HUNGARIAN UNIVERSITY OF
AGRICULTURE AND LIFE SCIENCES

Hungarian University of Agriculture and Life Sciences

IMPACT OF TEMPORARY GROUNDWATER ELEVATION ON WINTER WHEAT YIELD

Theses of doctoral (PhD dissertation

György KEREZSI

Gödöllő

2025

Doctoral school

Name: Environmental Science Doctoral School (MATE)
Discipline: Environmental Sciences

Head of the school: Erika CSÁKINÉ Prof. Dr. MICHÉLI

institute director, full professor, full member of the Hungarian Academy of Sciences (HAS)

MATE, Szent István Campus

MATE, Institute of Environmental Sciences

Department of Soil Sciences

Supervisor(s): Dr. habil. Gábor GÉCZI, PhD

associate professor, deputy head of department

MATE, Institute of Environmental Sciences

Department of Environmental Analysis and Technologies

Dr. habil. István WALTNER, PhD

associate professor, head of department

MATE, Institute of Environmental Sciences

Department of Water Management and Climate Adaptation

....	....
Erika CSÁKINÉ Prof. Dr. MICHÉLI approval of the head of school	Dr. habil. Gábor GÉCZI, PhD approval of the supervisor

....

Dr. habil. István WALTNER, PhD
approval of the supervisor

Background and Objectives

Hungary's susceptibility to inland excess water and drought is unique (47% to 90% of the country's area). One key question for sustainable and safe biomass production is the effective regulation of the groundwater balance through economically sustainable water management. Climate models predict more frequent droughts in the future across Europe, including Hungary, while due to local, intense downpours, sudden floods and water inundations will also become more frequent. The average annual water deficit ranges between 200–250 mm. To mitigate harmful water shortages, rational water retention must be ensured. Hungarian legislation defines the order of flood relief (Decree 10/1997. (VII. 17.) KHVM) and details of inland excess water damage (Act CLXVIII of 2011), but it does not regulate the time and volume of drainage. The topic of this thesis is the investigation, under controlled lysimetric conditions, of the effect of temporary inland inundation on winter wheat. The aim was to analyse plant responses at various water depths (0, –30, –60 cm) and durations (3, 6, 9, 12 days), in terms of both quantitative (yield) and qualitative (e.g. protein, gluten, Zeleny value) parameters. Special attention was given to data obtained by remote sensing (UAV – drone) and by hand-held SPAD measurements that supported early detection of physiological status. The practical relevance of the dissertation lies in refining management threshold values along which farmers can decide on retaining or draining water. The research also covered relationships among water stress, vegetation indices from drone aerial images (GNDVI, BNDVI), and the SPAD relative chlorophyll content index (RCI), characterised using regression models. This may establish a new methodological basis for precision water management, particularly to mitigate climate change impacts. The complexity of the investigations also enabled exploration of how interannual weather differences affected treatment efficacy. Statistical methods applied (MANOVA, ANOVA, Welch test, Games–Howell post hoc, multivariate correlation and curve fitting) ensured scientific soundness and validity of the results.

Materials and Methods

Experimental Site: Lysimeter Station

I conducted the experiments at the Lysimeter Station of the Water Management and Irrigation Research Centre (ÖVKI) in Szarvas, Hungarian University of Agriculture and Life Sciences (MATE). The volume of each gravity lysimeter is 1 m^3, 80% of which is occupied by a soil column of Vertisol (an expansive clayey soil) type in the vessels; this rests on a 10 cm gravel layer to collect any water passing through the system precisely. The lysimeters are connected to individual measuring vessels in underground measuring cellars, allowing water level to be set on the communicating-vessels principle. With gravity/compensation lysimeters, water level can be maintained in the vessels in a way comparable to field conditions but partially closed—and thus precisely traceable.

Experimental Plant:

In the investigations I used the 'GK Déva' winter wheat variety, a bearded, mid-season, milling (A1 farinograph) type. It was bred by crossing the Basilica and Izidor varieties using the doubled-haploid method. It shows outstanding resistance to yellow and stem rust and to Fusarium. It can be grown safely throughout Hungary, with excellent adaptability and high yield potential.

Set-up of Experimental Treatments:

I set up the inland-excess-water simulation in 64 lysimeter vessels. I examined three main water levels:

i. 0 cm: water level up to the soil surface (two-phase soil condition);
ii. -30 cm: water level maintained 30 cm below the surface ;
iii. - 60 cm: water level maintained 60 cm below the surface.

These levels were applied for different durations (3, 6, 9, 12 days), plus a treatment with continuous -60 cm water level and a non-water treated control; thus, I examined 13 treatments plus the control.

Sowing and Crop Management

Wheat was sown in October of 2018, 2019, and 2020, with 17.5 g of seed placed in each 1 m^2 lysimeter vessel. Each year, every vessel received the same amount of complex NPK (15-15-15%) basal fertiliser by hand application, and crop care was uniform.

Start of Treatments

The experiments began on 2019-05-07, 2020-01-27, and 2021-04-29. The 2020 season was deliberately started earlier because late-winter/spring inland excess water is the “real” season in the region.

Data Collection Methods I

Measurement of Relative Chlorophyll Content Index (RCI) with the Konica Minolta SPAD 502 Plus

I measured leaf relative chlorophyll content with a Konica Minolta SPAD 502 Plus. The instrument measures the optical density difference of light transmitted through the leaf at two wavelengths: 650 nm (the range of maximal chlorophyll activity) and 940 nm (reference to compensate for leaf thickness and moisture). Measurements were taken on the photosynthetically most active leaves, with 15–20 repeats per lysimeter, and results were averaged. I recorded the average of the partial measurements in the measurement log.

Biometric Measurements and Harvest

Before harvest I measured plant height. Harvest was manual with uniform stubble height; then I weighed the aboveground sheaf mass. Threshing was performed with a small-plot thresher.

Measurement of Wheat Quality Parameters

I assessed grain quality parameters using a Foss Infratec™ NOVA grain analyser based on near-infrared transmittance (NIT) technology. Without milling, the instrument rapidly and accurately determines moisture, protein, gluten, starch, and ash contents. It complies with international standards (e.g. ISO 12099, EN 15948) and is accepted in international grain trade.

