Thesis of the PhD dissertation

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METHODOLOGICAL STUDY OF SOIL CARBON MEASUREMENTS AND SOIL CARBON SURVEYING

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INTRODUCTION AND OBJECTIVES

The current trends in crop production (on a national, European, and global scale) focus on understanding the organic carbon conditions of our soils and managing them in harmony with our long-term environmental goals. This research takes a practical approach, aiming partly to make the methodology used in the research more applicable to crop production. To make cultivation a conscious decision-making process, it is necessary to develop methods that allow for the monitoring of the soil's organic matter conditions, as well as the direction and extent of its changes, while considering time, financial and equipment needs of examination.

Animal-derived manure and slurry play a key role in managing organic matter through cultivation. By examining the utilization of precision manuring, the accurate use of available organic fertilizers for the greatest potential benefit could become a reality in the future.

The research thesis concerning the development, refinement, and reduction of resource and time requirements in the methodology used for surveying organic carbon in cultivated areas includes the following:

- Among the sample strategies studied (Random, Grid, Latin Hypercube Sampling), which is the most efficient for assessing organic carbon conditions in a cultivated area with heterogeneous soil properties, at multiple depths? How does the representativeness/performance of these methods change with the density of sample points?
- What estimation performance can be expected from an organic carbon prediction model based on mid-infrared spectral data, depending on the sample selection method used (Kennard-Stone sampling, k-means sampling, Latin Hypercube sampling), and varying calibration/validation sample ratios?

Focusing on improving the organic carbon condition of cultivated soils, also develop a method for monitoring the soil carbon processes, which can be integrated into crop production practices:

- With what estimation accuracy can the methodology tested in the previous section be applied to predict the organic carbon conditions of the area with a larger number of samples?
- What is the short-term (2-year) impact of pelletized poultry manure applied in different doses on the organic carbon content of the soil, and to what extent does it pay off in areas with different soil properties?
- Is the mid-infrared (MIR) spectral range suitable for monitoring the persistence of organic fertilizers in the soil, and can this organic carbon monitoring methodology be integrated into the soil survey system used in crop production?

Testing the organic carbon survey methodology of this research for solving complex problems:

- Can the methodology used in the research be applied to map the organic carbon stock of a large (~1500 km²) cultivated area with highly heterogeneous soil down to a depth of 1 m? To what extent can the reliability of the map in question be improved by adding additional dependent covariates (topography and proximal sensing data)?

MATERIALS AND METHODS

The experiments and surveys were conducted at three locations. The methodology used at the locations, which can also be interpreted as phases of the research, builds on one another, and the division of materials and methods follows this logic.

1. Érsekcsanád – Kanális

The first survey area is located near Érsekcsanád, a cultivated land covering 4.62 hectares. One of the key factors in shaping its soil conditions was the former floodings of the Danube, which led to the formation of floodplain marks (frequent vertical and horizontal texture changes). The elevation ranges from 85 meters above sea level on the eastern side to 87 meters on the western side. The soil conditions within the area are characterized by strong heterogeneity, particularly in terms of the frequent changes in the soil's physical properties. On the western side, at a lower elevation and closer to the Danube Valley Main Canal, the groundwater is relatively close to the surface (1-2 meters, depending on water levels and weather conditions), making the developed reductive conditions around 1 meter depth another defining factor (Figure 1).

Figure 1. The soil profile at the eastern end of the sample area clearly shows the reductive conditions in the depth and the groundwater level within 1 meter of the surface.

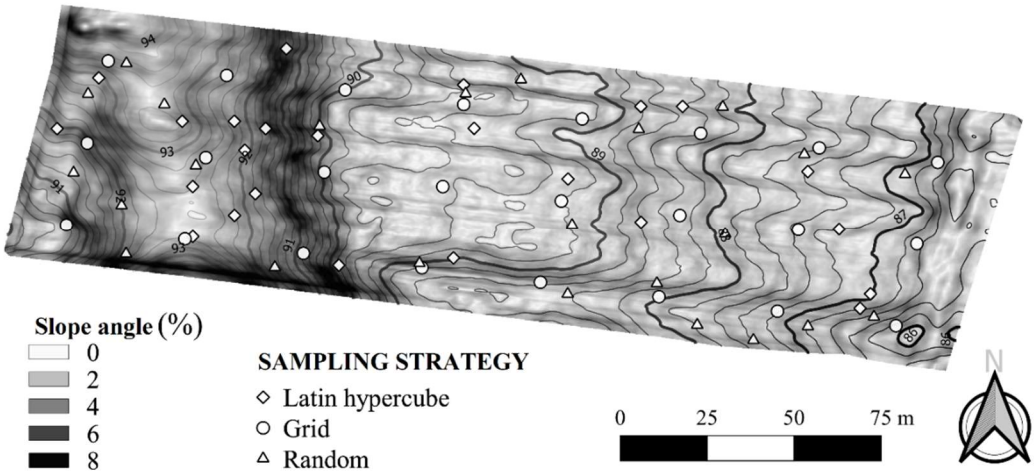

Figure 2. Illustration of the overall sampling strategy, distinguishing between different sampling approaches.

During the development of the sampling strategy, the goal was to investigate the influence of different sampling patterns on the results of organic carbon mapping. For the survey, we selected three sampling methods, each with 24 sample points (Figure 2):

- Random Sampling (RANDOM or RND)
- Grid Sampling (GRID)
- Latin Hypercube Sampling (LHS).

For each sampling point, a 100 cm^3 undisturbed sample (Eijkelkamp 07.53.SC) was collected from three depths: 0-20 cm, 20-50 cm, and 50-100 cm. The undisturbed samples were taken from the center of the respective sampling depth range.

The **sample preparation** following the sampling was carried out in the same manner for all experiments. During preparation, visible plant and animal residues were removed, then the samples were dried and subjected to gravimetric volume measurement before being sieved through a 0.2 mm mesh.

First, I measured the organic carbon content of the samples using the Walkley-Black method and the $CaCO_3$ content using a calcimeter. This was followed by capturing the mid-infrared (MIR) reflectance spectra.

In selecting calibration samples necessary for the estimation models, the aim was to use a sampling algorithm that would select samples best representing the heterogeneity of the given sample population. The most commonly used sampling algorithms are KSS (Kennard-Stone Sampling), KMS (K-means Sampling), and LHS (Latin Hypercube Sampling), and their performance was compared with different calibration/validation ratios.

The mid-infrared (MIR) spectra were recorded using a Bruker Alpha II Fourier-transform infrared spectrometer manufactured by Bruker Optics. the DRIFT module attached to the instrument is specifically designed for analyzing solid, powdered samples. The protocol followed during the examination was based on the Standard Operation Procedures document developed by the World Agroforestry Center Soil-Plant Spectral Diagnostics Lab. During the measurements, the diffuse spectral reflectance of the samples was recorded in the spectral range of 400 to 4000 1/cm. For background radiation measurements, I used a gold standard with known spectral characteristics, which was measured before each analyzed sample. Each sample was measured in 3 repetitions, with the software used for the measurement creating an average from 48 irradiations for each repetition.

In the **preprocessing of the spectral measurement results**, the first step was to average the results from the repeated measurements, and subsequent steps used only the average spectrum for further processing. Next, to reduce the sawtooth effect caused by local spectral range variability, I applied a smoothing procedure based on moving average calculations. Following spectral preprocessing, outlier values due to reasons such as measurement errors or sample mix-ups were filtered out, using Mahalanobis and H distance values.

For the **establishment of the prediction model**, Partial Least Squares Regression (PLSR) was employed, a commonly applied model for quantitative determinations. To validate the estimates made by the model, we created a composite statistical indicator specifically for this study. This indicator utilizes the statistical parameters of the estimates, combining RMSE (Root Mean Squared Error) and R^2 (Coefficient of Determination). The indicator summarizes R^2 and RMSE values in one variable, on a normalized scale, based on the formula used for calculating NDVI (Normalized Difference Vegetation Index):

$$\mathbf{(R2\text{-}RMSE) / (R2+RMSE)}$$

According to this formula, an increase in R^2 and a decrease in RMSE will increase the value of the indicator. Therefore, the composite statistical indicator is directly proportional to the accuracy of the tested model.

