Contents

EFFECT OF DIFFERENT LEVELS OF SOIL COMPACTION APPLIED DURING SOWING ON MAIZE AND SUNFLOWER

Introduction

Soil structure fundamentally influences the effectiveness of field crop production. In more compacted soils, sown seeds emerge with greater difficulty, root development is weaker, and delayed and uneven emergence affects the timing and effectiveness of subsequent agronomic operations. The main problem caused by uneven emergence is that later-emerging plants never catch up with earlier ones; the earlier plants become dominant, absorb more water and nutrients, shade the others, and as a result, yield per unit area decreases. According to research, under optimal conditions seed emergence occurs within 6–8 hours, meaning that 95% of plants emerge from the soil within this period.

In order to minimize the heterogeneity of soil conditions during cultivation, the opportunities provided by precision farming must be applied already at the sowing stage, in addition to tillage operations. This is achieved by seeders equipped with dynamically adjustable downforce, which automatically regulate sowing depth and the pressure of depth-control wheels according to the soil compaction of each field section. This ensures that sowing is optimally adapted to soil conditions, resulting in the most uniform emergence possible.

During the research, the primary experimental factor was the different levels of soil compaction (downforce) applied during sowing, accompanied by comprehensive soil testing of the study areas and satellite-based remote sensing monitoring of crop development. Our objective was to verify the yield increase achievable through the treatments in maize and sunflower. The diversity of soils in Hungary is not only evident among regions, but often within a single 8–10 hectare field, where two or three different soil types may occur, and soil properties—especially compaction—show considerable variability. As a result of the research, we proposed a crop production technology that enables farmers using precision agriculture to fully exploit the potential of their available equipment.

Materials and Methods

Various manufacturers market planter units with similar characteristics that are capable of sowing under different levels of soil pressure. Different manufacturers express downforce in different units, and the terminology used often varies as well. In the Precision Planting system used in this study, the term “downforce” (soil pressure; literally: pressing force) is applied, while elsewhere the terms “margin” (approximately: operating range) or “gauge wheel load” are used. In this study, the values were defined with reference to Precision Planting equipment.

Numbering of Experimental Treatments:

1. No additional soil pressure (0 kg)
2. Low soil pressure (approximately 300 lb = 136 kg)
3. Medium soil pressure (approximately 500 lb = 227 kg)
4. High soil pressure (approximately 900 lb = 408 kg – excessive compaction around the seed)

Sowing was carried out as soon as possible after rainfall, because dry soil cannot be compacted; therefore, the treatments would have been relatively ineffective under dry conditions. At almost all locations, sufficient area was available to surround the experimental plots, allowing edge effects to be largely eliminated. However, at one site this was not possible, and therefore edge effects slightly distorted the results during evaluation.

Table 1: Setup of the Experiments (Map of Experimental Sites in Figure 1)

Kísérleti hely-település (számozás az 1. ábrán)	**Cég neve:**
Szőreg (6)	Karotin Kft.
Újszeged (5)	Agroplanta Kft.
Öthalom (4)	Kotogány Árpád
Algyő (3)	Agroplanta Kft.
Dóc (2)	Karotin Kft.
Bugac (1.2)	Bugaci Aranykalász Zrt. és Mezőgazda Kft.
Bugac (1.1)	Bugaci Aranykalász Zrt. és Mezőgazda Kft.

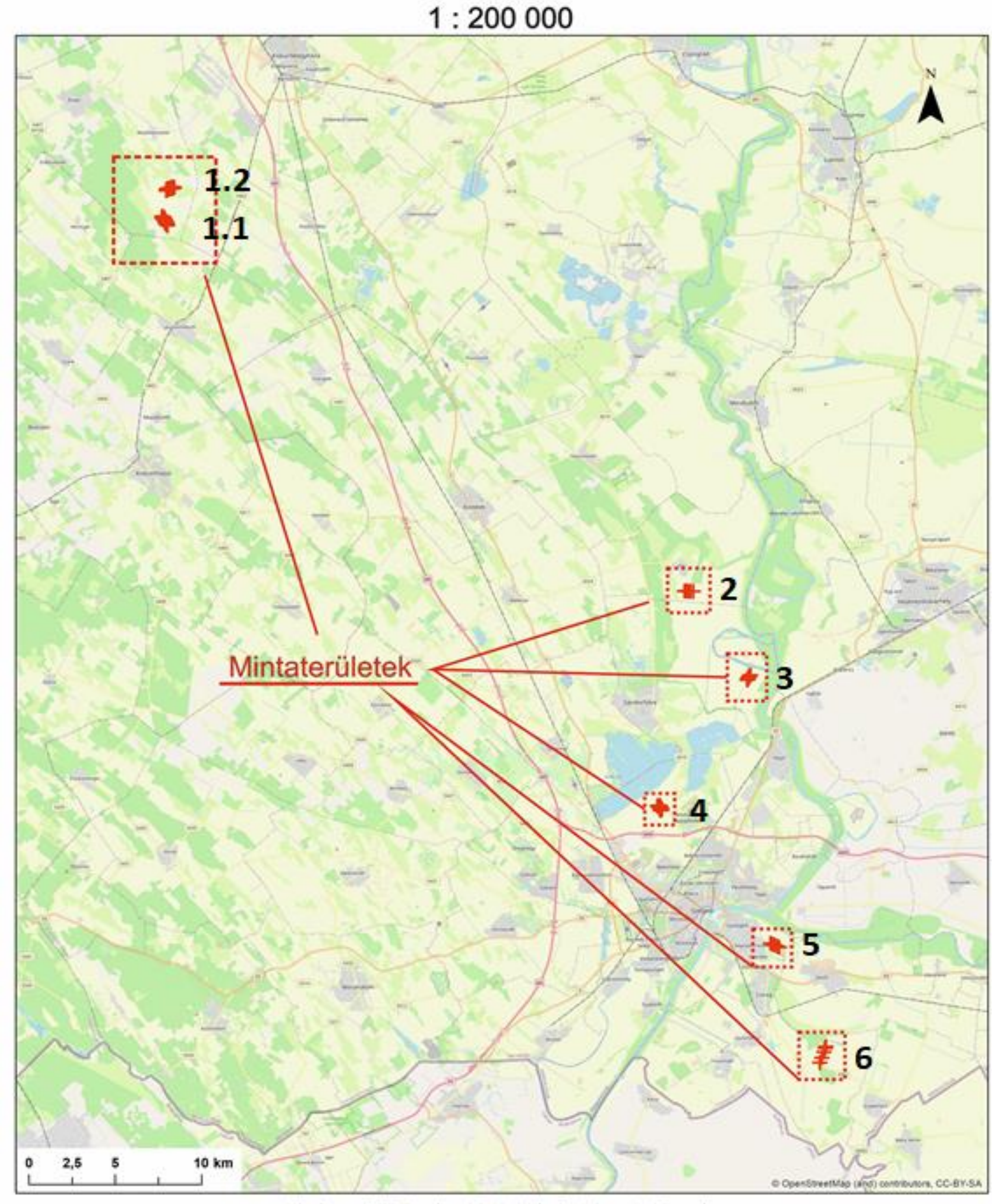


Figure 1. Experimental Sites (Explanation in Table 1)

At 55 locations, 110 soil samples were collected using an auger from the surface layer (0–30 cm) and the subsurface layer (30–60 cm), with each sample consisting of the average of three closely spaced point samples. The three subsamples were mixed, and one composite sample was prepared for each layer, which was then subjected to laboratory analysis. This method ensured that the samples were representative of a small soil area and minimized random variability caused by local heterogeneity. This is particularly important for improving comparability with NDVI and yield data.

