Theses for doctoral dissertation (PhD)

EVALUATION OF CERTAIN QUALITATIVE PARAMETERS OF MAIZE USING TRADITIONAL AND MACHINE LEARNING-BASED METHODS

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1. BACKGROUND AND OBJECTIVES OF THE DOCTORAL DISSERTATION

In recent decades, food security has emerged as one of the most pressing problems facing humanity, the solution of which can primarily be found in increasing the quantity and quality of agricultural production. One of the main reasons for the difficulties in global food supply is that the world population is growing significantly, and according to current forecasts, this trend will continue. According to estimates, the global population will reach 9 billion people by 2050 (Roberts, 2011; Mohammed et al., 2021a), and by 2100 it is expected to be between 9.6 and 12.3 billion people (Gerland et al., 2014). The continuous growth of the population and the increasing demand for agricultural products and natural resources are placing an increasing burden on the environment and exerting continuous pressure on the agricultural sector. Accordingly, agricultural development can be a key factor in addressing food challenges (Ramasamy and Moorthy , 2006). Several constraints affecting agricultural production include climate change (Juhász et al ., 2020), greenhouse gas emissions (Harsányi et al ., 2021a; Mohammed et al., 2021b), drought (Mohammed et al ., 2022a, 2022b, Harsányi et al., 2021b), soil degradation (Takács et al, 2021; Khallouf et al, 2021; Hateffard et al, 2021), and soil salinization and contamination (Mohammed et al ., 2021a). The negative effects of climate change can cause adverse weather conditions that hinder agricultural production and threaten food supplies (Elbeltagi et al ., 2020).

Agriculture plays a key role in the sustainability and development of human society. The agricultural sector not only includes crop production, but also contributes significantly to the global food supply (Lynch et al., 2020). Field crop production is one of the most important sectors of agricultural production, playing a fundamental role in global food production (Ragán et al., 2024) and in meeting the food needs of a growing population (Gerland et al., 2014). As the world population grows, the demand for food is also constantly increasing, which makes it even more important to maintain and increase agricultural productivity. In order to ensure food security and prevent hunger, it is crucial to produce sufficient quantities of food of appropriate quality. However, global climate change is further increasing the pressure on agricultural production, as extreme weather conditions and water scarcity negatively affect crop yields (Raza et al., 2021). Therefore, it is of utmost importance to apply sustainable agricultural practices that contribute to increasing crop yields and protecting the environment (Mohammed et al., 2022). As part of this, it is essential to apply new technologies, plant breeding processes and precision agriculture, as well as to preserve biodiversity and introduce sustainable farming methods.

In this context, maize is considered a crop of strategic importance in human nutrition (Tanumihardjo et al., 2019). Maize is one of the most widely grown and consumed cereals in the world, especially in developing countries, where it serves as a staple food source. Due to its high productivity and favorable yields per hectare, maize plays a significant role in feeding a growing population. Maize is not only used as a food (e.g. in the form of flour, cornmeal, popcorn), but also as an important raw material for industry, for example in the production of biofuels and animal feed.

Through the use of sustainable agricultural practices and new technologies, maize can contribute to improving global food security while mitigating the environmental burdens resulting from growing food demand.

Maize yield and starch content are influenced by a number of agricultural factors, including crop type, irrigation and fertilization. Crop type refers to the methods and practices used during tillage, which can include both traditional and innovative, precision methods. Modern cultivation techniques, such as the use of high-quality hybrids, mechanization and pest control, can significantly increase maize yield and quality. According to a study by Khan et al . (2018), modern cultivation techniques can increase yield by up to 30% and starch content by 15 % compared to traditional methods. This indicates that the introduction of modern technologies and innovative agricultural practices can provide a significant competitive advantage for maize producers.

New technologies, such as big data (big data), artificial neural networks (ANN) and machine learning are revolutionizing the agricultural sector and can significantly improve the efficiency of maize production. These data-driven methods offer accurate and sustainable solutions to challenges in agriculture (Raj et al., 2021). The development of digital data collection and analysis methods has enabled us to understand the complexity of agricultural systems with a modern, data-driven approach. The big Data analysis – through the application of high spatial and temporal resolution data and machine learning algorithms – offers significant opportunities in precision agriculture. These methods support the development of predictive models, yield optimization and sustainable decision support, which can lead to a more efficient understanding of agronomic systems

(Kamilaris et al., 2017). In particular, large datasets from remote sensing play an important role, the structured processing and integration of which is a prerequisite for modern precision crop production (Huang et al ., 2018).

ANNs are a type of machine learning algorithm that mimics the way the human brain works and processes data. This allows neural networks to make predictions based on past data and identify complex patterns . In the case of maize production, ANNs can analyze multiple parameters and predict yield and starch content.

These predictions can be used to optimize agricultural practices based on the conditions of a specific region or farm. ANN models offer farmers the opportunity to make data-driven decisions on planting dates, cultivation methods, and irrigation and fertilization strategies, thereby increasing the efficiency and sustainability of maize production.