Érsekcsanád – Érréve

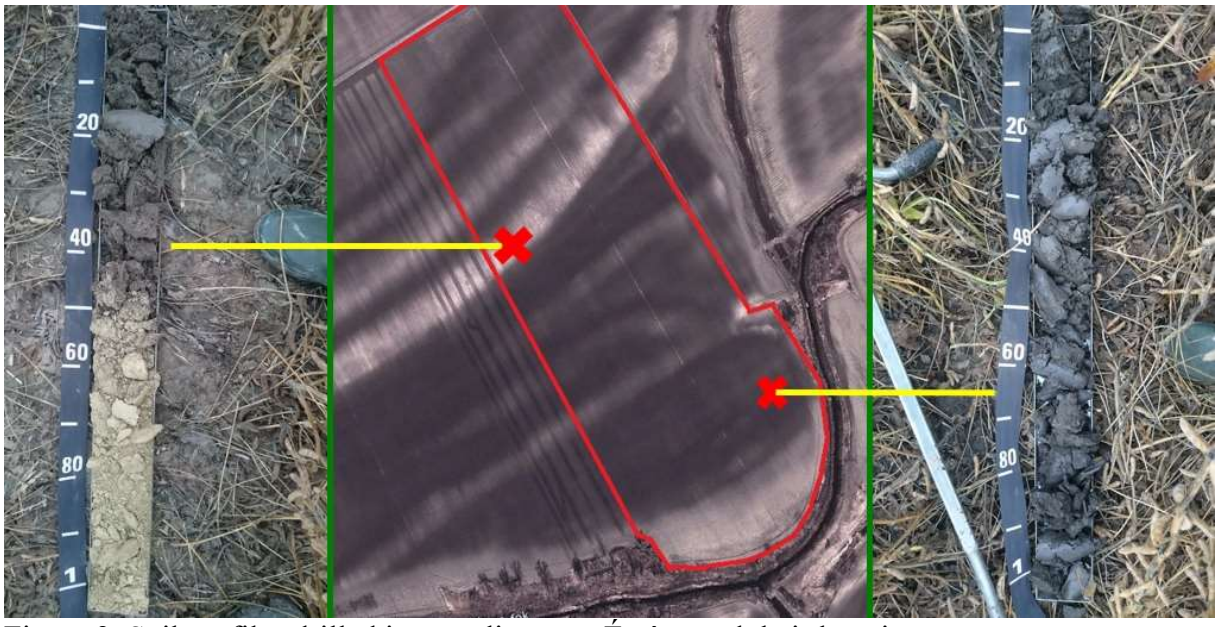

Figure 3. Soil profiles drilled in sampling area Érréve and their locations.

The precision fertilization experiment is located on a 24.3 ha arable field outside of Érsekcsanád. The soil conditions are also significantly influenced by the former flooding of the Danube River, resulting in alternating coarse and fine-textured soil layers both horizontally and vertically (Figure 3).

The field features floodplain soil strips running perpendicular to the cultivation, oriented northeast-east-west, characterized by higher elevations and soil materials with lower clay and silt fractions. These less-favoured soil patches (in agronomic terms) and the fine-textured alluvial soil strips between them served as the foundation and main focus of the experiment.

The organic manure used in the experiment contained the following nutrients per 100 kg of dry matter: 4:4:4 kg NPK and 7 kg Ca.

In the experimental area, soybeans were grown in the year preceding the experiment, and maize was grown in the first year of the experiment. Apart from the treatments, there were no differences in the growing technology of the plots (soil cultivation, sowing, plant care), the technology applied in the experiment was an additional component to the basic crop production technology.

The experiment included two types of treatments: Partial Treatment (FK) and Full Treatment (TK). In partial treatment, only certain targeted, less-favoured soil strips within the plot were treated, while for Full Treatment, the pelletized manure was uniformly applied across the entire experimental plot. Two doses were applied: 250 kg/ha and 500 kg/ha. The plots created (FK250, FK500, TK250, TK500, Control) are illustrated in Figure 4.

Figure 4. Plots for organic fertilization with indicated treatments (Source: Google Earth, 2022).

The sequence of treatment and sampling was as follows:

Preliminary Survey – October 2018;

Treatment – October 2018;

First Sampling – May 2019;

Second Sampling – September 2019;

Third Sampling – August 2020.

Soil sampling points were positioned along the soil strips, as shown in Figure 5. The goal was to monitor changes in the organic carbon conditions of these variable soil strips, so the sample rows marked with letters were placed within these strips.

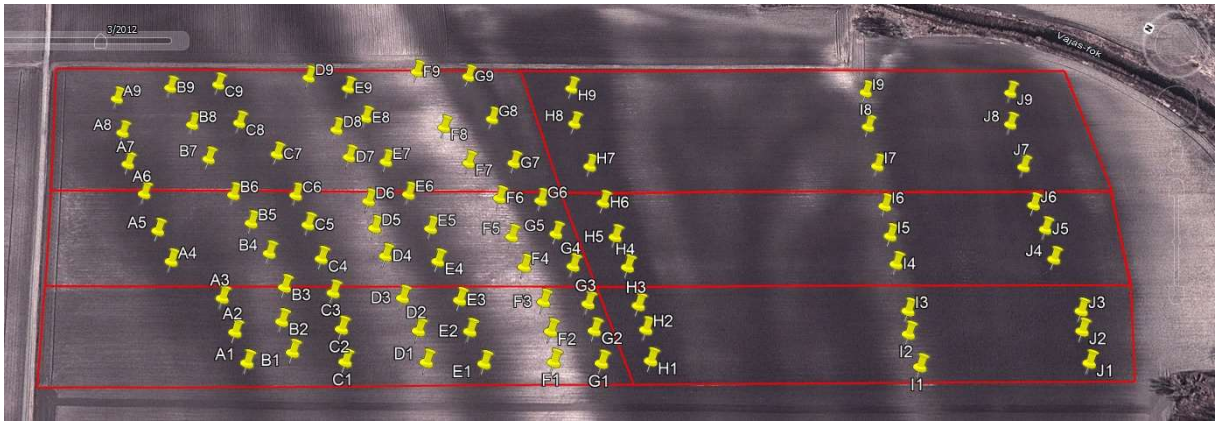

Figure 5. Placement of sampling rows and points within the experimental plots (Source: Google Earth, 2022).

Each plot contained three sampling points. During sampling, I marked the sampling location within a 2-meter radius of the pre-designated point according to GPS to ensure representativeness. Samples were taken from depths of 0-10 cm, 10-20 cm, and 20-30 cm, resulting in a total of 270 samples from the 90 sampling points. In addition to soil sampling, yield measurements were conducted in the year following the organic fertilization.

After preparation, the MIR spectra of the samples were recorded. Using the LHS algorithm, 10% of the samples best representing the spectral variance of the sample population were selected. The carbon content of the selected samples was measured with an elemental analyzer, and the $CaCO_3$ content was measured with a calcimeter. Based on these measurements, a PLSR model was developed using the MIR spectra to estimate the carbon and calcium content of the remaining samples.

The **elemental analysis** was conducted using the Elementar VarioMAX Cube CNS automatic analyzer. The samples analyzed ranged between 800 and 1000 mg in weight. The analyzer was operated in CNS mode, utilizing a TCD (Thermal Conductivity Detector) to measure the relative concentration of carbon in the gas mixture.

Data Processing and Topographic Analysis:

The preparation and handling of the elevation points were performed using the "fields" R package, specifically the TPS (Thin Plate Spline) regression function. After interpolating the elevation data, slope and aspect variables were extracted from the resulting DTM (Digital Terrain Model) using the SAGA GIS software. The covariates used for the optimization of the model included: Elevation, Slope aspect, Slope gradient.

3. Kenya – Eastern Slope of Mount Kenya

Mount Kenya is Africa's second-highest mountain, an inactive stratovolcano, with its highest point reaching 5199 meters. Its slopes are deeply carved by glaciers, and its base primarily consists of volcanic rock and ash, with some metamorphic rock present.

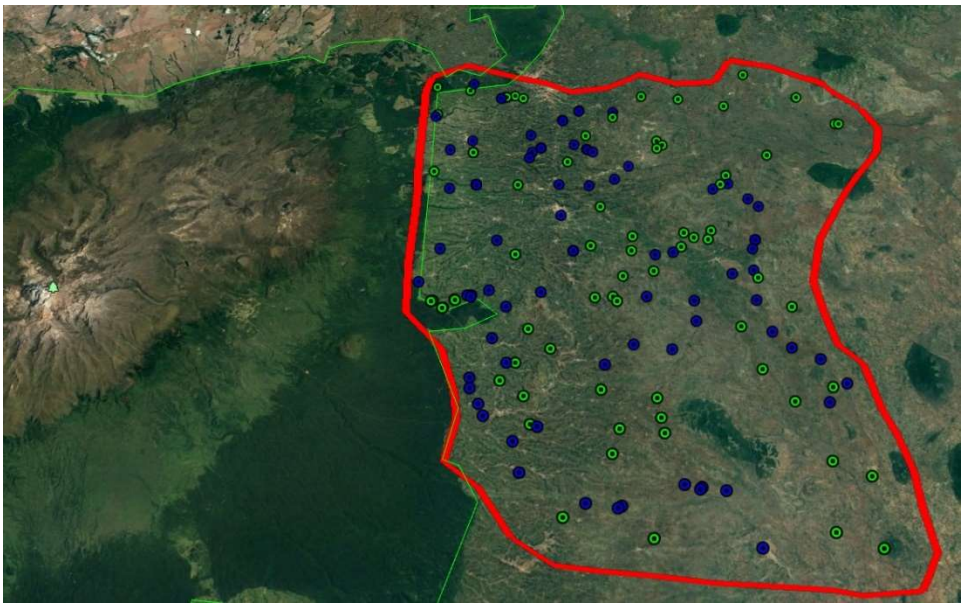

Figure 6. Eastern slope of Mount Kenya, with the study area and sampling points marked. Green markers: 2015, Blue markers: 2019 (Source: Google Earth, 2024).