The 110 undisturbed samples were collected at the central point using a sampling cylinder with a volume of 100 cm^3.

Parameters Analyzed:

• pH (H_2O) • Total soluble salts (w/w %)• $CaCO_3$ (w/w %)• Arany plasticity index and physical soil texture (reduced nutrient analysis) • Humus content (w/w %)• $NO_2^- + NO_3^-$–N (mg/kg) • AL-P_2O_5 (mg/kg) • AL-K_2O (mg/kg) • Bulk density (g/cm^3)• Moisture content (w/w %)

• Particle size distribution (in mm): • <0.002• 0.005–0.002• 0.01–0.005• 0.02–0.01• 0.05–0.02• 0.25–0.05• >0.25 (Fraction codes in the tables: lt002; b002_005; b005_01; b01_02; b02_05; b05_25; gt25)

RESULTS

Cumulative Distribution Curves of Particle Size Categories

Figure 2 shows the cumulative particle size distribution curves of several representative soil samples. This also confirms that the 110 samples collected by us represent the full range of Hungarian soils in terms of physical texture. Therefore, our findings can be extended with high reliability beyond the study area to all soils in Hungary.

The sampling locations were as follows:
42: Bugac, site 4, 30–60 cm;
31: Bugac, site 3, 0–30 cm;
231: Bugac, site 23, 0–30 cm;
282: Dóc, site 28, 30–60 cm;
272: Dóc, site 27, 30–60 cm;
332: Algyő, site 33, 30–60 cm;
322: Algyő, site 32, 30–60 cm.

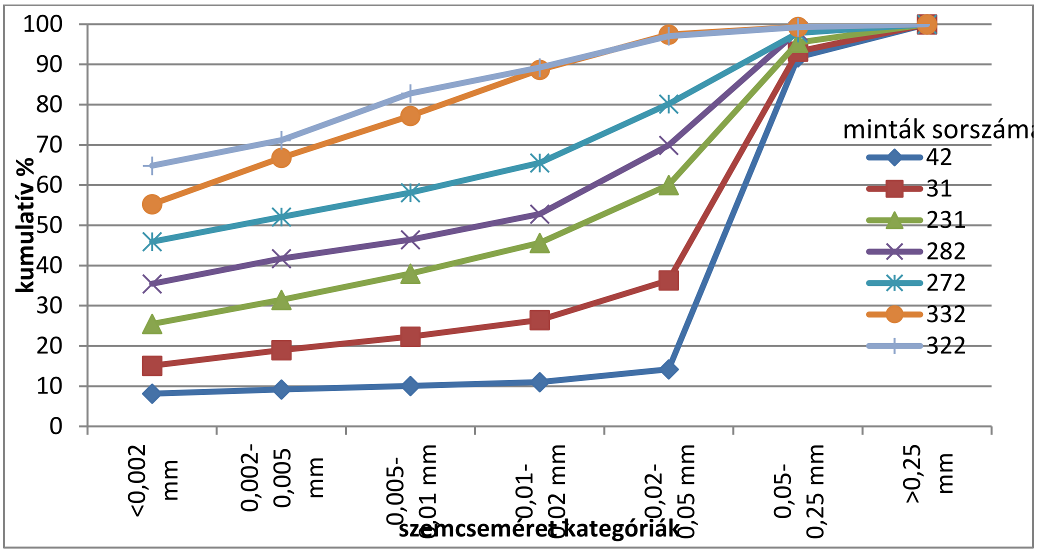


Figure 1. Representativeness of the Particle Size Distribution of the Samples

Characterization of Soils Using Two Aggregated Variables

Seventeen different soil properties were measured in the 110 soil samples. These properties are obviously not independent of each other. The soil samples themselves are also not independent, since samples taken from the same field are necessarily more similar to each other than those taken from different fields. In such cases, dimension-reduction methods are commonly applied in statistics.

These methods calculate hypothetical variables from the original variables that are completely independent of each other (with zero correlation), while the first such hypothetical variable explains the largest proportion of the variance caused by all original variables, the second explains less, and so on.

We applied this dimension-reduction procedure both to analyze relationships among variables and to assess similarities among soil samples. The similarity of the examined soil parameters in two-dimensional space (reducing the 17 actually measured variables to two theoretical variables) is illustrated in Figure 3. The variables clearly cluster into four groups, and bulk density, which is important for root growth, stands out as a distinct group separated from the others.