The main parameters assessed were:

i. protein content;
ii. gluten content (wash-out gluten);
iii. Zeleny sedimentation value (ZSV) as an indicator of protein quality and gluten strength and
iv. W-value (deformation work required to stretch dough).

Data Collection Methods II (Remote Sensing)

Unmanned Aerial Imaging (Drone)

I acquired aerial images of the lysimeter vessels with a DJI Phantom 4 “agro” drone equipped with a special, modified NGB (near-infrared, green, blue) camera. Over the three years (2019–2021) I carried out 60 flights, of which I evaluated 29 dates in the dissertation. Selection was based on image quality and the availability of parallel SPAD measurements. While flights were manual in 2019, from 2020 I used the Pix4D Capture flight-planning software for automated data collection.

My Geospatial Evaluation and Image Processing (Figure 1.*)*

a) *Georeferencing*: Because images taken at different times had ~5 m spatial inaccuracy, the first and most important step was georeferencing. As reference I used a centimetre-accuracy orthomosaic acquired in 2025 with a DJI Matrice 300 RTK drone, produced with my colleague in Szarvas.

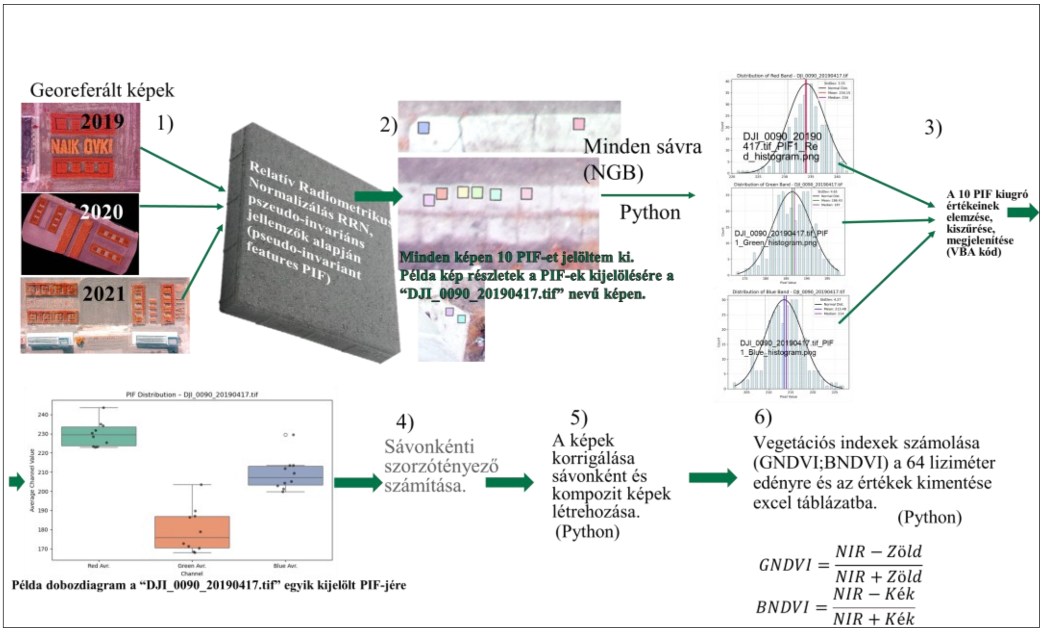

Figure 1. Flowchart of robust PIF-based normalization with linear scaling (or scaling factor-based PIF normalization with outlier handling) for the process of relative radiometric normalization of images after georeferencing, up to the calculation of vegetation indices

All earlier (2019–2021) images were fitted to this RTK-accurate orthomosaic using a third-order polynomial transform with at least 10 control points.

b) *Relative Radiometric Normalisation (PIF method)*:

To allow comparison among images taken under different illumination, I performed relative radiometric normalisation using pseudo-invariant features (PIFs). I selected a statistically stable, favourably illuminated image (DJI_0093.tif) as the reference; on every image I identified concrete paving slabs as PIFs; I filtered outliers from PIF samples (VBA and Excel); and I corrected all images to the reference with band-wise scale factors using Python (Figure 1.).

c) *Computation of Vegetation Indices:* From the normalised images I automatically computed GNDVI (Green Normalized Difference Vegetation Index) and BNDVI (Blue Normalized Difference Vegetation Index) values for each lysimeter vessel using Python scripts.

My Data Processing and Modelling Methods

Modelling Relationships between Vegetation Indices and SPAD

To describe relationships between drone-derived vegetation indices (GNDVI, BNDVI) and field-measured relative chlorophyll content (SPAD), I applied several models:

a) Second-order regression ($y = ax^2 + bx + c$) on the 2020 data to capture a non-linear (parabolic) relationship.

b) Michaelis–Menten model to capture saturation behaviour where SPAD approaches an asymptote as the index increases.

Methodology of My Statistical Analyses

Az adatok statisztikai kiértékeléséhez az R programnyelvet és az RStudio fejlesztői környezetet használtam, számos speciális csomag segítségével (pl. dplyr, Hmisc, car, rstatix).

For statistical evaluation I used R and RStudio with packages for data handling, correlation, variance-homogeneity testing, normality checks, and visualisation. Prior to hypothesis testing, I checked assumptions:

Correlation: Pearson correlations among dependent variables (e.g., protein, yield) with Hmisc::rcorr().

Outliers: Multivariate outliers via robust PCA using mvoutlier.

Variance Homogeneity: Bartlett's test (normal data) and the more robust Levene's test.

Normality: Multivariate (Henze–Zirkler) and univariate (Shapiro–Wilk; Lilliefors/KS) tests on residuals.

I also used two-way grouped boxplots and interaction plots to visualise distributions, dispersion, and factor interactions (water level, duration).

My Hypothesis Testing Methods

Multivariate Analysis of Variance (MANOVA) in a two-factor randomized block design to test joint effects of water level, duration, and their interaction on multiple dependent variables (protein, gluten, yield, etc.).

Post hoc and Group Comparisons: Games–Howell (variance-heterogeneous, unequal n) and Welch's two-sample t-tests.