The sampling covered approximately 1500 km² (Figure 6). The climatic conditions of the area are significantly influenced by the proximity to the Equator. However, Mount Kenya acts as a distinct climatic unit within the East African arid and semi-arid region. The eastern slope receives more precipitation than the western slope and serves as a crucial watershed. Consequently, the natural vegetation is rich and complex. The small area of the eastern slope allows for the observation of changes in vegetation and soil development associated with variations in altitude and precipitation. This varied landscape is ideal for modeling the effects of precipitation and climatic conditions on soil organic carbon content. The soil conditions include Nitisols and Regosols in the dry areas (with annual precipitation of 600 mm), Nitisols and Phaeozems in the intensively cultivated areas,

and Histosols in the more humid regions (with annual precipitation of 1800-2000 mm) found in the highland moss-covered areas.

The aggregated organic matter map uses data from two different surveys. The sampling points from the 2015 and 2019 surveys are illustrated in Figure 6.

The first survey took place between December 2015 and January 2016, focusing on cultivated soils on the eastern slope of Mount Kenya. The sampling points were designated using CLHS (Conditioned Latin Hypercube Sampling), with input variables including precipitation, temperature, vegetation index, topographic moisture index, slope gradient, and calculated sampling cost (from a "resistance" map derived from slope data and road networks).

The designated sampling points included 77 points, of which 28 were open soil profiles and 49 were drilled profiles. Soil sampling was performed based on genetic horizons, with samples taken from depths of 0-20 cm, 20-50 cm, and 50-100 cm in the drilled profiles, totaling 269 samples. After sample preparation, a portion of the sample population's organic carbon content was determined using dry combustion. The remaining samples' organic carbon content was estimated using the MIR spectra and a predictive model.

In January 2019, a second, supplementary soil survey of organic matter on the eastern slope of Mount Kenya was conducted. Similar to the 2015 survey, sampling followed the CLHS strategy, using the same input data. The designated points numbered 100, with 69 points sampled (Figure 6). Samples were collected from depths of 0-20 cm, 20-50 cm, and 50-100 cm at each sampling point, resulting in a total of 207 samples. These samples were prepared and analyzed for organic carbon content using the Walkley-Black method.

To create the 0-100 cm organic carbon concentration map, we adapted R code based on previous work by the research team, with specific modifications for this task. The exact methodology and command sequences are part of a forthcoming publication.

Key Covariates for the Model:

- DEM (Digital Elevation Model),
- SR-B6: Landsat 8-9 SWIR (Short-wave Infrared) reflectance value,
- SAVI (Soil Adjusted Vegetation Index): A modified NDVI that corrects for soil brightness in low vegetation areas using a correction factor,
- Annual precipitation,
- Topographic diversity derived from SRTM (Shuttle Radar Topography Mission) data,
- Slope gradient and aspect,
- Landcover,
- TPI (Topographic Position Index).

RESULTS AND EVALUATION

Evaluation of Sample Selection Methods (Kanális)

To assess the performance of sample selection algorithms, a sufficiently heterogeneous sample population is required. The variability in organic carbon values at different depths is reflected in the different means and medians. The standard deviations for the 0-20 cm and 20-50 cm sample groups are nearly the same, whereas the standard deviation for the 50-100 cm samples differs, with a 1% significance interval.

The get information about the tested algorithms, first we calculated the representativity (Figure 7). The LHS (Latin Hypercube Sampling) method is characterized by the flattest saturation curve, meaning that the representativity stabilizes faster with increasing sample size. The KSS algorithm requies the most samples for the saturation of the representativity.

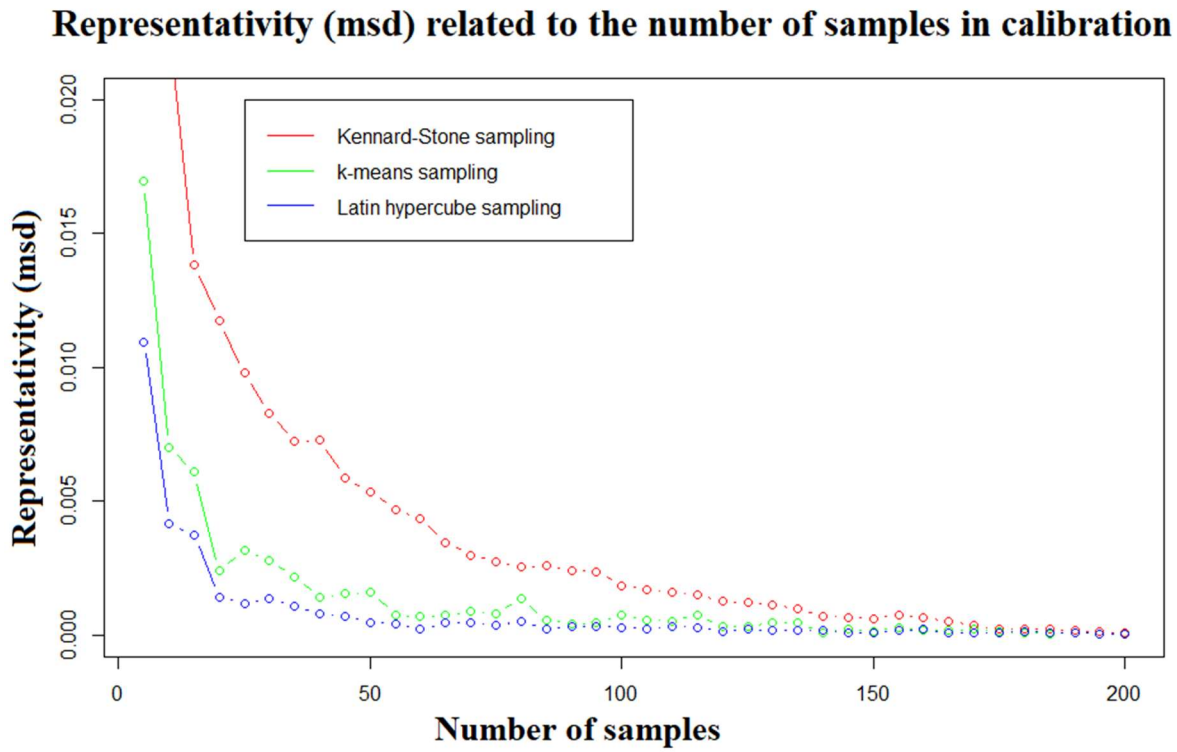

Figure 7. Performance of different sample selection algorithms in terms of representativeness (msd) for varying numbers of samples.

The three sample selection methods (LHS, KSS, KMS) were involved in a calibration/validation series, each step consists of 10% of the samples (10%/90% to 90%/10%). After cross-validating the models, we analyzed the R^2 and RMSE values and also created a combined, normalized statistical indicator based on the NDVI (Normalized Difference Vegetation Index) calculation formula:

$$(R^2 - RMSE) / (R^2 + RMSE)$$

This indicator ranges between -1 and 1, where higher values signify better model reliability.

The validation results indicate (Table 1 and Figure 8):

- The models' R^2 values were below 0.9 only for the KMS 10% and 20% sample sizes and the KSS 10% sample size, indicating generally high prediction accuracy despite significant heterogeneity,
- RMSE values decrease with increasing ratio for calibration, showing a negative correlation,
- The highest R^2 values were achieved with 80% sample size for KSS and LHS, and 90% for KMS,
- The combined R^2 and RMSE values suggest that while the highest prediction accuracy is obtained with 80% and 90% sample usage, both 10-20% and 80-90% calibration result in prediction inconsistencies. The former is due to calibration inaccuracies, while the latter may result from validation inaccuracies,
- The lowest (0.46) and highest (0.72) combined statistical indicators were observed for KMS sample selection,
- The performance of models shows the greatest similarity when using 40-60% of the samples,
- The models' performance changes the least when using 40% and 60% of the samples,
- The KSS-calibrated model's statistical indicator curve saturates at a 30% sample size, LHS at 50%, and KMS at 70%,

- For LHS and KMS algorithms, there is fluctuation in prediction accuracy at 10-30% and 70-80% sample sizes, while for KSS, significant fluctuation is only noted at the 90% sample size.

Table 1: Statistical indicators of models calibrated/validated with different sample sizes.