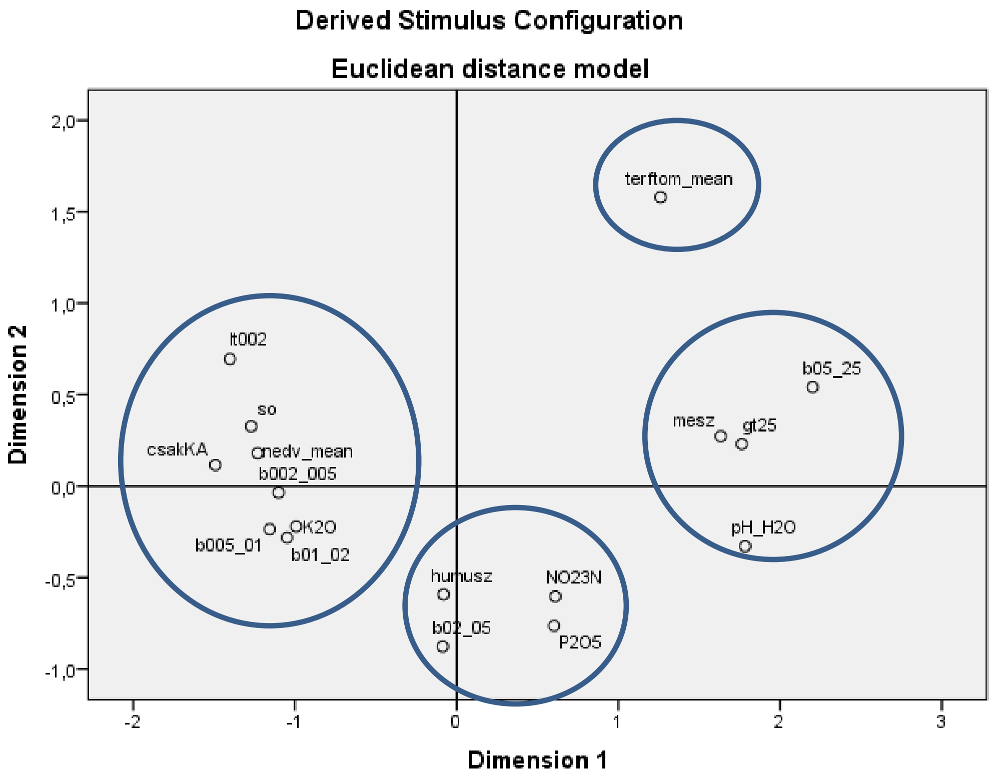


Figure 3. Soil Analysis Results in the Space Defined by the First Two Factors

FINAL CHARACTERIZATION OF SOILS IN TWO-DIMENSIONAL SPACE

Each of the 110 soil samples (55 sites sampled in two layers) was characterized by 17 variables (soil properties) based on laboratory analyses. Mathematically, this means that they were positioned in a 17-dimensional space. Determining the interactions operating in a problem with such complex geometry is an extremely complicated task.

To address this problem, dimension-reduction methods were developed, which use mathematical tools to transform multidimensional space into, for example, two-dimensional space. In this process, the similarities and differences among variables (their existing or missing correlations) are utilized. The properties of the surface soil layers displayed in two-dimensional space are shown in Figure 4

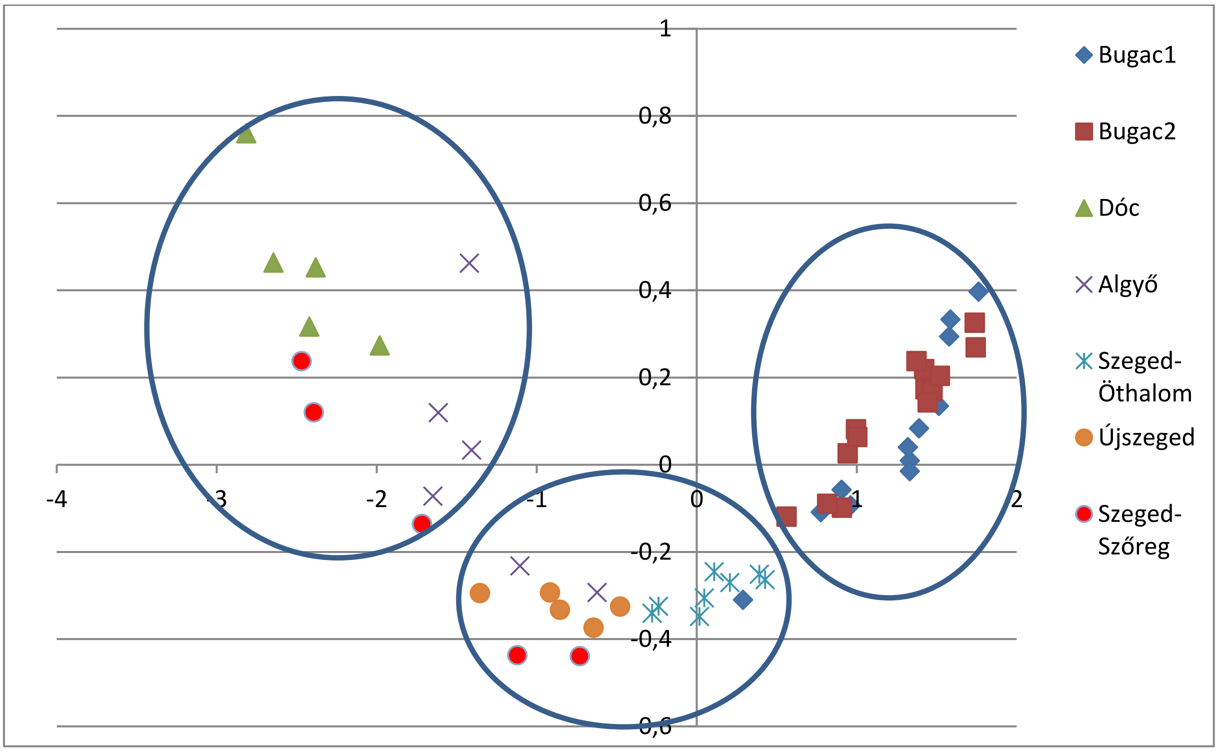


Figure 4. Sampling Sites in the Space Defined by the First Two Factors of the Surface Soil Layer

The soils are clearly arranged and can be divided into approximately three distinct groups: 1: Bugac1 and Bugac2; 2: Szeged-Öthalom and Újszeged; 3: Dóc, Algyő, and Szeged-Szőreg.

There is a slight overlap among the groups.

In the case of the subsurface layer, the two-dimensional representation is less clear, which can be attributed to the homogenizing effect of cultivation.