Results and Discussion

The aim was to understand how different water-level and duration treatments affected winter wheat quality and yield over three years, and to explore links between drone-derived vegetation indices and SPAD. The dataset comprised 168 observations (56 lysimeter vessels × 3 years) for yield and quality; parallel UAV-VI and SPAD pairs were n=448 in 2019, n=440 in 2020, n=192 in 2021 (total n=1084).

Correlations and Outliers

Pearson correlations showed strong positive associations among quality parameters—especially protein vs. gluten ($r = 0.989$, $p < 0.001$), protein vs. Zeleny ($r = 0.961$, $p < 0.001$), and Zeleny vs. W ($r = 0.909$, $p < 0.001$)—indicating coordinated responses of quality traits to treatments, while yield correlated only moderately with quality. Robust PCA (mvoutlier::aq.plot, α=0.001) identified outliers, warranting further checks.

For the examination of multivariate outliers, I applied the mvoutlier::aq.plot() function at a significance level of $\alpha = 0{,}001$. The method identified 54 outliers out of the 168 observations, which accounted for 32% of the data. The first two robust principal components explained ~97,2% of the total variance, so the two-dimensional point cloud reflected the essential structure of the data well. The outliers were concentrated mainly in rows 113–146 and 148–168, which may indicate that certain treatment combinations produced unusual results, or that data-quality issues were present that required further checking.

Two-way Boxplots and Interaction Plots

Distributional differences across treatment combinations were clear for quality traits; e.g., deep and/or longer water coverage often increased protein vs. control, whereas 0 cm/12 days tended to decrease it; Zeleny patterns aligned with protein/gluten and were sensitive to water-level × duration. For yield, patterns were more balanced; water level had a clearer main effect than duration. Interaction plots showed non-parallel lines for quality traits (evidence of interaction), especially at –60 cm (U-shaped across durations), while yield curves were largely parallel (weak interaction), with deeper water levels associated with reduced yield.

Assumption Checks and MANOVA

Bartlett's tests indicated heteroscedasticity among durations for most variables, whereas between water-level classes variances were more homogeneous for quality traits (not for yield). MANOVA showed significant effects of water depth, duration, year, and water-depth × duration interaction on the joint pattern of the five variables, with effect sizes ordered: Year » (Depth ≈ Duration) > Interaction.

Univariate ANOVAs

For quality (protein, gluten, Zeleny, W), all main effects (year, depth, duration) and the depth × duration interaction were significant; thus quality responds in a complex manner requiring fine-tuning of both factors. For yield, depth and year were significant, but duration and depth × duration were not—implying that, in the studied range, treatment duration may be irrelevant for yield optimisation. Across all variables, year was dominant.

Residual Normality

Graphical diagnostics were acceptable; formal tests indicated deviations mainly due to multivariate outliers (16–26 observations with large robust Mahalanobis distances). Robust/permutation approaches and sensitivity analyses excluding outliers are advisable.

Detailed Post hoc Findings

Given variance heterogeneity, I used Games–Howell and Welch tests. For protein, time-duration contrasts showed complex, year- and depth-specific patterns. Zeleny exhibited similar complexity, with 2019 at –60 cm showing 9-day and continuous treatments outperforming 3-day. For yield, post-hoc tests detected significant differences that ANOVA main effects might not reflect: e.g., in 2021 at –60 cm, continuous inundation produced significantly lower yield than 12 days, whereas in 2020 at –60 cm the continuous treatment outperformed the 3-day and 9-day ones. Relative to control, treatments generally increased yield in 2019 and 2020, while 2021 responses were mixed. (Figure 2.).

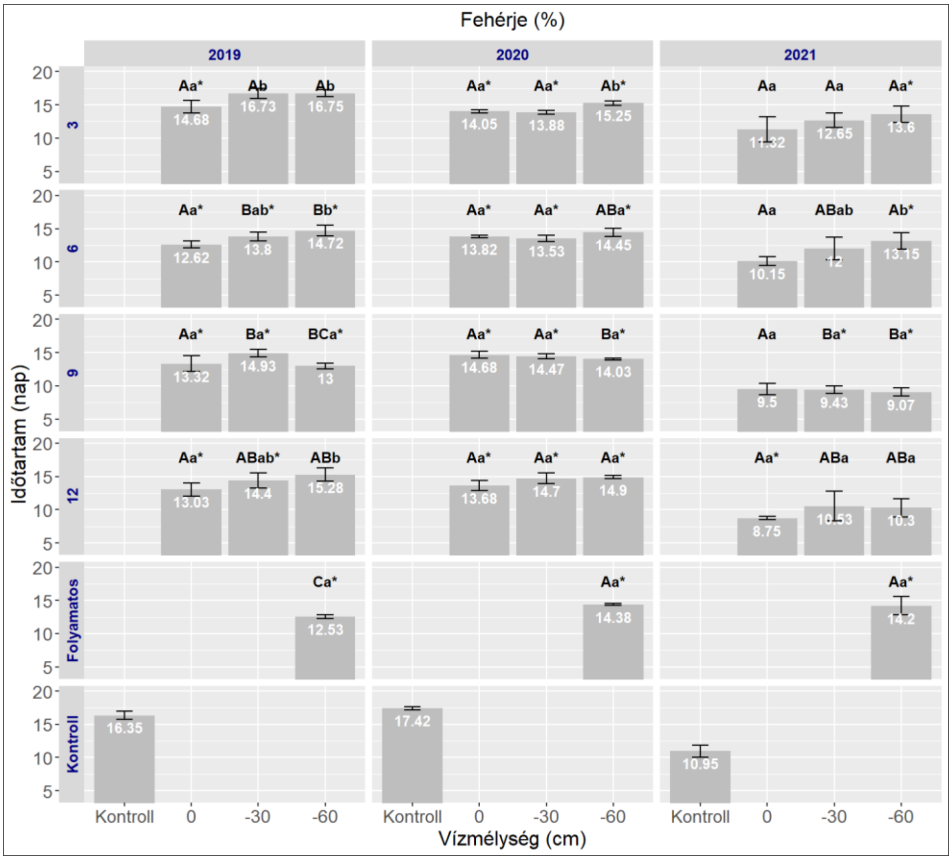

Figure 2.: Protein content by water level and duration treatments (2019–2021), shown as a column chart with mean ± standard deviation error bars (with CLD notation)

Compared to the control, the effect of the treatments also varied by year: in 2021 certain treatments improved, whereas in 2020 almost all of them decreased the protein content. Examining the effect of water depth, the –60 cm level was often associated with lower protein, especially for the shorter (3–6-day) treatments. For example, in 2019 at a –60 cm water depth the longer, continuous treatment gave the best protein result, while in 2020 at the same depth the 9-day treatment stood out.

