49	8.21	1.00	0.94
ECa_{40cm} (mS/m)	29.40	8.19	0.94	1.00
BD_{20cm} (t/m^3)	1.30	0.39	-0.74	-0.66
BD_{40cm} (t/m^3)	1.17	0.33	-0.62	-0.61
dW_{20cm} (%)	38.30	10.79	0.58	0.59
dW_{40cm} (%)	50.70	14.67	0.58	0.51
$Clay_{20cm}$ (%)	28.28	4.03	0.70	0.68
$Clay_{40cm}$ (%)	29.03	4.34	0.62	0.40
OM_{20cm} (%)	3.39	0.28	0.77	0.89
OM_{40cm} (%)	2.66	0.83	0.76	0.60
$C_{act.20cm}$ (mg/kg)	527.23	110.00	0.74	0.65
$C_{act.40cm}$ (mg/kg)	430.11	124.15	0.72	0.74

Tables 2 and 3 show the basic statistics characterizing the observed soil properties in the 0.2 m and 0.4 m depth layers, respectively. The average values of the properties show that the soil in the studied field has good levels of the observed indicators. The higher values of the coefficient of variation (Coef. Var.) for ECa_{20cm} and ECa_{40cm} compared to $V_{20cm} = 14.9\%$ and$V_{40cm} = 15.4\ \%$ is the result of the 12 measurements being counted as individual rather than group data. Taking into account the grouping of the data for the measured ECa_{20cm} and ECa_{40cm} in the entire field, the obtained values of the corresponding coefficient of variation differ by less than 5% from the total V_{20cm} and V_{40cm} (*Kardashevski and Mitkov, 1977*). A similar result can be expected regarding the variation in the other indicators in the tables. At values of coefficient of variation around and below 30 %, it can be assumed that the spatial variability of the given indicator obeys the normal distribution (*Kardashevski and Mitkov, 1977*). The higher BD values in the upper soil layer (0.2 m) are probably the result of the movement of agricultural machines during the harvest and the lower relative humidity in it.

Table 2

Mean and range statistics for 0.2 m sample depth

Variable	Mean	Confidence -95,000%	Confidence 95,000%	Std.Dev.	Coef.Var.
ECa_{20cm} (mS/m)	26.49	21.27	31.70	8.21	31.00
BD_{20cm} (t/m$^{3)}$	1.30	1.05	1.55	0.39	30.20
dW_{20cm} (%)	38.30	31.44	45.16	10.79	28.18
$Clay_{20cm}$ (%)	28.28	25.72	30.84	4.03	14,25
OM_{20cm} (%)	3.39	3.21	3.57	0.28	8.15
$C_{act.20cm}$ (mg/kg)	527.23	457.34	597.13	110.00	20.86

Table 3

Mean and range statistics for 0.4 m sample depth

Variable	Mean	Confidence -95,000%	Confidence 95,000%	Std.Dev.	Coef.Var.
ECa_{40cm} (mS/m)	29.40	24.19	34.60	8.19	27.86
BD_{40cm} (t/m$^{3)}$	1.17	0.96	1.38	0.33	28.38
dW_{40cm} (%)	50.70	41.38	60.02	14.67	28.93
$Clay_{40cm}$ (%)	29.03	26.27	31.79	4.34	14.96
OM_{40cm} (%)	2.66	2.13	3.19	0.83	31.21
$C_{act.40cm}$ (mg/kg)	430.11	351.24	508.99	124.15	28.86

The spatial variation of the observed soil indicators is represented by spatial resolution maps shown in Figures 3 and 4. Each of the maps was obtained using the Scanfield-5S system methodology. The maps combine information on the values of the observed parameter and the georeferencing of this information within the studied field. The different color representation of the field sections is integrated into a legend explaining what notional mean values are expected from the presented metric in the respective sections.