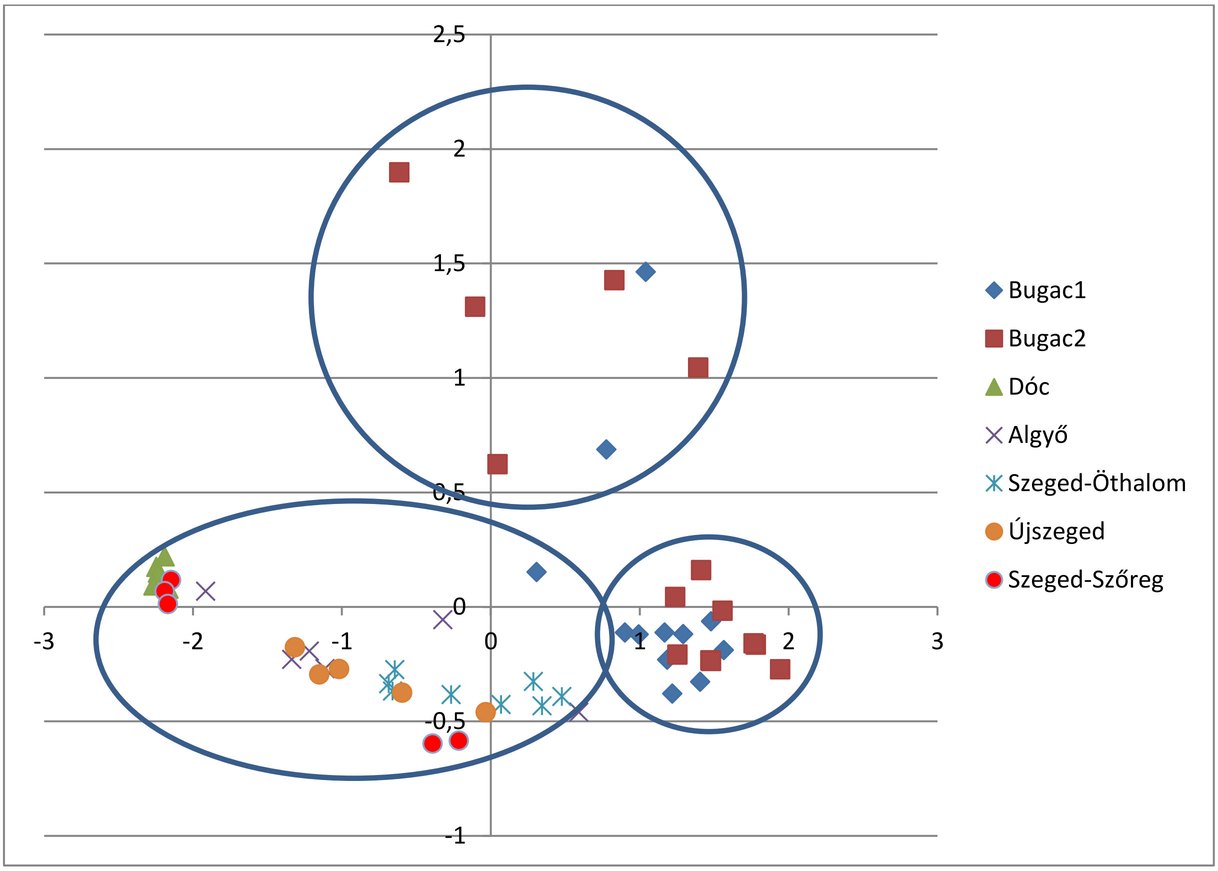


Figure 4. Sampling Sites in the Space Defined by the First Two Factors of the Subsurface Soil Layer

Typically, the samples from Bugac differ markedly from the others. A more detailed examination shows that these are saline soil samples. In the case of the subsurface layer, the Bugac samples and all other samples can be classified into two separate categories, and the Bugac samples with saline subsoil may form a distinct subgroup.

PENETROMETER TESTS DIRECTLY CHARACTERIZING SOIL COMPACTION

At 40 locations corresponding to the laboratory soil sampling points, penetrometer measurements were also carried out at the two experimental sites in Bugac. Based on the penetrometer data, the sampling points were classified into five groups. In the classification process, primary consideration was given to maximum penetration depth (cm), followed by maximum soil resistance (Newton). Subsequently, a calculation method was developed in which these properties were combined into a single index, allowing the groups to be distinguished from each other on a linear scale.

The complex penetration index was calculated as follows:

KPM = log(maxFORCE × (90 − maxDEPTH))

Table 1. Soil Classification Based on Penetrometer Measurements

Complex Penetration Index

Tukey HSD

csoport2	N	Subset for alpha = 0.05				
		1	2	3	4	5
5	9	3,743545				
4	5		3,831903			
3	14			3,926798		
2	5				4,057766	
1	7					4,361741
Sig.		1,000	1,000	1,000	1,000	1,000

1. It is clearly evident that the complex penetration index distinctly separates the five groups from each other; therefore, we developed an appropriate soil property index that enables the evaluation of experimental results based on penetration resistance measurements.
2. Subsequently, we examined how and to what extent these groups characterize soil properties that can be measured in the laboratory and whose interpretation is well understood. For this purpose, discriminant analysis was applied, which allows the separation of qualitative variables (in our case, the five groups) based on continuous variables (in our case, laboratory-measured soil properties). As a first step, all measured soil properties were included in the analysis.
3. We also examined the correspondence between the groups identified by discriminant analysis and the actual groups, the results of which are presented in the table below. Out of 40 cases, 35 samples (87.5%) were classified into the correct group, and in 37 cases

they were placed either in the correct group or at most in an adjacent group (92.5%). Only in three cases (7.5%) were samples assigned to more distant groups.

4. From this, it can be concluded that penetrometer measurements provide a comprehensive characterization of multiple soil properties (not limited exclusively to physical soil properties), and that the classification based on penetrometer data can adequately represent productivity groups that emerge as the combined result of these complex soil property sets.

táblázat A penetrométeres talajcsoportok predikciója a talajtulajdonságokkal

csoport2 * Predicted Group for Analysis 1 Crosstabulation

		Predicted Group for Analysis 1					Total
		1	2	3	4	5	
	1	5	2	0	0	0	7
	2	0	5	0	0	0	5
csoport2	3	**1**	0	13	0	0	14
	4	0	0	0	5	0	5
	5	0	**1**	**1**	0	7	9
Total		6	8	14	5	7	40

We also repeated the above analyses by including only the reduced nutrient analysis instead of all soil tests. The significance of this approach lies in the fact that these tests are performed on virtually every field where soil sampling is conducted to refine nutrient management. Therefore, if samples could also be reliably classified based on these data, the results could be generalized much more broadly, even without conducting penetrometer measurements, relying solely on indices calculated from routine soil analyses.

Since the second table above, showing the results of the discriminant analysis, contains numerous variables that fall outside the scope of the reduced nutrient analysis, we did not have high expectations for this approach. This expectation was confirmed. On the following page, we present the agreement between the groups formed in this way and the actual groups. Twenty-two samples were classified into the correct group (55%), and 30 samples into the correct or at most an adjacent group (75%), which is not sufficiently accurate.

We therefore conclude that penetrometer measurements provide a much more comprehensive picture of soil conditions than reduced nutrient analysis results, although they represent this information in a highly complex manner. Their advantage, however, is that they are easy and simple to perform and are considerably less expensive than mechanical composition analyses based on soil samples taken from multiple layers. Since they contain substantial additional information compared to reduced nutrient analyses, this extra information can be used to determine sowing depth in precision farming practices.