	The ratio of samples used for calibration								
	10%	20%	30%	40%	50%	60%	70%	80%	90%
KSS R^2	0,885	0,924	0,934	0,938	0,939	0,936	0,944	0,952	0,93
KSS RMSE	0,258	0,209	0,193	0,188	0,186	0,187	0,18	0,174	0,186
KMS R^2	0,895	0,835	0,907	0,92	0,927	0,906	0,957	0,944	0,969
KMS RMSE	0,246	0,308	0,231	0,211	0,215	0,21	0,165	0,17	0,157
LHS R^2	0,914	0,904	0,901	0,922	0,937	0,939	0,93	0,951	0,948
LHS RMSE	0,225	0,235	0,23	0,213	0,187	0,187	0,202	0,169	0,167

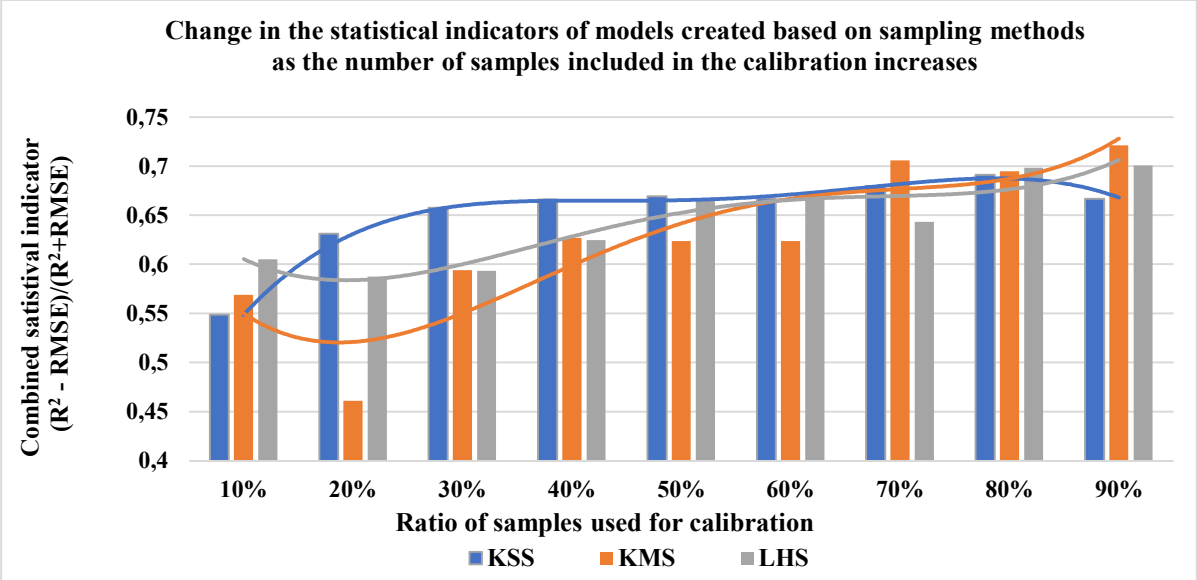

Figure 8. The combined statistical indicator for models calibrated using different sample selection methods.

Soil organic sarbon survey (Kanális)

In comparing different sample point selection methods, C density values were calculated from the organic carbon results, which represent the amount of organic carbon present in 1 m² of area to a depth of 1 meter. "krieg" interpolation was applied to create C density maps. The formula for C density and its dimensions is as follows:

$$C_{DENS} = \rho_b * C_{org}\% * h_{SOIL} = [t/m^3 * kg/t * m] = [kg/m^2]$$

ρ_b = Bulk density [t/m³]

Corg% = Soil organic carbon content [%]

h_{SOIL} = Depth of the soil column being calculated [m]

The most information-dense and thus the most accurate interpolation maps are the "SUM" maps created from all 72 points of the three sample collections, which serve as a reference for comparison. The color coding of the TOC [kg/m²] scale is consistent across different depth representations for better comparability.

In the interpolations for the 0-20 cm depth (Figure 9), most of the soil patches visible on the SUM map are recognizable across different maps; however, their extent and the interpolation values show significant variations.

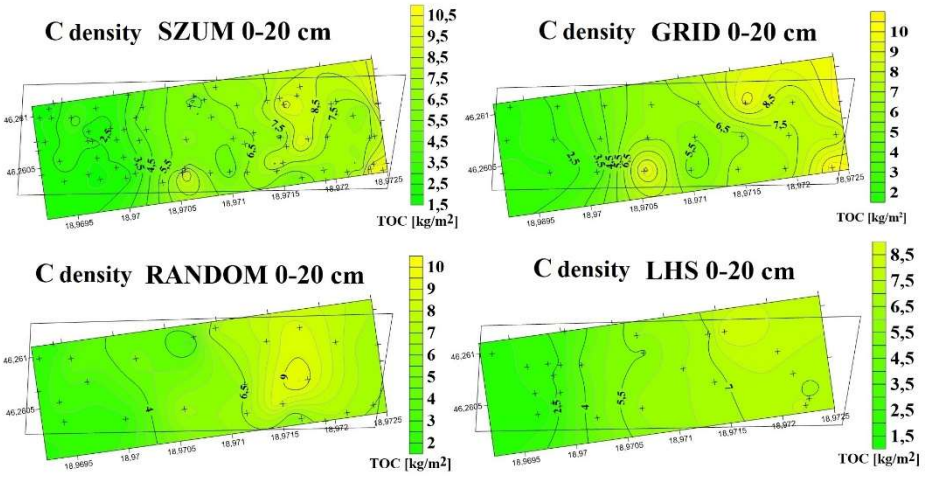

Figure 9. C density map for the 0-20 cm depth using aggregated and various sample point selection methods. The color scale of the maps ranges from 0 to 20 kg/m².

The most significant differences between the maps from individual sample collections and the SUM map are observed at the 50-100 cm depth (Figure 10). The GRID map most accurately reflects the placement of soil patches and general soil conditions.

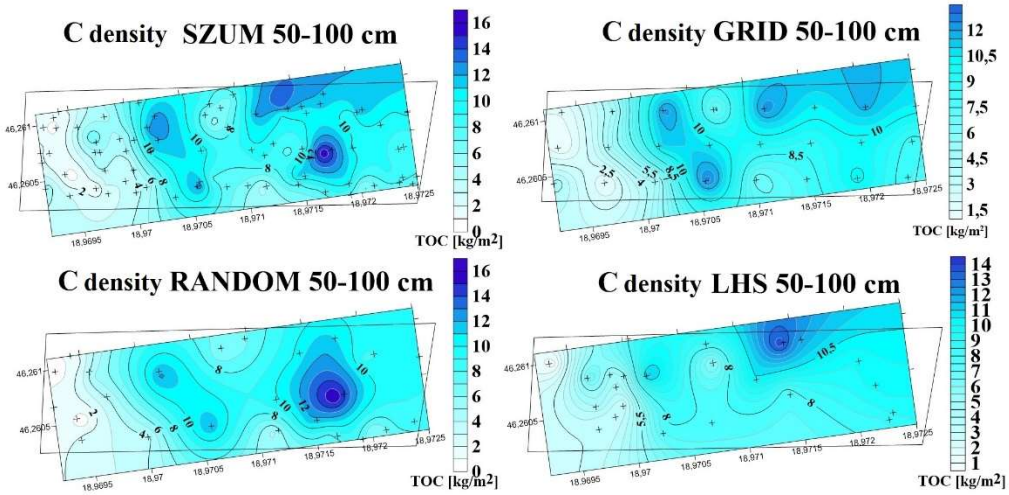

Figure 10. C density map for the 50-100 cm depth using aggregated and various sample point selection methods. The color scale of the maps ranges from 0 to 20 kg/m².

To better illustrate the differences between various interpolations, difference maps were created by subtracting the results of interpolations from individual sample collections from the interpolation of the map containing all 72 points (Figures 11 and 12).

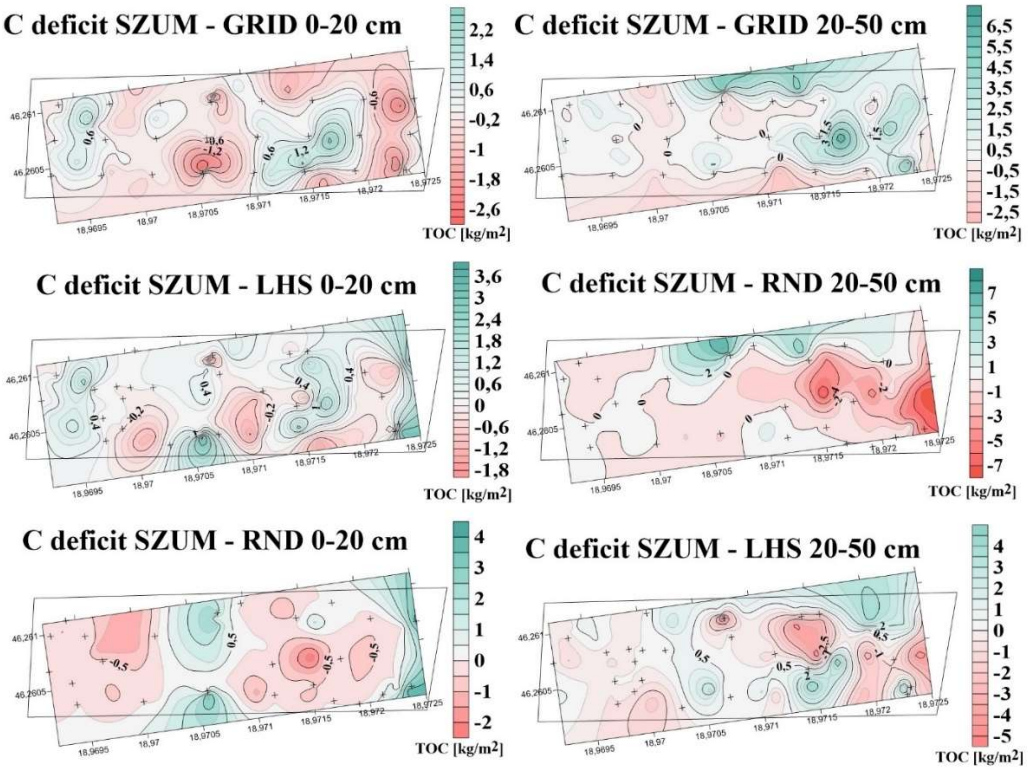

Figure 11. Difference between interpolations created from aggregated points and those from different point selection methods, shown as a map.