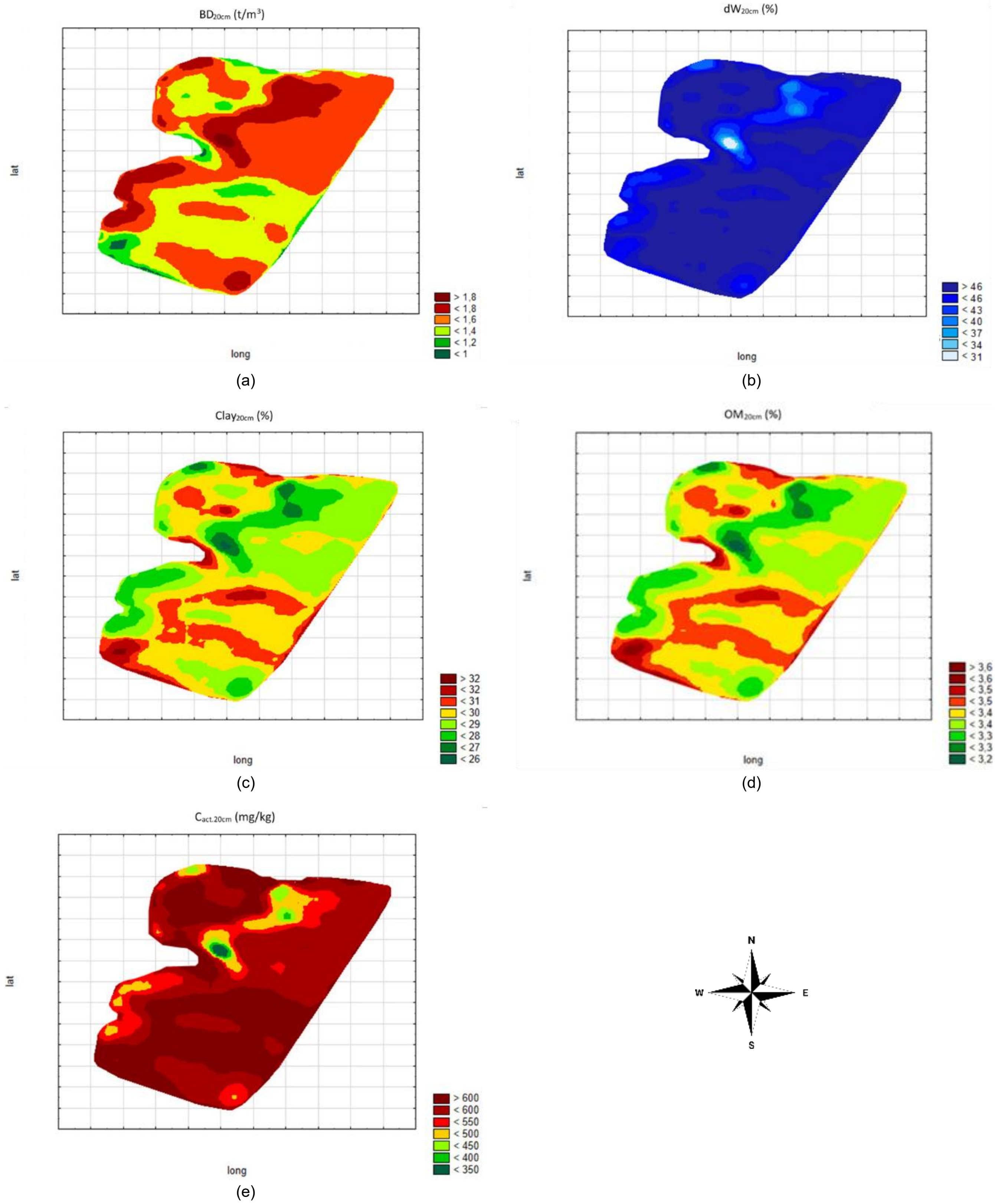

Fig. 3 - Spatial resolution maps of soil properties in the layer with a depth of 0.2 m:
(a) - bulk density (BD); (b) - relative humidity (dW); (c) - clay content (Clay);
.(d) - organic matter (OM); (e) - activated carbon ($C_{act.}$)

The presented spatial models of the observed properties of the soil are quantitatively related to the spatial variation of its ECa in the two layers - ECa_{20cm} and ECa_{40cm}. The analysis of the spatial resolution maps from Fig. 3 shows that 72 % of the field area is occupied by sections in which the volume density of the soil (BD_{20cm}) has a value falling within the confidence interval for the general average value. Similar results are also observed for the other indicators of this soil layer, and for active carbon ($C_{act.20cm}$) the relative share of these areas reaches 90 %. These results mean that the soil in the topsoil is consolidated around some good levels of its indicators. Slightly lower relative humidity values (dW_{20cm}) are an expected result around the harvest period. The obtained levels of the biological indicators (OM_{20cm} and $C_{act.20cm}$) testify to a fairly good activity of microorganisms in the soil.