SUMMARY TABLE OF EXPERIMENTAL RESULTS

Table 5. Average Maize Yield Results (t/ha)

év	Soil Pressure Treatment	**Bugaci Aranykalász Zrt.**	**Mezőgazda Kft.**	**Karotin Kft.**	**Agroplanta Földi László**	**Kotogány Árpád**
2020	**1**	5,39	5,34	12,44	9,72	11,62
	2	5,28	5,12	11,62	9,80	11,66
	3	4,88	4,59	11,64	9,88	11,60
	4	6,27	6,46	11,49	9,64	11,62
2021	**1**	1,97	1,91	6,74	8,28	7,89
	2	1,73	1,70	7,15	8,33	8,08
	3	1,49	1,43	6,83	8,34	8,18
	4	1,69	1,66	6,99	8,22	8,06

5. Table 5. Average Sunflower Yield Results (t/ha)

év	Soil Pressure Treatment	**Bugaci Aranykalász Zrt.**	**Mezőgazda Kft.**	**Karotin Kft.**	**Agroplanta Földi László**	**Kotogány Árpád**
2020	**1**	2,75	2,62	3,80	2,72	2,98
	2	2,81	2,84	2,88	2,80	3,00
	3	2,86	2,92	2,52	2,81	2,50
	4	2,78	2,73	2,88	2,34	1,84
2021	**1**	1,93	1,95	2,78	2,89	2,76
	2	1,91	1,87	2,55	2,94	2,82
	3	1,94	1,98	3,24	2,90	3,02
	4	1,86	1,77	2,98	2,87	2,78

ANALYSIS OF SUNFLOWER YIELD RESULTS IN BUGAC USING DIFFERENT STATISTICAL METHODS

The treatments were coded using two-digit numbers, where the tens digit represented the number of the soil pressure treatment (1–4), and the units digit indicated salinity (1: present, 0: absent). In this way, eight separate treatments containing unequal numbers of samples could be analyzed, in which salinity was derived from soil properties.

The data revealed that the treatments had a significant effect. Of the total variance, 57.8% was explained by the treatments, which is considered a good value in terms of yield estimation. It was found that yields were lower on non-saline sandy soils than on saline but deeper-lying, more compact soils. Within these groups, the means of Treatments 1 and 2, as well as Treatments 3 and 4, did not differ significantly from each other. The saline and non-saline treatments without soil pressure (10 and 11) also did not differ significantly.

As shown in Figure …, the effect of soil pressure treatments is opposite on compact saline soils and loose sandy soils: increasing soil pressure has a negative effect on sandy soils and a positive effect on compact soil patches.

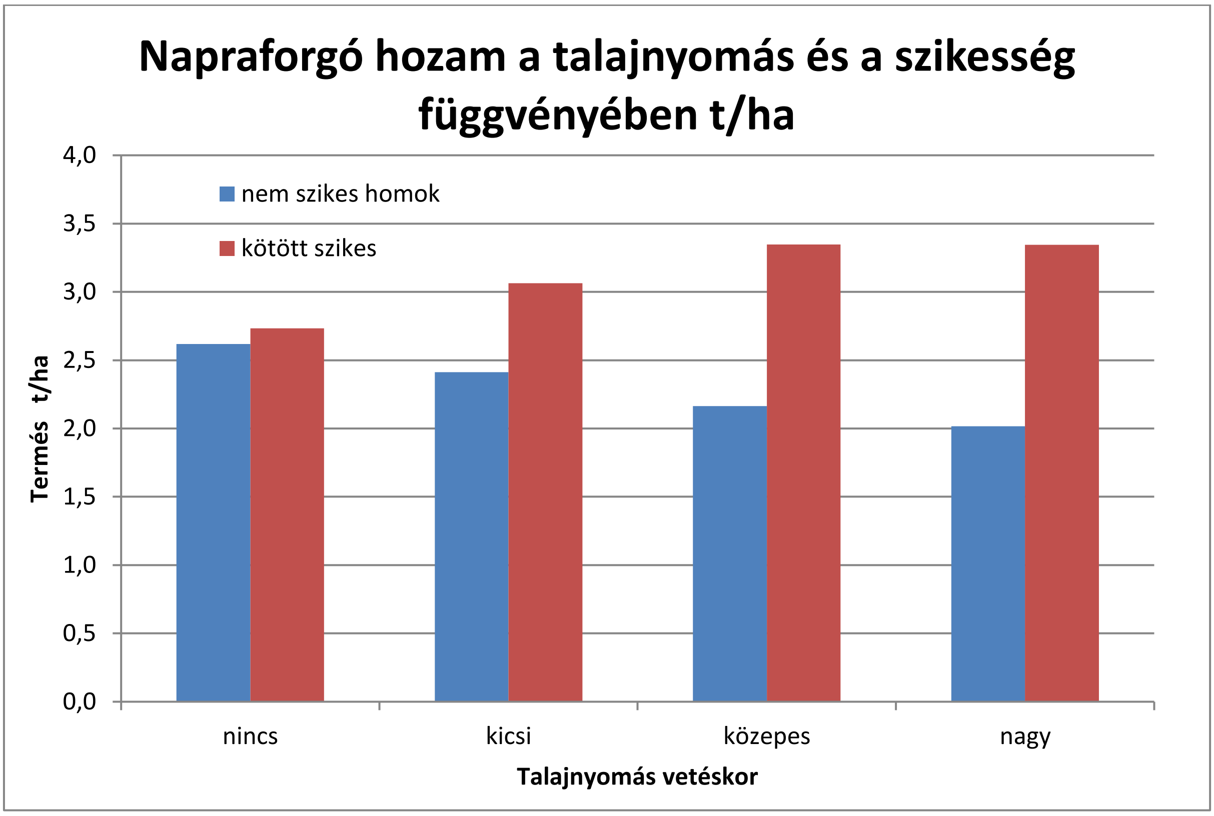


Figure 6. Sunflower Yields and Influencing Factors in Bugac

The above figure also shows that the effects of the treatments differ between compact saline soils and sandy soils. Therefore, we also examined their effects on yield results using multifactor analysis of variance, considering separately the treatment (referred to as KISERLET in the table below), salinity, and the interaction between the two. The main effect of treatment was not significant, whereas the main effect of salinity and the interaction between treatment and salinity were clearly significant.

In the next step, we applied a more complex method, the General Linear Model (GLM), which is capable of handling both continuous variables (NDVI) and qualitative variables (treatment, salinity) simultaneously. Both continuous and categorical variables proved to have significant effects, and together they were able to explain 65.3% of the total variance in yield.

ANALYSIS OF MAIZE YIELD RESULTS IN BUGAC USING DIFFERENT STATISTICAL METHODS

In the case of maize, under these conditions, a significant difference in yield was observed only between treatments with and without applied soil pressure (Figure …).