In Figure 3., in the examination of the Zeleny value I obtained similarly complex results. The effect of duration was likewise year- and water-depth-specific here. For example, in 2019 at –60 cm depth both the 9-day and the continuous treatment yielded a markedly better Zeleny value than the short, 3-day treatment.

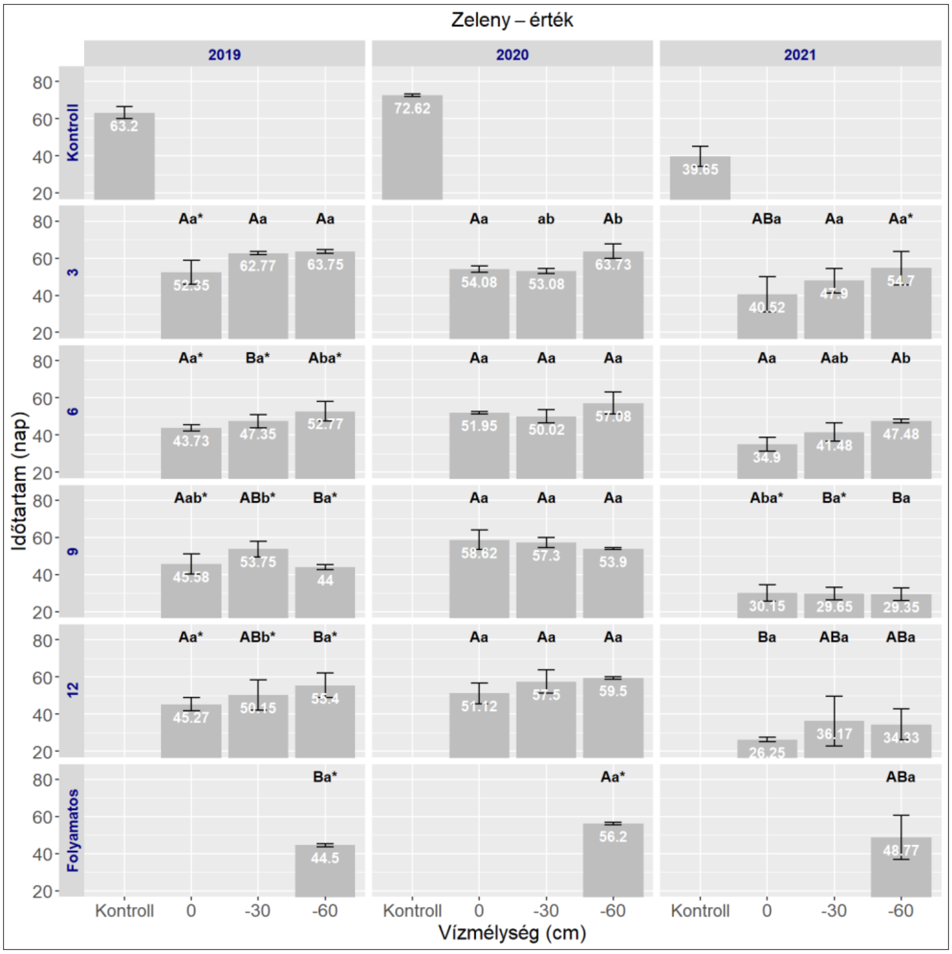

Figure 3.:The Zeleny value by water level and duration treatments (2019–2021), presented as a column chart with mean and standard deviation error bars (with CLD notation)

Compared to the control, the treatments, with the exception of a few cases in 2021, rather had a negative effect, especially in 2020, when I observed a widespread, statistically strong decrease.

In Figure *4*, in the case of yield, the comparisons by duration likewise showed a year- and water-depth-dependent pattern, but in contrast to the ANOVA, here the post-hoc tests detected significant differences. For example, in 2021 at –60 cm depth the continuous inundation produced a significantly lower yield than the 12-day treatment, while in 2020 it was precisely the opposite, with the continuous treatment being the best.