The deficit map shows negative values where the subtracted interpolation has higher values (marked in red) and positive values where the subtracted interpolation has lower values (marked in green). This visual representation helps to better demonstrate the characteristics of the sample point selection methods beyond the general assessment of the resulting interpolation. The color scale values for the deficit maps of each depth are consistent.

In the deficit maps for the 0-20 cm depth (Figure 11), negative values are predominantly observed on the SUM-GRID and SUM-RND maps, indicating higher values on the GRID and RANDOM maps. The difference maps for the 20-50 cm depth show lower deviations between GRID and LHS compared to the SUM-RANDOM map, which has the highest deficit values among the three difference maps. For the 50-100 cm depth, the RANDOM map shows deviations both positively and negatively compared to the SUM map (Figure 14). For GRID and LHS, deviations are generally positive, though negative deviations are more dominant when considering the entire area.

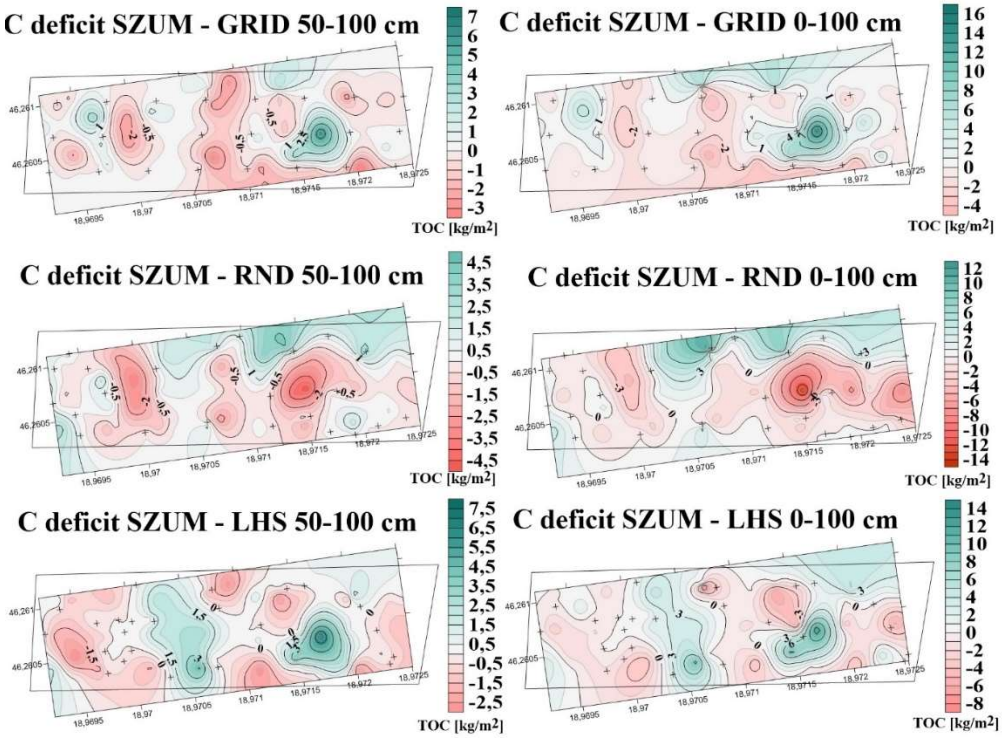

Figure 12. Difference between interpolations created from aggregated points and those from different point selection methods, shown as a map.

The 0-100 cm difference map summarizes the overall interpolation error for the full depth of sampling (Figure 12). The largest negative deviation was seen with the SUM-RND method, while the largest positive deviation was with the SUM-GRID method. The greatest difference between the maximum negative and positive deficit values (the sum of the absolute values of the differences) was with the SUM-RND method, indicating the largest distortion of the interpolation for given points. Conversely, the smallest value was for the SUM-GRID method, suggesting the GRID map has the lowest chance of high-value errors in sampling.

Examination of the effect of sample density on interpolation volume

To investigate the applicability of sample collections for assessing organic carbon conditions, the interpolations were tested with the aim of quantifying differences between sample collections. A series was created where the number of points used for interpolation was gradually reduced (24-20-16-12-8-4 sample points), and then the volume of interpolation was calculated for each given number of points. This volume represents the amount of carbon stock found over the entire area at the examined depth. These calculated volumes were compared to the volume of the interpolation using all 72 points (highest information density).

To make the differences at various depths comparable, I calculated the percentage deviation relative to the 72-point interpolation (Figure 13). The GRID method resulted in the smallest change (highest reliability) as the number of sample points was reduced. For 20 and 16-point interpolations, LHS showed the smallest error percentages and the lowest variability.

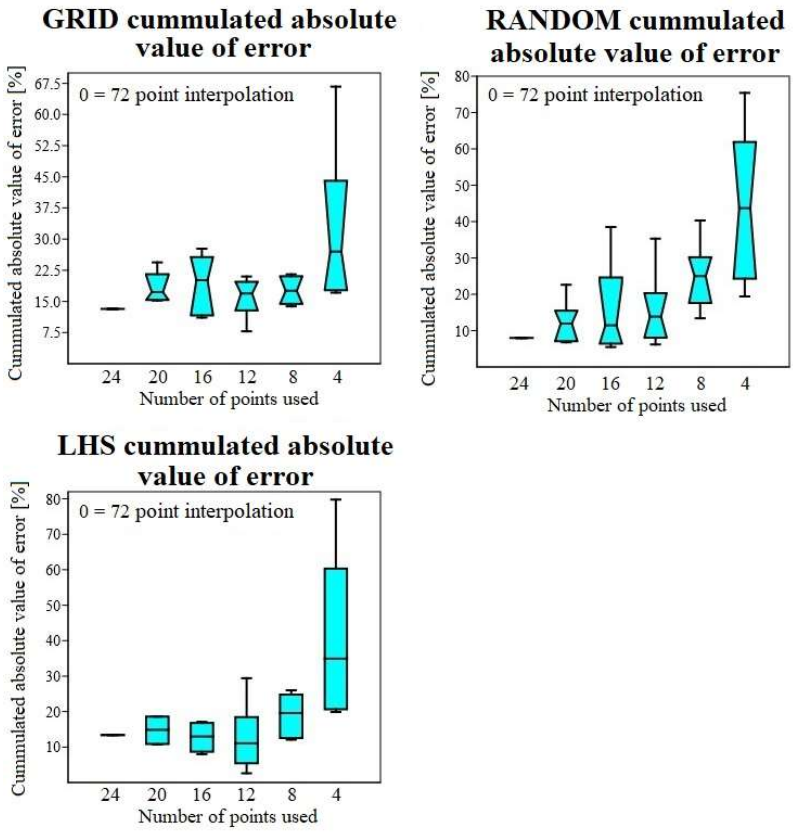

Figure 13. Summary figure of volume calculations deviations from interpolations with different sample sizes.

In the next step, I calculated the standard deviation, mean, and variance of interpolation volumes for each group created by reducing sample points (by sampling method, number of sample points, and depth, e.g., GRID 12 points, 0-20 cm). To understand the variability within groups, I computed the modified relative variance, defined as follows:

$$\mathbf{D = (\sigma^2 / V_{SZUM}) * 100}$$

σ and σ^2 are the standard deviation and variance, respectively,

V_{SZUM} is the volume value of the 72-point interpolation for the respective depth group.

The modified relative variance is a dimensionless indicator, expressed as a percentage after multiplying by 100. For better interpretability of the variability of interpolation results calculated with reduced sample sizes, the modified relative variance values are also depicted (Figure 14).

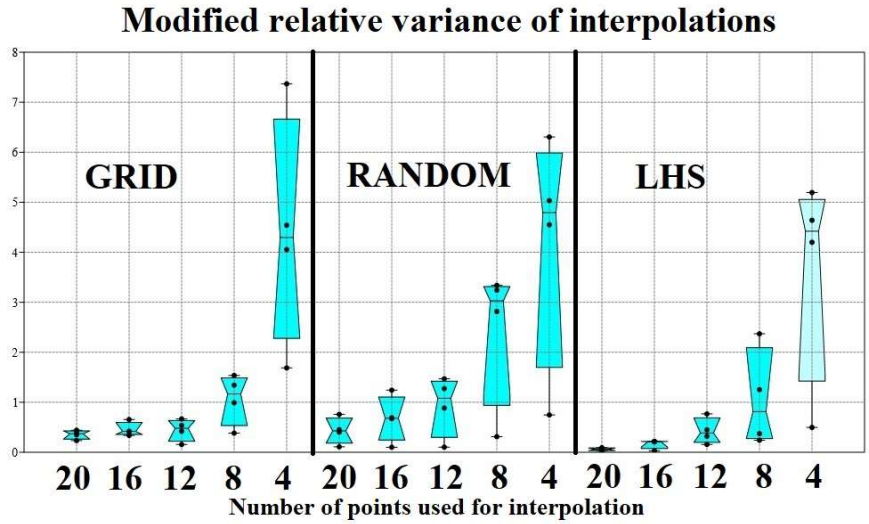

Figure 14. Modified relative variance of interpolations for the 4 different depths (0-20, 20-50, 50-100, 0-100 cm) within each sample point reduction.