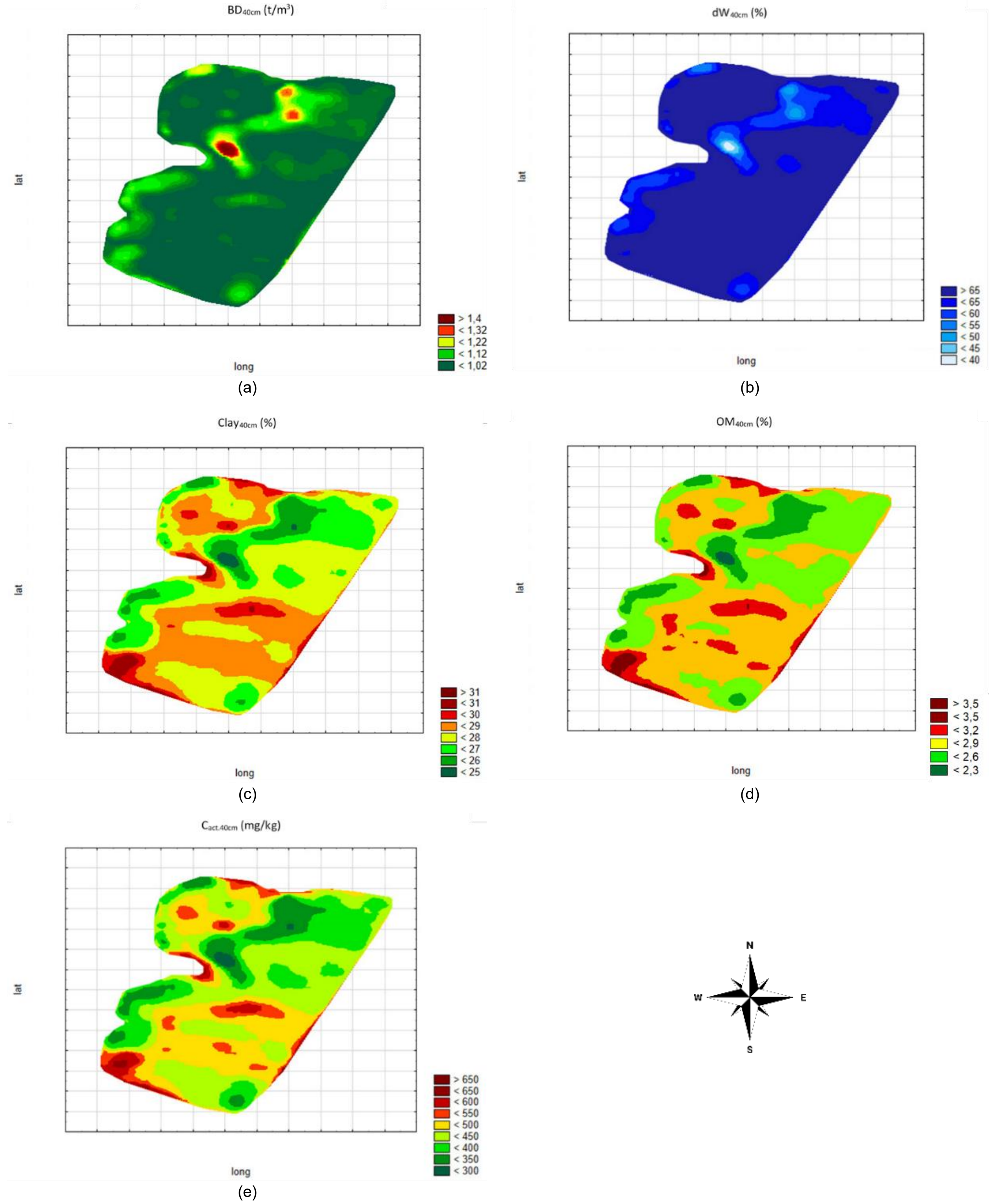

Fig. 4 - Spatial resolution maps of soil properties in the layer with a depth of 0.4 m
(a) - bulk density (BD); (b) - relative humidity (dW); (c) - clay content (Clay);
(d) - organic matter (OM); (e) - activated carbon ($C_{act.}$)