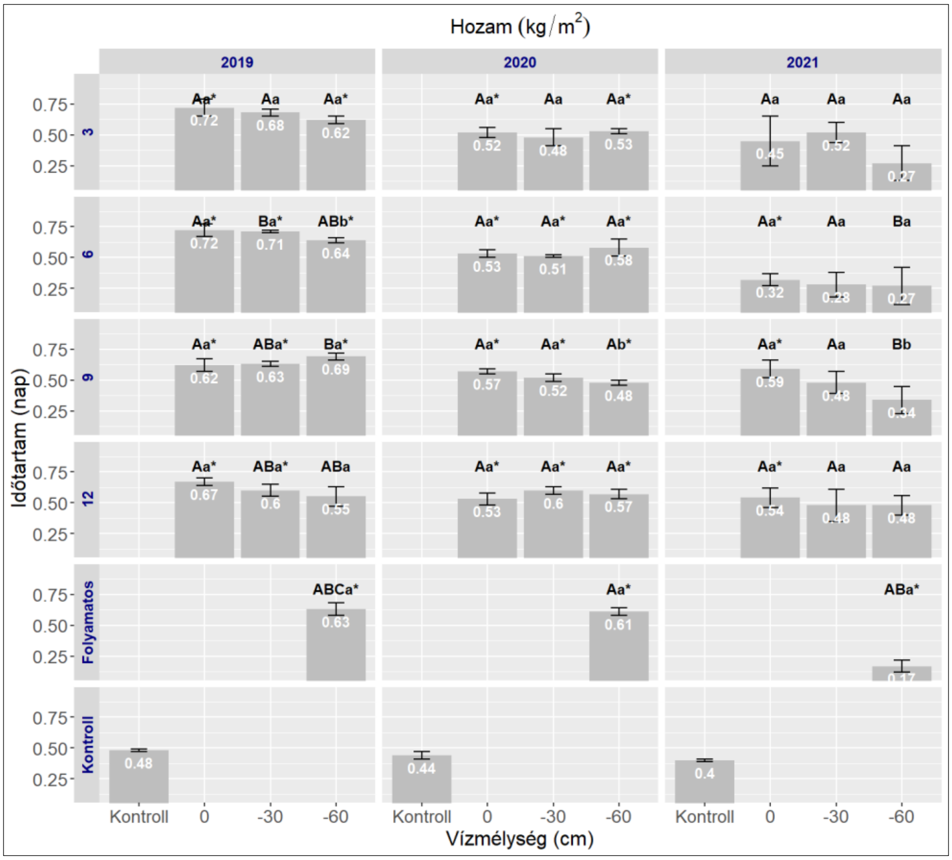

Figure *4*. Yield by water level and duration treatments (2019–2021), presented as a column chart with mean and standard deviation error bars (with CLD notation)

Compared to the control, the treatments consistently increased yield in 2019 and 2020, while in 2021 their effect was more mixed. Differences between water depths appeared mainly for the 9-day treatments in 2020 and 2021, where the –60 cm level's yield fell short of that at 0 cm.

Examination of the relationship between vegetation indices and SPAD relative chlorophyll content

To develop models suitable for estimating SPAD values, I used the 2020 data, since in this year the methodological requirements were met: the relationship was physiologically interpretable (positive correlation), and the conditions for model fitting were also appropriate. The fitted second-order polynomial regression models (for GNDVI and BNDVI), when validated on the 2019 and 2021 data, also showed acceptable accuracy, with mean absolute error (MAE) (Thesis 7).

Finally, by fitting Michaelis–Menten type curves I examined the sensitivity of the two indices. Based on the results, GNDVI proved to be the more sensitive and more accurate predictor of leaf chlorophyll content (SPAD) of the two indices examined, even though the overall strength of the relationship was limited. The maximum SPAD value estimated by the GNDVI model was higher, and the fitting error (RMSE) also proved to be lower compared to BNDVI.

To develop models suitable for estimating SPAD values, I used the 2020 data, since in this year the methodological requirements were met: the relationship was physiologically interpretable (positive correlation), and the conditions for model fitting were also appropriate. The fitted second-order polynomial regression models (for GNDVI and BNDVI), when validated on the 2019 and 2021 data, also showed acceptable accuracy, with mean absolute error (MAE) (Thesis 7).

Finally, by fitting Michaelis–Menten type curves I examined the sensitivity of the two indices. Based on the results, GNDVI proved to be the more sensitive and more accurate predictor of leaf chlorophyll content (SPAD) of the two indices examined, even though the overall strength of the relationship was limited. The maximum SPAD value estimated by the GNDVI model was higher, and the fitting error (RMSE) also proved to be lower compared to BNDVI.

Conclusions and Recommendations

My statistical analysis examining the effects of water-level and duration treatments in winter wheat provided numerous significant observations that offer deeper insight into yield and into quality indicators—particularly protein content and the Zeleny index. Based on the interactions detected by the ANOVA models, it clearly emerges that neither water level nor the duration of inundation alone is sufficient for reliably predicting production outcomes; rather, their combined effect, together with year-specific environmental factors, plays a decisive role in shaping the results.

The multivariate statistical examinations clearly showed that the effect of year is extremely strong on the ensemble of the variables studied (Wilks = 0,02248, $p < 2{,}2e\text{-}16$), and this holds true for each quality attribute separately as well. In addition, the main effects of water level and duration also significantly influenced protein, gluten, and Zeleny values. For example, based on the ANOVA results, the effect of water level on protein content appeared with $F = 14{,}85$, $p = 1{,}59e\text{-}08$, while the effect of duration was $F = 10{,}20$, $p = 2{,}41e\text{-}07$.

The quality properties of winter wheat—such as protein content, gluten content, the Zeleny index and the W value—move closely together, which is supported by the very high correlation values ($r = 0{,}955$–$0{,}989$, $p < 0{,}001$). This indicates that these quality characteristics respond jointly to the water-level and duration treatments, meaning that favourable effects manifest simultaneously in several indicators.

Yield, however, shows only weak positive correlation with the quality parameters ($r = 0{,}155$–$0{,}206$), that is, an increase in yield does not necessarily go hand in hand with an improvement in quality. This observation also confirms that achieving quantitative and qualitative objectives may require different strategies.

The deviations relative to the control depended in almost all cases on the combined influence of water level and duration. In particular, the combination of a –60 cm water level and a 9-day treatment showed a consistently positive effect on protein content. This treatment can induce a moderate stress state that stimulates the physiological mechanisms responsible for protein synthesis, while not drastically reducing yield. In contrast, the short, 3-day treatments repeatedly produced weaker results, whether in terms of yield or quality parameters. The effects of continuous treatments differed by year, which further increases technological uncertainty.

In the yield analysis, the effects of water level and duration also showed a diverse pattern. In 2020 several treatments caused significant yield increases compared to the control, while in 2021 most of the differences were not significant. The most effective treatments differed by year, again highlighting the importance of environmental conditions. However, with respect to yield, significance was less frequently detectable, and when present often showed small effect sizes.

In examining the quality indicators—especially the Zeleny index—it clearly emerged that moderate water stress positively influences baking value. The reason is the concentration effect, during which the plant produces less starch, thus the proportion of protein components in the grain increases. This is supported by the statistical analysis as well, according to which the 9-day treatment typically led to higher Zeleny values, particularly at a –60 cm water level. At the same time, the deviations relative to the control differed strongly by year, which is also supported by the annual control values (e.g., 2019: 63,2; 2020: 72,6; 2021: 39,7). The strictest basis for comparison was provided by 2020, when the effects of the treatments came to the fore more clearly.

The multivariate statistical analysis further strengthened the significance of the year effect: according to the MANOVA, year had a strongly significant effect both for the quality indicators and for yield. In addition, the main effects of water level and duration were also significant, and the water-level × duration interaction likewise influenced the parameters examined, particularly in the case of protein content. Due to the lack of variance homogeneity, the application of the Welch test and the Games–Howell post-hoc procedures was justified; these made it possible to detect more precise differences among the treatments.