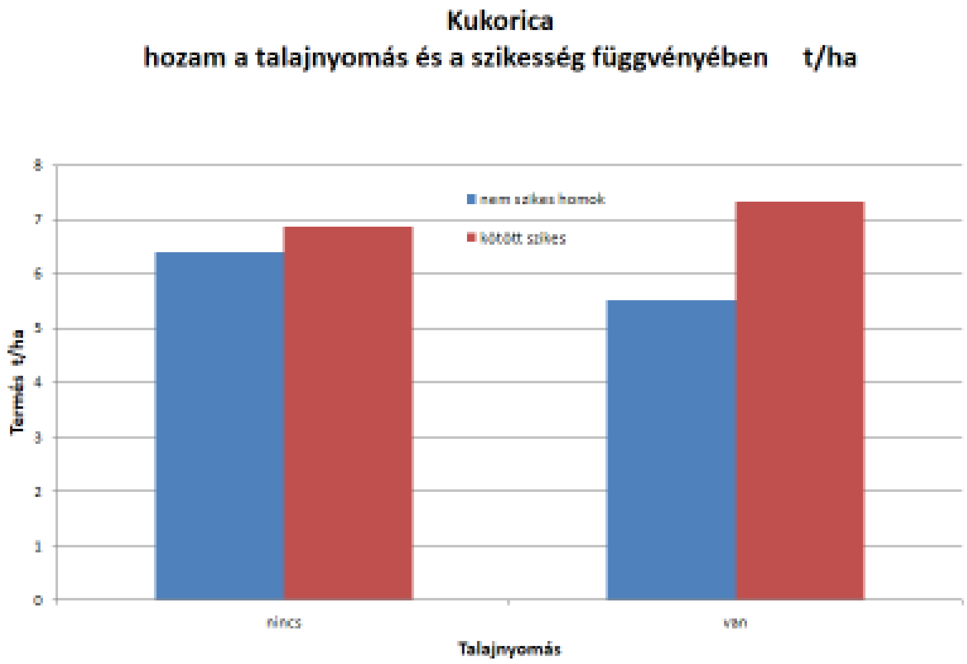


Figure 6. Maize Yields and Influencing Factors in Bugac

We also applied the GLM model in this case, treating treatment, salinity, and their interaction as independent explanatory variables. Both NDVI as a continuous variable and the qualitative variables had significant effects on maize yield. Together, they explained 49% of the total variance.

The analyses indicated that the effects of treatments on deeper-lying compact saline soils are fundamentally different from those on higher-lying loose sandy soils. In the case of maize, significant effects should be sought collectively between the treatment without additional soil pressure and all other treatments. While soil pressure has a positive effect on maize yield on compact saline soils, it has the opposite, negative effect on loose sandy soils.

ANALYSIS OF MAIZE YIELD RESULTS IN SZEGED-ÖTHALOM USING DIFFERENT STATISTICAL METHODS

Similarly to the above, yield data from the fourth experimental site in Szeged-Öthalom were also analyzed using various methods. This area is much more homogeneous in terms of productivity than the Bugac site. Interestingly, sunflower yields differ only slightly from those in Bugac, while maize yields are almost twice as high. This can be well explained by differences in water management between the two areas, as this site is located on loamy soil with good water retention capacity.

We examined the effect of treatments on maize yield using analysis of variance. Since no saline patches were present, only the four treatments were considered. Although treatment effects could be detected, they explained only 2.2% of the total variance in yield data. From a practical perspective, treatment had no or only negligible influence on maize yield.

The relationship between the July NDVI index and the yield harvested in September was analyzed using linear regression. With this method, 26% of the total variance could be explained, which is considered a good value at higher yield levels such as in this case.

Using the General Linear Model (GLM), both the four levels of soil pressure treatments and the NDVI index were included among the factors influencing yield. As expected, the explanatory power of the model was only slightly higher than that of the linear regression (26.4%), and the effect of treatments was not significant.

ANALYSIS OF SUNFLOWER YIELD RESULTS IN SZEGED-ÖTHALOM USING DIFFERENT STATISTICAL METHODS

At this experimental site, sunflower yield results showed an almost perfect normal distribution, indicating that the yield was shaped by a large number of factors, each having only a small modifying effect. No single factor had a strong influence that would have resulted in a skewed or bimodal distribution.

Using one-way analysis of variance, we examined the effects of the four different soil pressure treatments on sunflower yield. Overall, a strong significant effect was found, explaining 22.4% of the total variance in yield.

In the next step, we also used the General Linear Model (GLM) to examine the combined effects of the July NDVI index and soil pressure treatments on sunflower yield. The model intercept did not differ significantly from zero. Both influencing factors proved to be significant, but NDVI contributed very little to the explanatory power. Compared to the previous analysis of variance, the explanatory power of the model increased only slightly (23.3%).

EVALUATION OF THE EXPERIMENT USING MULTIPLE VEGETATION INDICES

The fourth experimental site (Szeged-Öthalom, Árpád Kotogány's field) was the only location where the sunflower and maize experiments were conducted side by side on relatively homogeneous soil, allowing direct comparison of the two crops in terms of parameters relevant to the study.

Calculation of Vegetation Indices

The NDVI (Normalized Difference Vegetation Index) is calculated as follows:

$$NDVI = (NIR - RED) / (NIR + RED),$$

where NIR is the reflectance measured in the near-infrared band and RED is the reflectance measured in the red band. For MOD09 data, Band 2 represents near-infrared reflectance (871–876 nm), and Band 1 represents red reflectance (620–670 nm) (Rouse et al., 1974).

Rouse, J.W., Jr., Haas, R.H., Deering, D.W., Schell, J.A., Harlan, J.C. (1974). Monitoring the vernal advancement and retrogradation green wave effect of natural vegetation. NASA GSFC Type III Final Report, Greenbelt, MD, 371 pp.

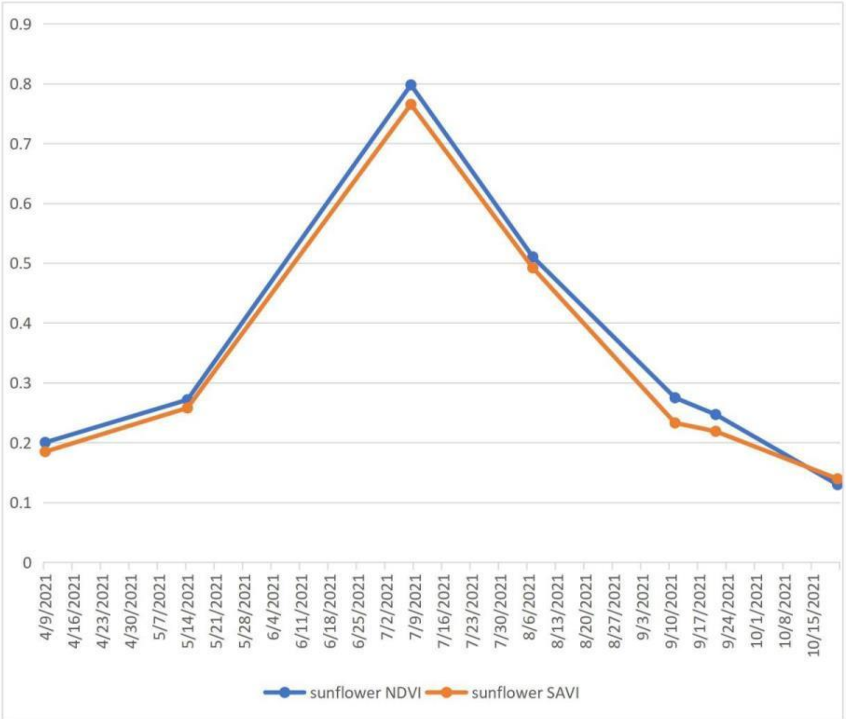
The SAVI (Soil-Adjusted Vegetation Index) is calculated as follows:

$$SAVI = ((NIR - RED) / (NIR + RED + L)) \times (1 + L),$$

where L is the soil brightness correction factor. The value of L varies depending on vegetation density or cover: in areas with very high vegetation cover, L = 0; in areas without vegetation, L = 1. Generally, L = 0.5 performs well in most situations and is the default value. When L = 0, SAVI = NDVI (Huete, 1988).