Summarizing the results, it can be said that for GRID and LHS methods, the uncertainty of interpolation—presumed for assessing the organic carbon stock in the area—increases significantly when reducing from 8 to 4 sample points. In contrast, for RANDOM points, variability is significant even for 16, 12, and 8-point maps.

Figure 15 shows a comparison of interpolations from reduced sample sizes on the same scale.

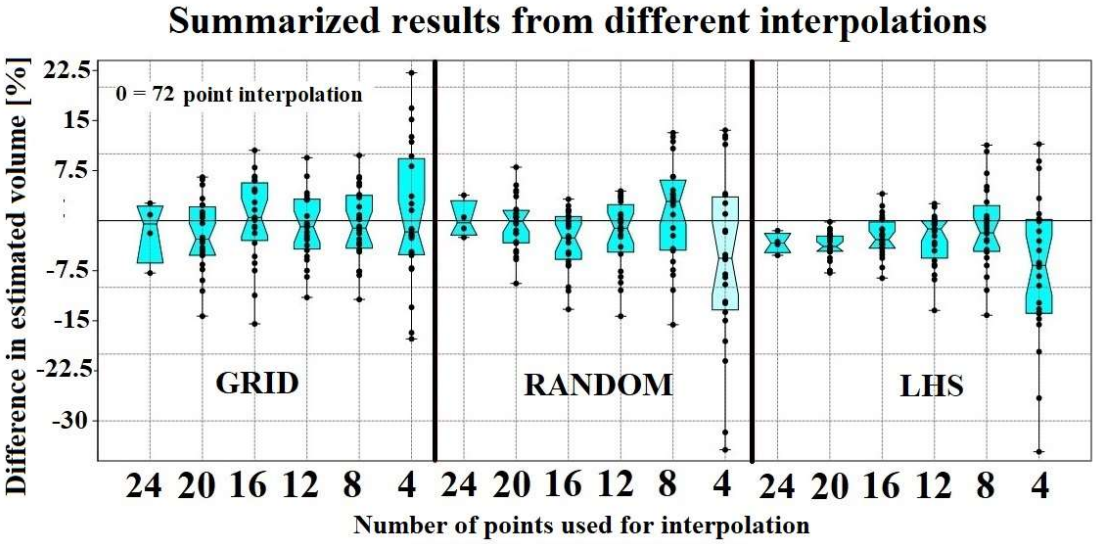

Figure 15. Representation of percentage deviations of interpolations with different sample sizes on a unified scale.

Based on this figure, LHS exhibits the lowest variability, except for the 4-point interpolation, which is lowest for GRID. The means (median and average) of the interpolations are closest to zero for GRID. For LHS, the mean of every sample size group is below zero, while for RANDOM, values fluctuate around zero after the 20-point interpolation, both above and below zero. For GRID, the variability of 20, 16, 12, and 8-point interpolations is high but changes little with reduced sample points, indicating high and constant information loss. For RANDOM and LHS, variability increases with each reduction in sample points. For RANDOM, even 20-point interpolation shows high variability, which does not change or increases in subsequent steps. For LHS, variability increases slightly with each reduction starting from 24 points. It is important to note that low variability does not always mean low deviation from zero. For example, while LHS20

has low variability, RANDOM20 values cluster around zero despite higher variability, resulting in similar absolute deviations (Figure 14).

Monitoring the impact of precision organic fertilization under different soil conditions (Érréve)

In presenting the effects of pelletized organic fertilization, I considered only the top 0-10 cm depth of organic carbon data due to the incorporation depth, as the effects of fertilization are expected to be most measurable at this depth.

First, I examined quantitative changes in the soil organic carbon. I divided the data into three groups: (1) Control and two dosage treatments, (2) 500 kg/hectare, and (3) 250 kg/hectare. I considered any plot that did not receive treatment as a control, as well as all plots from the preliminary survey. The reverse order of dosages results from the physical arrangement of the plots. Results shown in Figure 16 exclude both patch and full-area treatments, thus qualifying all of the shown data as controls.

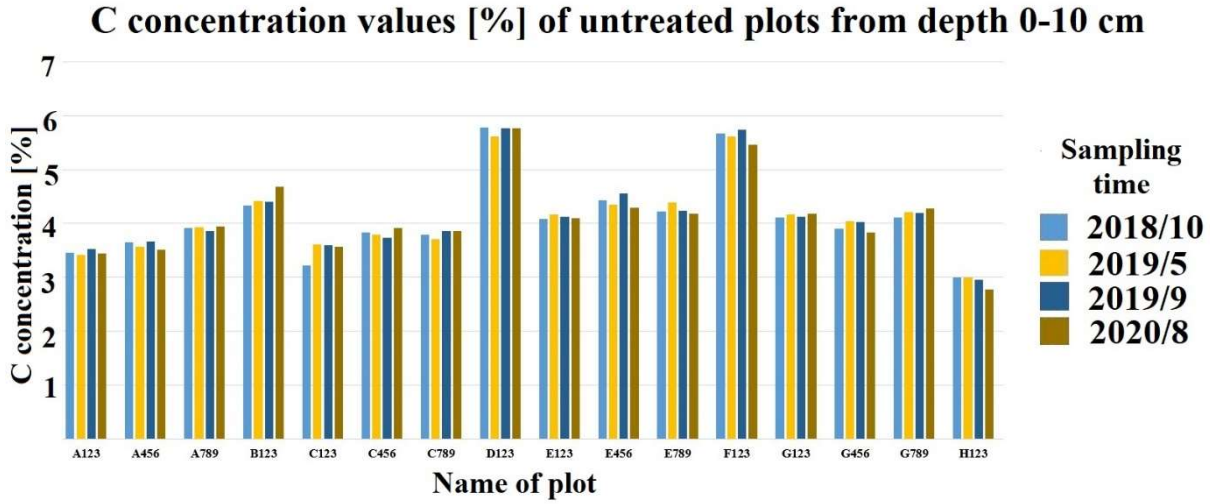

Figure 16. Organic carbon content in untreated (Control) areas.

The average values of each plot come from three sample points. The change in organic carbon content in the soil of each plot varies, showing natural dispersion in the data. This variability suggests that there is no consistent trend in organic carbon changes among the untreated plots.

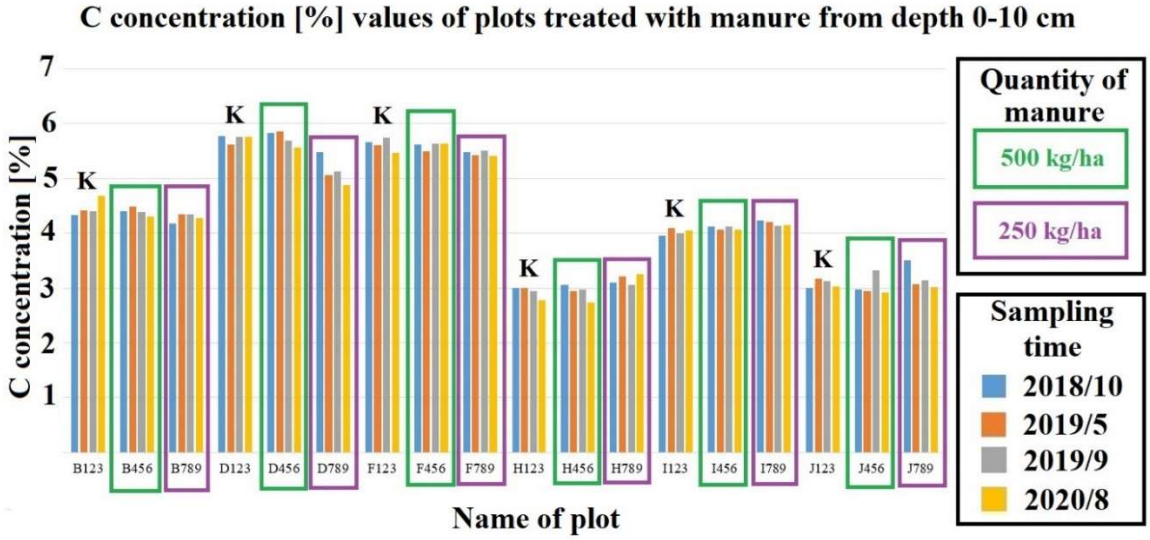

Figure 17. Comparison of carbon content of soils from treated plots with control plots.

When examining the results of fertilized plots, considering data dispersion, there is no visible or statistically significant quantitative difference due to the treatments (Figure 17). The results from organic carbon mapping based on different depths are presented in the appendix of the thesis, with the coefficients of determination listed in Table 2.

Table 2. Coefficients of determination for the produced maps (Érréve).

R2 values – Érréve	0-10 cm	10-20 cm	20-30 cm
Crossvalidation	0,838	0,825	0,834
External validation(20%)	0,90	0,90	0,91

The collected spectra were subjected to principal component analysis, including the organic fertilization applied (Figure 18).