Based on the above, the conclusion can be drawn that the optimisation of water-level and duration treatments in winter wheat is extremely context-dependent. There is no single universally best treatment; strategies tailored to the objective (e.g., yield maximisation or quality improvement) and specific to the year and soil water regime are required. The 9-day treatment at a –60 cm water level offered a favourable compromise between yield and quality in multiple years, whereas short (3-day) and continuous inundation often produced less favourable results.

The interaction of water level and duration was also significant for several quality parameters—for example, with respect to the Zeleny index $F = 3{,}21$, $p = 0{,}0054$.

In 2020, for instance, at a –30 cm water level a significant yield difference appeared between the 6- and 12-day treatments ($p = 0{,}009$), which indicates that in that year a longer-lasting moderate water stress created more favourable conditions for yield increase. The same year also showed that a 9-day duration at –60 cm water coverage resulted in a significant yield increase compared to the control ($p = 0{,}005$).

These mean that, at the same water level, it is not indifferent how many days the treatment lasts, and conversely: at the same duration, it is not indifferent how deep the water level is.

Therefore, when making treatment decisions, one must take into account the meteorological conditions characteristic of the given year, the soil's water-management properties, and the desired production goal (e.g., milling or feed wheat).

Ultimately, the analysis highlights that incorporating precision-agriculture approaches and UAV-based vegetation indices—particularly GNDVI—provides an opportunity for the chlorophyll content and vegetation status to be tracked accurately. This can be especially important in large arable crops, where handling spatial variability and year effects is key for optimising yield and quality.

New Scientific Results (Theses)

Thesis 1. I established that year effects dominantly determine the impact of water stress on winter wheat quantity and quality, with statistical strength exceeding that of treatments (3, 6, 9, 12 days; 0 cm two-phase soil; –30 cm; –60 cm). *Support*: MANOVA—Year $\lambda=0.02248$, $F=167.834$ vs. Depth $\lambda=0.56417$, $F=6.282$; Duration $\lambda=0.55753$, $F=4.737$ (all $p<2.2e\text{-}16$); univariate ANOVAs likewise show Year with the largest F for all variables.

Thesis 2. I verified that quality and quantity respond differently to the 3, 6, 9, 12-day durations and 0/–30/–60 cm water levels: quality traits (protein, gluten, Zeleny, W) change jointly and complexly, whereas yield shows a partly independent pattern. *Support*: strong positive correlations among quality traits ($r=0.955$–0.989, $p<0.001$) but weak with yield ($r=0.155$–0.206); in ANOVAs, for quality all main effects and depth×duration are significant, while for yield duration and depth×duration are not.

Thesis 3. I confirmed that effects on quality (protein, Zeleny) are context-dependent: in favourable years, any stress worsens quality vs. control; in unfavourable years, short moderate stress can statistically improve quality (concentration effect). Support: Welch tests-2020 (high-quality year) most treatments significantly reduced protein and Zeleny vs. control; in 2021, –60 cm × 3 or 6 days increased protein significantly; the positive Zeleny shift at –60 cm × 3 days did not remain significant after Holm correction.

Thesis 3. I confirmed that effects on quality (protein, Zeleny) are context-dependent: in favourable years, any stress worsens quality vs. control; in unfavourable years, short moderate stress can statistically improve quality (concentration effect). Support: Welch tests—2020 (high-quality year) most treatments significantly reduced protein and Zeleny vs. control; in 2021, –60 cm × 3 or 6 days increased protein significantly; the positive Zeleny shift at –60 cm × 3 days did not remain significant after Holm correction.

Thesis 6. I verified that a continuously maintained –60 cm water level has no consistently beneficial effect on winter wheat; it is strongly year- and parameter-dependent—often unfavourable, sometimes advantageous. *Support*: Protein—2021, continuous worse than 9/12 days ($p\approx0.009$; 0.035); 2019, continuous better than 3/12 days ($p<0.001$; 0.038). Zeleny—2020, continuous worse than 12 days ($p\approx0.004$); 2019, continuous better than 3 days ($p<0.0001$). Yield—2021, continuous lower than 12 days ($p \approx 0.005$); 2020, continuous better than 3/9 days ($p \approx 0.026$; 0.003).

Thesis 7. With second-order polynomial regression I showed that SPAD can be estimated from GNDVI (MAE 4.83) and BNDVI (MAE 4.71). For the full 2020 dataset ($n=440$):

$$SPAD(GNDVI) = -177.25 \cdot GNDVI^2 + 235.27 \cdot GNDVI - 25.64$$

$$SPAD(BNDVI) = -167.54 \cdot BNDVI^2 + 246.17 \cdot BNDVI - 38.15$$

Publications Related to the Dissertation Topic

[1]K. György, K. Ágnes, and J. Mihály, “Examination of Red Clover Optimum Harvesting Status in Seed Production With Unmanned Aerial Systems (UAS),” JOURNAL OF CENTRAL EUROPEAN GREEN INNOVATION, vol. 12, no. 3, pp. 3–19, 2024.

[2]C. Bozán, N. Túri, J. Körösparti, B. Kajári, G. Kerezsi, E. Katona, and I. Nagy, “Harmadrendű öntözőművek felmérése a TIVIZIG működési területén,” in Magyar Hidrológiai Társaság XL. Országos Vándorgyűlése, 2023.

[3]J. Körösparti, N. Túri, B. Kajári, G. Kerezsi, L. Pásztor, and C. Bozán, “A belvíz-veszélyeztetettség talajtani összefüggései,” in XVIII. Kárpát-medencei Környezettudományi konferencia : Absztraktfüzet = XVIII. Carpathian Basin Environmental Science Conference : Book of Abstracts, 2023, p. 39.

[4]J. T. Körösparti, B. Kajári, G. Kerezsi, N. Túri, T. Szőcs, É. Kun, and C. Bozán, “A felszín alatti vizek kitermelésének hatása a belvíz-veszélyeztetettségre,” in Magyar Hidrológiai Társaság XL. Országos Vándorgyűlése, 2023.

[5]S. Priya, V. Mónika, K. György, K. Balázs, H.-K. Béla, B. B. Emese, M. Gaál, and G. Gergő, “Dataset: Geographical distribution and reed cover of Hungarian fishponds.” 2023.