A similar analysis can be made for the spatial resolution maps from the deeper soil layer - 0.4 m (fig. 4). Here, the predominant part (81 %) of the soil has a bulk density $BD_{40cm} < 1.02\ t/m^3$, which suggests the appearance of a positive (left) asymmetry in the normal and distribution. An asymmetry in the normal distribution is also assumed for the relative humidity, but here it should be negative (right), since for 83 % of the layer area, the relative humidity is $dW_{40cm} > 60$ %. The average levels of biological indicators (OM_{40cm} and $C_{act.40cm}$) in this layer are lower than the previous layer (0.2 m), but still remain good.

Together, the two sets of spatial resolution maps outline that the soil in the surveyed field has a deep (up to 0.4 m) and thick humus horizon and has good levels of bulk density ($\sim 1.3\ t/m^3$). This implies that such technologies are applied in the cultivation of crops that ensure sustainability of the resources in the soil of that field.

CONCLUSIONS

The presented DSC method offers the possibility of digitalization of soil analysis, the key point of which is the use of information on soil electrical conductivity (ECa) and its relationship with soil properties through mathematical models. The DSC application methodology is distinguished by a dynamic functional scheme that provides timely information on the state of the soil. The creation of a digital soil model allows traditional soil analysis to become proactive. The adaptive soil sampling scheme used can be designed only after the spatial variability of ECa in the soil of the entire field has been measured. As the spatial variation of ECa increases, the number of places from which soil samples need to be taken also increases. It can be said that soil heterogeneity is a leading factor in the preparation of the sampling scheme. In conventional soil analysis methods, its heterogeneity is based on external signs in the field and a large number of samples, which vary depending on the standard used.

The five observed indicators: bulk density (BD_{20cm}, BD_{40cm}), relative humidity (dW_{20cm}, dW_{40cm}), clay content ($Clay_{20cm}, Clay_{40cm}$), organic matter (OM_{20cm}, OM_{40cm}) and active carbon ($C_{act.20cm}, C_{act.40cm}$) have a significant correlation with ECa, which is confirmed by the results in Table 2. The application of the DSC method is an opportunity for a reliable and adequate presentation of the change in these indicators for 100% of the field area.

The created spatial resolution maps are a convenient tool for visualizing and evaluating the condition of the soil in a given field. It was found that the spatial variability of ECa in the upper two layers of the soil is about 15 %, which is sufficient reason to consider this soil as sufficiently homogeneous. This is also confirmed by the results in the spatial resolution maps, where from 72-90 % of the field area is occupied by soil, whose indicators have values close to the average for the entire field. The levels of biological indicators are quite good for a soil that is engaged in agricultural production and the soil can be considered healthy and the applied agricultural practices sustainable.

The integrated solution of the intelligent Scanfield-5S system provides a practical tool for soil assessment when soil properties are related to ECa. The application of mathematical models requires the use of both precise measuring instruments and methods that determine individual soil parameters with the smallest possible error. The presented soil analysis solution demonstrates a way to digitally transform the most important resource in agriculture - soil. The Scanfield-5S system can provide farmers with reliable solutions tailored to their needs and applicable to modern technologies. One such solution is the creation of a variable rate application (VRA) maps. Such a map can be used for sowing, fertilizing with liquid or solid fertilizers, watering and other agricultural operations that are advisable to be carried out with a high degree of precision. Another potential option is the issuance of carbon certificates that would allow farmers to declare the amount of carbon accumulated in their fields. In addition to the direct benefits of carbon certificates, farmers will have information on how much their farming practices contribute to improving soil health.

Another proven option for determining soil health is to compare its experimental indicators with its corresponding reference indicators using the Harrington function. The minimum difference between the obtained functions is an indicator of soil health, i.e. it tends to its natural state.

The digital soil model created by the DSC method is specific to the studied field, but has the potential for universality.

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