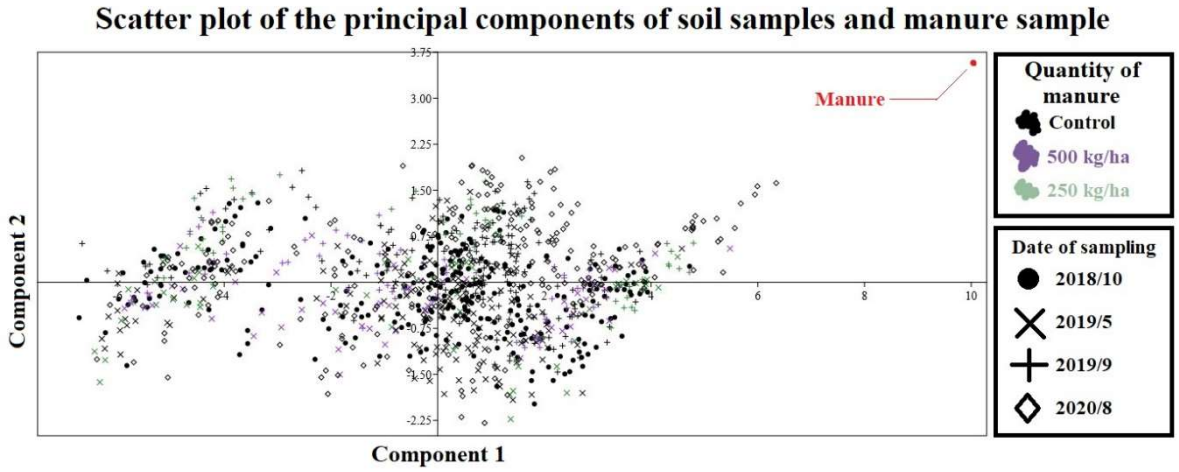

Figure 18. Principal Component Analysis of Collected Spectra

The primary goal was to determine how many principal components explain the variance in the data. Due to the low differences between data points and the high inherent dimensionality, the number of principal components was chosen based on the point at which the magnitude difference between spectra of organic fertilizer and soil samples ceased to be significant. Consequently, 11 principal components were used for further analysis. The objective was to compare principal components to assess similarities between soil samples and the applied organic fertilizer. Similarity indices appropriate for spectral data, such as Cosine and Pearson coefficients, were used for comparing principal components (Figure 19).

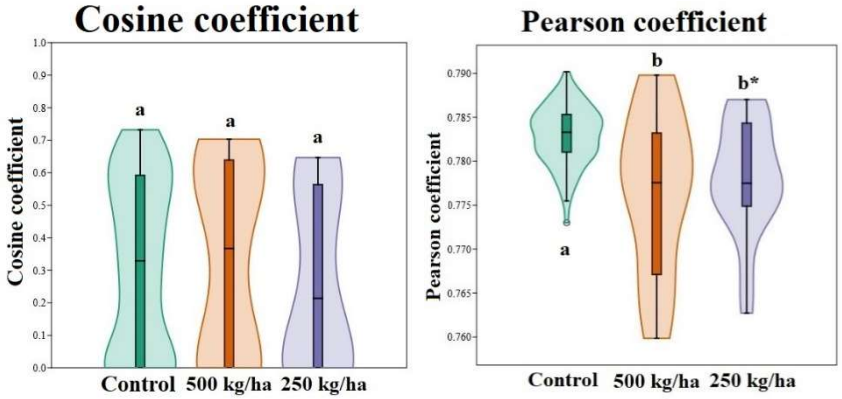

Figure 19. Similarity analysis of soil samples and applied organic fertilizer spectra

The Cosine similarity analysis did not provide significant results, but the Pearson coefficient showed significant ($p < 0.05$) differences between untreated and treated soils. Using the Pearson coefficient, I aimed to further analyze differences on a sampling time basis. A difference

calculation was performed to measure the variability between the Pearson coefficients of control and treated plots, and the confidence intervals for these differences were compared (Figure 20).

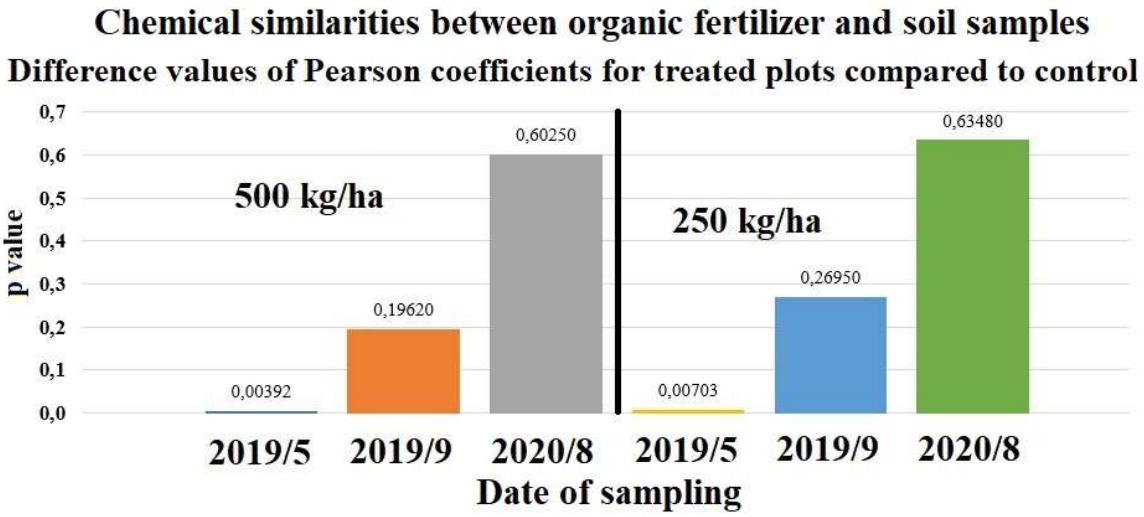

Figure 20. Difference values of Pearson coefficients for treatments compared to control

The figures show that the spectral similarity of soil samples to organic fertilizer was highest in treated plots during the initial sampling, with significant differences ($p < 0.05$). This difference gradually decreased with each sampling, with the initial significant difference no longer evident after six months, though the confidence interval remained not too high ($p \sim 0.2$). After one and a half years, the confidence interval exceeded 0.6, indicating a further reduction in differences.

Table 3. Return on investment calculations for application of organic fertilization.

Patch treatment	**Control**				**500 kg/ha**				**250 kg/ha**			
Weight [t]	1,46	1,03	1,45	1,38	1,68	1,54	1,66	1,48	1,51	1,43	1,55	1,64
Area [ha]	0,176	0,179	0,185	0,185	0,203	0,204	0,206	0,206	0,203	0,198	0,192	0,192
Yield [t/ha]	8,32	5,76	7,83	7,42	8,23	7,52	8,03	7,16	7,40	7,19	8,08	8,53
Treated area [ha]	0	0	0	0	0,077	0,078	0,077	0,077	0,076	0,075	0,073	0,073
Ratio of treated area [%]					38	38	37	37	38	38	38	38
Treatment cost [HUF]					3 582	3 634	3 556	3 556	1 772	1 729	1 686	1 686
Avg. yield [t/ha]	7,33				7,74				7,80			
Average cost [HUF/ha]	0				17 615				8 807			
Income - Treatment [HUF]	**476 629**				**502 845**				**506 926**			

Full area treatment	**Control**				**500 kg/ha**				**250 kg/ha**			
Weight [t]	1,25	1,12	1,29	1,32	1,75	1,68	1,73	1,67	1,69	1,70	1,84	1,68
Area [ha]	0,21	0,21	0,22	0,22	0,22	0,22	0,22	0,22	0,23	0,23	0,24	0,24
Yield [t/ha]	5,88	5,20	5,87	6,01	8,11	7,62	7,76	7,51	7,47	7,32	7,78	7,12
Treated area [ha]	0	0	0	0	0,216	0,220	0,222	0,222	0,226	0,231	0,236	0,236
Ratio of treated area [%]					10 003	10 214	10 305	10 305	5 243	5 363	5 469	5 469
Treatment cost [HUF]	5,74				7,75				7,42			
Average cost [HUF/ha]	0				10 207				5 386			
Income - Treatment [HUF]	**372 992**				**493 637**				**477 133**			

Considering the results of precision organic fertilization, it is crucial to eliminate edge effects from the data. Consequently, specific subareas within the plots were defined for accurate examination without distortion. Both patch and full-area treatments were found to increase returns effectively, with the most significant return on investment observed in areas with generally favorable agronomic soil properties.

Organic carbon orediction map for heterogeneous terrain (Kenya)

The organic carbon concentration data from the two surveys (2015 and 2019) conducted on the eastern side of Mount Kenya were treated as a dataset for basic descriptive statistical calculations. No statistically significant differences were found between depths. The spatial distribution of sample points is significant within the elevation range of 1400 m (2100 m a.s.l. – 700 m a.s.l.). The highest sample density is between 1400 m and 1100 m a.s.l. Statistically significant differences ($p < 0.001$) were found between 0-20 cm and 50-100 cm samples. For 0-20 cm and 20-50 cm samples, the p-value was 0.09362, close to the 5% confidence interval. The smallest p-value (0.1764) was found for samples from 20-50 cm and 50-100 cm, indicating the lowest probability of a significant difference.

The organic carbon prediction map created from the prediction data is shown in Figure 21. The statistical reliability of the map increased significantly due to the adddition of topographic an sensimal sensing covariables. The average R^2 value for maps not optimized with additional covariates was 0.59, improving to 0.82 after incorporating further parameters.