[6]P. Sharma, M. Varga, G. Kerezsi, B. Kajári, B. Halasi-Kovács, E. Békefi, M. Gaál, and G. Gyalog, “Estimating Reed Bed Cover in Hungarian Fish Ponds Using NDVI-Based Remote Sensing Technique,” WATER, vol. 15, no. 8, 2023.

[7]P. Sharma, M. Varga, G. Kerezsi, B. Kajári, B. Halasi-Kovács, E. Békefi, M. Gaál, and G. Gyalog, “A dataset on the geographical distribution, bounds, and reed cover of Hungarian fishponds,” DATA IN BRIEF, vol. 49, 2023.

[8]N. Túri, J. Körösparti, B. Kajári, G. Kerezsi, and C. Bozán, “A hazai talajcsövezés szükségességének kérdése az elmúlt évek aszályainak tükrében,” in Magyar Hidrológiai Társaság XL. Országos Vándorgyűlése, 2023.

[9]B. Kajári, J. Körösparti, G. Kerezsi, N. Túri, C. Bozán, and van L. Boudewijn, “Belvíz monitorozása szegmentálással, felügyelt osztályozással és gépi tanulással SENTINEL 2-es műholdfelvételeken,” in A Magyar Hidrológiai Társaság XXXIX. Országos Vándorgyűlés dolgozatai, 2022, pp. 19–26.

[10]G. Kerezsi, N. Túri, B. Kajári, J. Körösparti, and C. Bozán, “Az M44-es gyorsforgalmi út vonalas létesítményen lehatárolt felszíni vizek összegyülekezési helyeinek elemzése,” in A Magyar Hidrológiai Társaság XXXIX. Országos Vándorgyűlés dolgozatai, 2022, pp. 1–10.

[11]J. Körösparti, G. Kerezsi, B. Kajári, N. Túri, and C. Bozán, “Harmadlagos öntözőművek terepi szintű műszaki állapotfelmérésének lehetőségei kijelölt mintaterületeken,” in A Magyar Hidrológiai Társaság XXXIX. Országos Vándorgyűlés dolgozatai, 2022, pp. 1–13.

[12]J. T. Körösparti, B. Kajári, G. Kerezsi, N. Túri, L. Pásztor, and C. Bozán, “A területhasználat racionalizálásának hatása Magyarország síkvidéki területeinek belvíz-veszélyeztetettségére,” JOURNAL OF CENTRAL EUROPEAN GREEN INNOVATION, vol. 10, no. Suppl 2, pp. 21–37, 2022.

[13]N. Túri, J. Körösparti, B. Kajári, G. Kerezsi, M. Zain, J. Rakonczai, and C. Bozán, “Spatial Assessment of the Inland Excess Water Presence on Subsurface Drained Areas in the Körös Interfluve (Hungary),” AGROKÉMIA ÉS TALAJTAN, vol. 71, no. 1, pp. 23–42, 2022.

[14]C. Dr. Bozán, J. Körösparti, N. Túri, G. Kerezsi, and B. Kajári, “AKK Belvízi veszélyeztetettség felülvizsgálata Stratégiai forgatókönyvek.” 2021.

[15]G. Kerezsi, J. Körösparti, N. Túri, B. Kajári, and C. Bozán, “A belvizek táp- és szennyezőanyag terhelésének vízminőségi vizsgálata a Szarvas környéki mezőgazdasági táblákon,” IN MINDEN CSEPP SZÁMÍT: IV. VÍZTUDOMÁNYI NEMZETKÖZI KONFERENCIA. ABSZTRAKT KÖTET = EVERY DROP COUNTS: 4TH INTERNATIONAL CONFERENCE ON WATER SCIENCES. ABSTRACT VOLUME, 2021, P. 8.

[16]C. Bozán, J. Körösparti, N. Túri, B. Kajári, G. Kerezsi, and L. Pásztor, “A belvíz.veszélyeztetettségi térképezés módszertani fejlődése a NAIK ÖVKI GIS műhelyében,” in Klímaváltozás okozta kihívások - Globálistól lokálisig, 2020, pp. 57–70.

[17]A. Laborczi, C. Bozán, J. Kőrösparti, G. Szatmári, B. Kajári, N. Túri, G. Kerezsi, and L. Pásztor, “Application of Hybrid Prediction Methods in Spatial Assessment of Inland Excess Water Hazard,” ISPRS INTERNATIONAL JOURNAL OF GEO-INFORMATION, vol. 9, no. 4, 2020.

[18]N. Túri, J. Körösparti, G. Kerezsi, B. Kajári, and C. Bozán, “Kutatás támogatás pilóta nélküli légi járművekkel a NAIK ÖVKI-ben.” 2020.

[19]C. Bozán, J. Körösparti, N. Túri, G. Kerezsi, and B. Kajári, “AKK Belvízi veszélyeztetettség felülvizsgálata.” 2019.

[20]G. Kerezsi, N. Túri, J. Körösparti, and C. Bozán, “Lendületben az agrárinnováció,” in Lendületben az agrárinnováció, 2019, pp. 55–66.

[21]G. Kerezsi, B. Kajári, N. Túri, J. Körösparti, and C. Bozán, “Vízvisszatartás tervezése belvizes területen UAV légifelvételből készített digitális magassági modell alapján,” in XXI. Századi vízgazdálkodás a tudományok metszéspontjában, 2019, pp. 111–116.

[22]J. Körösparti, C. Bozán, N. Túri, G. Kerezsi, B. Kajári, L. Dr. Pásztor, and A. Laborczi, “: Kedvezőtlen vízgazdálkodási állapotú mezőgazdaságilag művelt területek nagy felbontású belvíz-veszélyeztetettségi és kockázati térképezése a 10.07. belvízvédelmi szakasz területén.” 2019.

[23]J. Körösparti, C. Bozán, N. Túri, G. Kerezsi, B. Kajári, L. Pásztor, and A. Laborczi, “Kedvezőtlen vízgazdálkodási állapotú mezőgazdaságilag művelt területek nagy felbontású belvíz-veszélyeztetettségi és kockázati térképezése Tiszakécske közigazgatási területén.” 2019.