Huete, A.R. (1988). A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment*, 25(3), 295–309.

The two vegetation indices examined reach their highest values in July (Figure …); therefore, treatment differences were evaluated based on these data.



6. *Figure. Sentinel-Based Vegetation Indices for Sunflower (Öthalom))*

In the case of sunflower, SAVI and NDVI differ slightly from each other, with SAVI values being slightly lower than expected.

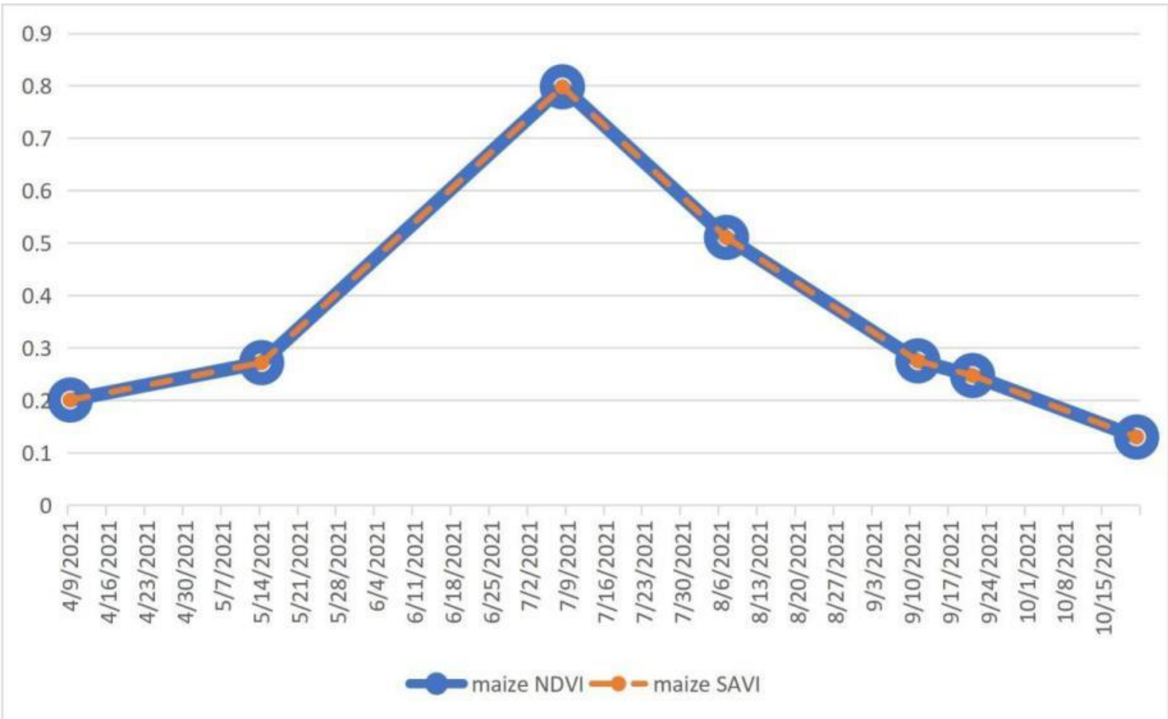
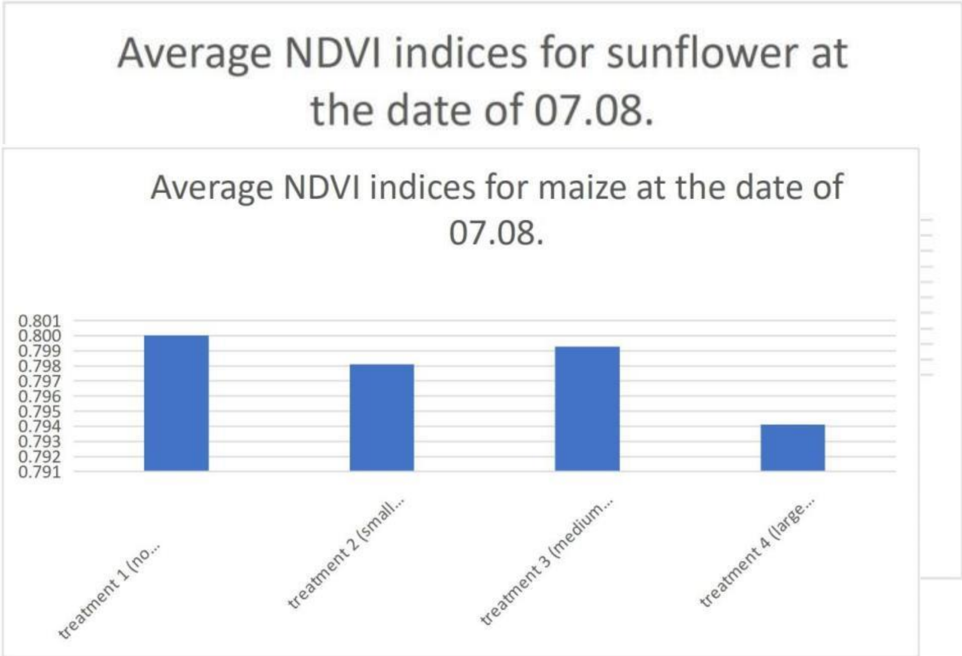


Figure 7. Sentinel-Based Vegetation Indices for Maize (Öthalom)

Figure 7. Average NDVI Indices of Sunflower as Affected by Treatments (Öthalom)



11 Figure 7. Average NDVI Indices of Sunflower as Affected by Treatments (Öthalom)

In this month, based on the NDVI indices, the optimum for sunflower was Treatments 3–4 (high or very high soil pressure), while for maize it was Treatments 1–3 (all except very high soil pressure).

CHAID ANALYSIS OF NDVI INDICES DEPENDING ON SOIL PRESSURE TREATMENTS AND EXPERIMENTAL SITES

We also tested an additional method in order to improve these values. This was the CHAID decision tree method (Chi-square Automatic Interaction Detector). In addition to changing the statistical method, we also included further explanatory variables, such as the three spectral bands (BLUE, RED, NIR) of the satellite images used to calculate the NDVI index, and two artificial variables derived from the combined soil properties.

An advantage of the CHAID method is that it can handle both continuous and qualitative variables, does not require a normal distribution, and presents factors with significant effects in a visually clear manner. Its disadvantage is that it is highly prone to model overfitting, which can be avoided through careful data preparation and appropriate selection of model-fitting parameters.