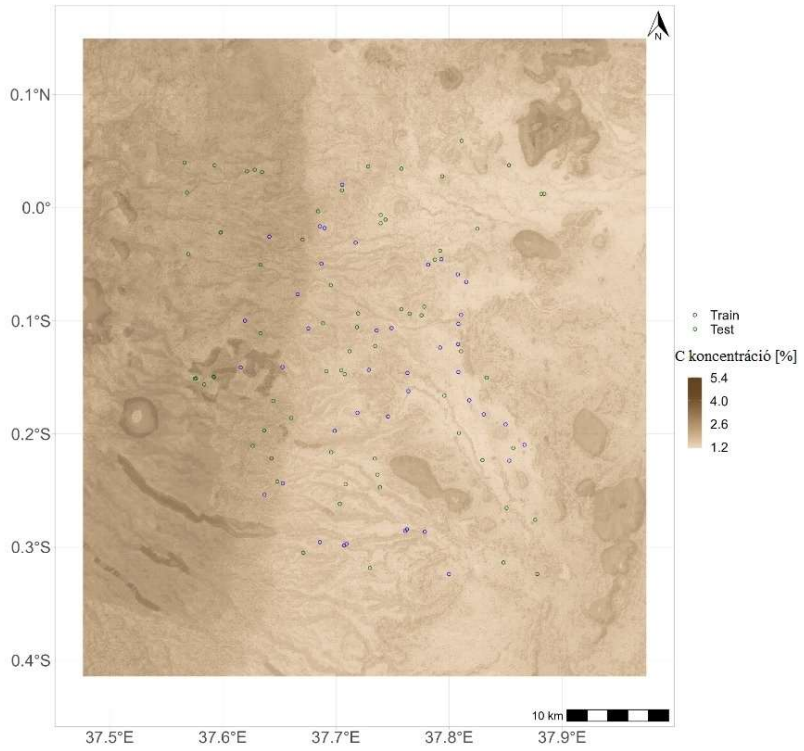

Figure 21. Soil organic carbon map for the study area in Kenya.

CONCLUSIONS AND RECOMMENDATIONS

Evaluation of sample selection algorithms (Kanális)

Based on the performance statistics (R^2 and RMSE) of models built from MIR spectral data with varying calibration/validation ratios, the following recommendations can be made:

- For 10% Calibration Sample Ratio, LHS (Latin Hypercube Sampling) provides the highest representativeness,
- All three sampling methods (LHS, KSS, KMS) yield models with good predictive reliability ($R^2 \geq 0.9$),
- For a 30% calibration sample size, the KSS approach is recommended due to its efficient performance with at this relatively low sample size,
- Highest predictive accuracy achieved with the KMS sampling approach.

If cost reduction is a priority while maintaining accuracy, the KSS approach with a 30% calibration ratio is advisable. For situations where only 10% of the samples can be analyzed, LHS is recommended. For scenarios where predictive accuracy is paramount regardless of cost, KMS with a 70% calibration sample size is recommended.

Soil organic sarbon survey (Kanális)

The spatial and vertical distribution of organic carbon values from the sampled area ensures significant heterogeneity for the study. Results show a significant difference in organic carbon concentrations between the 50-100 cm depth and surface layers, validating the effectiveness of methods in assessing depth-specific organic carbon conditions.

The biggest advantage of **Grid sampling** is constant point density, resulting in uniform interpolation effects across the area. The consistent point density minimizes the impact of outliers or measurement errors, ensuring that the interpolation accurately reflects the overall area. Grid sampling provides the best representation of depth-specific soil conditions and has the lowest deviation in difference maps.

Varying point density leads to unequal effects on interpolation in **Random sampling**. Points that are isolated from others have a larger impact, potentially causing errors in interpolation, especially with large, extended outlier values.

The uniformity of the sampling point density in Latin Hypercube Sampling (LHS) is determined by the input data used for calibration. Significant local changes in this data will result in higher density of sampling points. A limitation of the method is that smaller soil patches, which have developed independently of the input data (elevation), may not appear or may not appear in their true extent in LHS interpolations. The method can be applied with good performance in organic carbon inventory under the following conditions:

- The input data available for the algorithm is presumed to be closely related to the soil organic carbon value, and
- The pedometric relationships of the characteristic soil type in the sampling area align with the vertical profile of soil horizons according to soil genetics, and
- The likelihood or frequency of deep soil patches with extreme values within the area is low.

Subsequently, we examined the effect of the number of sampling points on the quality of the interpolation information. The goal was to perform a relative analysis of the performance of sampling methods, both compared to themselves and to other methods.

- For grid network and LHS-based sampling, a minimum of 8 points/4.62 ha sampling density was required to eliminate estimation inaccuracies.
- The highest accuracy for 0-100 cm organic carbon inventory is expected from LHS-based sampling.

- An exception is at the 50-100 cm sampling depth, where grid-based sampling demonstrably provided the smallest interpolation error. At an 8-point sampling density, the interpolation error was half that of LHS and RANDOM interpolations at similar sampling densities.

It can be stated that the second phase of results also confirmed the previous conclusion. For 1-meter organic carbon inventory, LHS-based sampling is recommended in the following cases:

- Shallow or underdeveloped soils,
- Situations where the topography or other remotely sensed variables are closely related to the developed soil.

Grid-based sampling is recommended:

- For soils where the connection between the soil surface and the underlying soil horizons/layers is interrupted by some soil genetic process: alluvial and slope debris soils, and anthropogenic soils,
- Where depth conditions are crucial for organic carbon inventory: organic soils.

Tracking the effects of precision organic fertilization under different soil conditions (Érréve)

Based on the results, organic fertilization did not cause quantifiable changes in the soil's organic carbon content. In the principal component analysis scatterplot of MIR spectral data, organic fertilizer is clearly separated from soil samples, achieving sufficient differentiation for comparison. Subsequently, Pearson's coefficient proved to be the most suitable for examining the differences in principal component data. A significant difference was found in the similarity to organic fertilizer between the control and treated soil sample principal component values. This difference remains significantly different from the control during sampling after fertilization, but the confidence interval's gradual decrease over 2 years indicates the disappearance of organic forms introduced with organic matter, presumably through transformation and oxidation.

The cost-benefit analysis reveals that both patch treatment and full area treatment are cost-effective, leading to the following technological recommendations for precision organic fertilization:

- Precision soil improvement (treatment of less favorable soil patches) is less cost-effective but still recommended,
- The highest return is achieved with full area treatment,
- As an optimized technology, the treatment of more favorable (in terms of agronomic properties) soil patches is recommended for cost and risk-effective returns.

Mapping organic carbon conditions on heterogeneous topography (Kenya)

Soil samples from the northeastern side of Mount Kenya show significant heterogeneity in organic carbon values within relatively small areas. Numerous topographical and climatic factors influence soil organic carbon content, making accurate mapping of soil conditions in the area particularly complex. The R^2 value of the initially prepared organic carbon maps could be significantly increased (from 0.59 to 0.82) by optimizing the estimation model with additional variables. Based on the high coefficient of determination of the interpolated points on the prepared organic carbon map, it can be stated that the established interpolation estimation model can serve as a starting point for other areas with similarly heterogeneous topography and climatic conditions.

NEW SCIENTIFIC RESULTS

Based on the research findings, the following new scientific results have been established:

7.1. For carbon stock survey, Latin Hypercube Sampling (LHS) based soil sampling conditioned with topological data and surface properties may lead to incorrect results for alluvial and anthropogenic soils (due to soil layers) and organic soils (due to significant depth conditions). For these soils, a grid-based sampling strategy is recommended.

7.2. Reducing the sampling density by 66% (1900 m²/sample point to 5800 m²/sample point) for each of the three sampling point selection methods examined resulted in a maximum 7% decrease in representativeness during the organic carbon survey. Additionally, both LHS and grid-based sampling show at most a 15% deviation from the original information content even with an 84% reduction in the original sample size (1900 m²/sample point to 11600 m²/sample point).

7.3. Using the mid-infrared spectral data-based organic carbon estimation models presented in the thesis, an estimation accuracy of over 90% (Cross-validation $R^2 = 0.9$ and 0.97) is expected, even with a 10% calibration sample fraction, regardless of the number and heterogeneity of the samples, when employing the sample selection methods used in the thesis (Kennard-Stone sampling, k-means sampling, Latin Hypercube sampling).

7.4. Pelletized poultry manure was detectable among soil-bound organic compounds for up to one year ($p < 0.01$). By the second year, only statistical traces of the manure could be detected ($p \leq 0.2$ and $p \leq 0.6$), irrespective of the applied dose.

7.5. The methodology presented in the thesis can be integrated into agricultural practice. With annual soil sampling, it is possible to track the persistence of plant organic residues and organic fertilizers.

7.6. All organic fertilization procedures examined in the research were cost-effective in terms of crop yield. However, under the given conditions, fertilizing better-quality soil patches may be more favorable both economically and for atmospheric carbon sequestration compared to treating the entire area. Therefore, I recommend the implementation of precision manuring ont he better-quiality sol patches.

7.7. The methodology used (optimized interpolation with additional variables) enabled the creation of a high-precision ($R^2 = 0.82$) soil organic carbon concentration map for a large (~1500 km²) area characterized by high topographical and climatic heterogeneity.

KEY PUBLICATIONS

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