[24]N. Túri, J. Körösparti, G. Kerezsi, B. Kajári, and C. Bozán, Belvízkárokkal érintett területek kiterjedésének felmérése és terméskiesés becslése drónnal készült légifelvételek felhasználásával. Szarvas: Szent István Egyetem Agrár- és Gazdaságtudományi Kar, 2019.

[25]N. Túri, J. Körösparti, G. Kerezsi, B. Kajári, and C. Bozán, “Application of UAV remote sensing and GIS techniques for precision sampling in agricultural researches and practices.,” in 18th Alps-Adria Scientific Workshop : Alimentation and Agri-environment : Abstract book, 2019, pp. 166–167.

[26]N. Túri, J. Körösparti, G. Kerezsi, B. Kajári, and C. Bozán, “Pilóta nélküli légijárművek a precíziós mezőgazdaság szolgálatában.” 2019.

[27]N. Túri, J. Körösparti, G. Kerezsi, and C. Bozán, “Pilóta nélküli légi járművek alkalmazása mezőgazdasági és növénykísérleti területek felmérésére, monitorozására.,” in Lendületben az agrárinnováció, 2019, p. 95.

[28]N. Túri, Á. Kun, G. Kerezsi, B. Kajári, J. Körösparti, and C. Bozán, “Talajcsövezett mintaterületek drónfelvételekből készített digitális adatbázisa, valamint mintavételi rajzolatok alapján elvégzett terepi vizsgálatok.,” in Magyar Hidrológiai Társaság XXXVII. Országos Vándorgyűlés, 2019.

[29]T. Norbert, K. János Tamás, K. György, and B. Csaba, “Talajcsövezett területek azonosítása békés megyében távérzékelt valós színes felvételek kiértékelése segítségével,” in Alkalmazkodó Vízgazdálkodás, 2018.

[30]N. Túri, Á. Kun, G. Kerezsi, J. T. Körösparti, and C. Bozán, “Talajcsövezett mezőgazdasági területek működőképességének felmérése - terepi tapasztalatok,” in A Magyar Hidrológiai Társaság által rendezett XXXVI. Országos Vándorgyűlés dolgozatai, 2018.

[31]N. Túri, J. T. Körösparti, G. Kerezsi, and C. Bozán, “Advantages of rational control of soil moisture regime to prevent and mitigate the adverse effects of climate change in Békés County,” in 17th Alps-Adria Scientific Workshop, 2018, pp. 102–104.

[32]J. Körösparti, N. Túri, G. Kerezsi, and C. Bozán, Drónok használata a mezőgazdasági kutatásokban. 2017.

[33]N. Túri, J. T. Körösparti, G. Kerezsi, and C. Bozán, “Okszerű talajvízháztartás szabályozás lehetőségei Magyarország mezőgazdaságilag művelt területein,” in NAIK Fiatal Kutatói Napok II. szakmai konferencia. Publikációk. Szeged, 2017.12.14-15, 2017, pp. 45–51.

[34]N. Túri, J. Körösparti, G. Kerezsi, C. Bozán, I. Fabó, and F. Fehér, “Komplexen meliorált területek állapotfelmérésének gyakorlati tapasztalatai mintaterületek példáján,” in A Magyar Hidrológiai Társaság XXXV. Országos Vándorgyűlése, 2017, pp. 1–8.

[35]C. Juhász and G. Kerezsi, “Irrigation planning of apricot,” NÖVÉNYTERMELÉS, vol. 64, no. Suppl. 2, pp. 81–89, 2015.

[36]P. Tamás and G. Kerezsi, “A magyarországi potenciális szennyvíziszap elhelyezés térségi vizsgálata,” in Szennyvizek és szennyvíziszapok hasznosítása a régió fenntartható mezőgazdaságáért, 2015, pp. 53–58.

György Kerezsi's data (2025.09.16)
MTMT publication and citation summary table

Publication types	Count		Citation[1]	
	All	Detailed	Independent	All
I. Scientific journal articles	7			
in international journal in foreign language		3	8	23
in international journal in hungarian		0	0	0
in hungarian journal in foreign language		3	0	0
in hungarian journal in hungarian		1	2	2
II. Books	0			
a) Book as author	0			
in foreign language		0	0	0
in hungarian		0	0	0
b) Book as editor[2]	0			
in foreign language		0		
in hungarian		0		
III. Book chapter	4			
in foreign language		1	0	0
in hungarian		3	0	0
IV. Conference in journal or conference paper	12			
in foreign language		2	0	0
in hungarian		10	0	0
Publications (I-IV.)	23		10	25
Abstract[3]	4		0	0
Research data	1		0	1
Other scientific works[4]	7		0	0
All scientific publications	35		10	26
Hirsch index[5]			2	2
Educational publications	0			
Higher educational works	0			
Book in foreign language		0	0	0
Book in hungarian		0	0	0
Book chapter in foreign language		0	0	0
Book chapter in hungarian		0	0	0
Educational material	0		0	0
Titles of protection	0		0	0
Achievements	0		0	0
Popular science works	0			
Journal articles		0	0	0
Books		0	0	0
Other popular science works		0	0	0
Of public interest or unclassified publications[6]	0		0	0
More publications[7]	1		0	0
Other authorships[8]	0		0	0
Citations of edited publications			0	0
Citations in dissertations and other types			0	0
All publications and citations	36		10	26

György Kerezsi (Környezetgazdálkodás) (MTMT) https://m2.mtmt.hu/gui2/?type=authors&mode=browse&sel=10057...

Notes:
Numbers in the table are links. Clicking the number the programme will list the publications that are counted in the cell.
1 Without citations in dissertations and others. Citations in dissertations and others are counted at the end of the table.
2 Editors do not take part of the citations of the book
3 Only scientific abstracts.
4 All other, yet uncounted scientific works (except achievements and Protection forms), where the user is author, author of critical edition or Source edition author.
5 Without citations in dissertations and other types. The value of the row is based on the "All scientific publications" row.
6 Of public interest or unclassified publications where the authorship type of the user is not other.
7 Including all works that are not counted in other rows of the table.
8 Publications, where the user is not author, editor, author of critical edition or Source edition author.