The above analyses also showed that under relatively homogeneous conditions, NDVI reflects differences in soil properties, and in areas with highly diverse characteristics it is also a good indicator of yield. In the following analysis, NDVI was considered as the dependent variable, and its dependence on experimental site and treatment effects was examined simultaneously across all sites.

First, we used analysis of variance to examine the dependence of July NDVI indices of maize on the two factors mentioned above. Both experimental site and treatment effects were significant, and together they explained 85.9% of the total variance. This finding was also supported by the CHAID analysis. Experimental sites appeared at the highest hierarchical level, within which treatments had a significant effect on NDVI values.

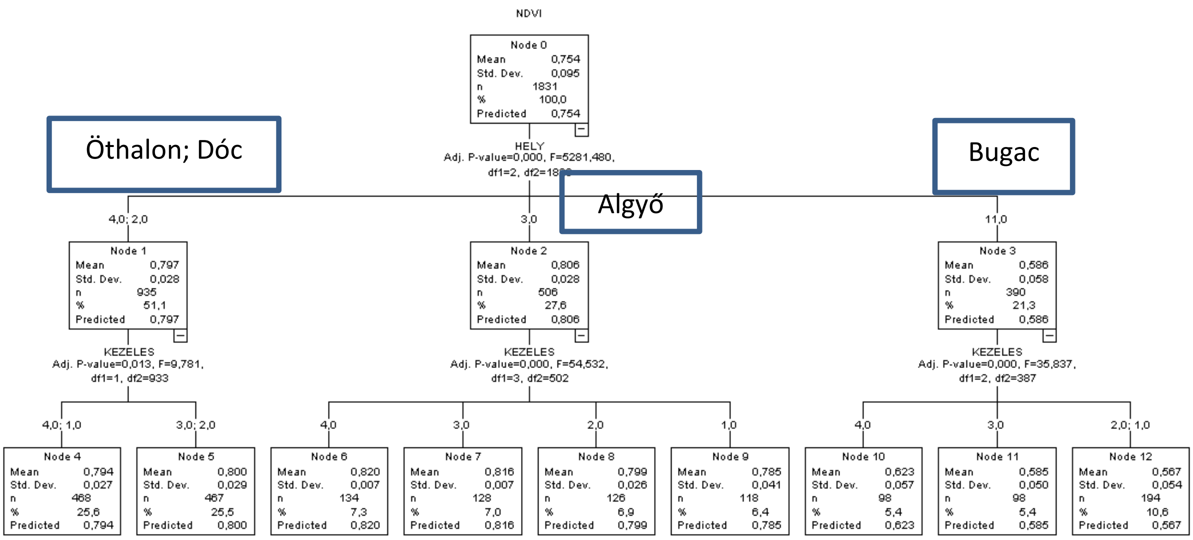


Figure 7. CHAID Decision Tree for Determining the Maize NDVI Index

A similar analysis was conducted for sunflower NDVI indices, but with different results. As a first approximation, multiple analysis of variance did not reveal a significant effect of treatments, whereas the effect of experimental sites was significant. Thus, primarily due to differences among experimental sites, 71.6% of the variance in NDVI indices could be explained.

In contrast, CHAID analysis clearly showed that, in addition to experimental sites having the strongest influence on sunflower NDVI indices, treatments were also important determinants of NDVI values within each site, although in different ways across locations.

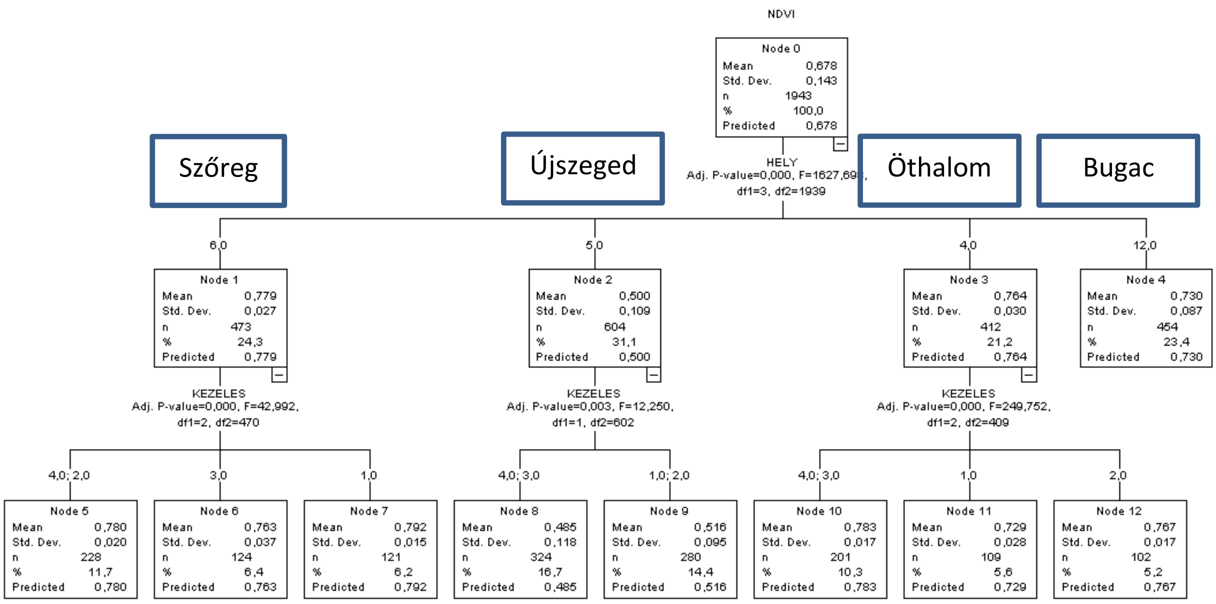


Figure 7. CHAID Decision Tree for Determining the Sunflower NDVI Index

THESIS-STYLE SUMMARY OF RESULTS

During the project, we demonstrated that routine soil analyses (reduced nutrient analysis) are not sufficient to assess the physical condition and compaction of soils. Soil properties derived from costly and time-consuming mechanical composition and bulk density analyses appear in a complex manner in properly conducted penetrometer measurements, which are fast, relatively inexpensive, and yield results relevant to crop production. Accordingly, we developed a classification system to support the determination of soil pressure values prior to sowing.

We confirmed the effects of soil pressure treatments on NDVI indices and yield. These effects depend on soil type and crop species. In general, they are negative on sandy soils and positive on more compact soils, and they are stronger in sunflower and weaker in maize.

We also demonstrated that advanced analytical methods (CHAID) are capable of revealing cause-and-effect relationships within fields and confirming the effects of soil pressure treatments. However, careful application of the method is required to avoid model overfitting.