However, the accuracy and reliability of ANN predictions depend largely on the quality, composition and size of the data used to train the model. Therefore, detailed, accurate and site-specific data collection is essential to maximize the benefits of ANN models in maize production (Harsányi et al., 2022). With reliable data, ANN models can serve as an effective tool to improve the efficiency and sustainability of maize production.

In Hungary, the application of ANNs (artificial neural networks) in agriculture is still a relatively new research area and has so far only been used to a limited extent in the study of maize production. Several domestic studies point out that in Hungary, maize yield and quality are mostly influenced by agricultural factors such as cultivation method, irrigation and fertilization (Harsányi et al ., 2023). Therefore, it is of utmost importance to examine the opportunities and challenges associated with the use of ANNs in predicting maize yield and starch content, with particular attention to the agronomic factors mentioned above. ANNs may be able to provide more accurate forecasts by analyzing these complex relationships, and thus support the improvement of the efficiency and sustainability of maize production. Taking the above aspects into account, I set the following goals in my research:

a) Analysis of the effect of different fertilizer treatments (N 0 kg/ha, P_2O_5 0 kg/ha, K_2O 0 kg/ha, (control); N 80 kg/ha, P_2O_5 60 kg/ha, K_2O 90 kg/ha, and N 160 kg/ha, P_2O_5 60 kg/ha, K_2O 90 kg/ha) on the starch content of maize.

b) Analysis of the effect of three tillage systems (winter ploughing (27 cm), strip tillage (23 cm), ripping (45 cm) on the starch content of maize.
c) Analysis of the effect of crop year (2017-2019) on the starch content of maize.
d) Analysis of the cumulative effect of the above factors on the starch content of maize.
e) of the suitability of artificial neural networks (ANN) (multilayer perceptron (MLP) and radial basis function (RBF) for predicting starch content in maize .
f) Evaluating the effectiveness of scenarios created using different input variables in predicting output outcomes .
g) Proving or disproving the hypothesis that the ANN-MLP machine learning model has better prediction efficiency for agricultural data than the ANN-RBF model
h) Proving or disproving the hypothesis that machine learning models perform more efficiently when the number of input variables is increased

2. MATERIAL AND METHOD

2.1. Study area and experimental setup

The field maize long-term experiment serving as the basis for the research was set up at the Látókép Crop Production Experimental Station of the University of Debrecen. The experiment is located on the Hajdúság Loess Ridge, providing an ideal location for complex, multi-factorial agricultural studies. The location of the experiment is an area with calcareous chernozem soil, which has a deep humus layer and good water retention capacity.

The experiment is a polyfactorial , three-replication, small-plot long-term experiment , which allows not only the independent effects of individual factors (soil cultivation, fertilization, irrigation), but also their interactions to be examined. The location of the plots and the three replications ensure statistically evaluable and reproducible results.

Tillage treatments include three methods:

- T1 – Winter ploughing (27 cm): classic deep-turning technology that helps to incorporate organic matter into the soil.
- T2 – Strip tillage (23 cm): aims to minimize soil disturbance, preserve the natural structure, and reduce energy consumption.
- T3 – Ripping (45 cm): technology that loosens deeper soil layers, which helps root development and water infiltration into deeper layers.

The three levels of fertilizer treatments are as follows:

- Control (N 0 – P_2O_5 0 – K_2O 0 kg/ha)
- Medium dose (N 80 – P_2O_5 60 – K_2O 90 kg/ha)
- High dose (N 160 – P_2O_5 60 – K_2O 90 kg/ha)

In addition, the experiment is divided into irrigated and non-irrigated zones, which also allows the analysis of the effect of water supply.

2.2. Climatic data

The year 2017 showed relatively balanced climatic conditions. The annual average temperature was 11.1 °C, while the total annual precipitation reached 569 mm, the highest value of the three years. During the maize growing season (April– September), a total of 242 mm of precipitation fell, which showed a relatively even monthly distribution (between 36–46 mm), providing favorable conditions for the development of the plant. Temperature conditions were moderate, with monthly average values between 21.6–23.2 °C and daily maximums between 32–34 °C in the summer months.

The year 2018 was warmer than the previous year, with an annual average temperature of 12.3 °C. During the maize growing season, the monthly average was above 20 °C for several months (July: 22.4 °C; August: 24.0 °C), and the effect of warming is clearly visible on the heat map. However, this year was the driest both on an annual basis (435 mm) and during the growing season (230 mm).

2019 was the warmest of the three years, with an annual average of 12.4 °C and daily maximums around 35 °C in several months. The summer months were extremely hot, as confirmed by the heat map: extensive and intense red patches in June, July and August indicate persistent heat waves. However, it was not the driest year in terms of precipitation. Annual precipitation was 456 mm, with 300 mm during the growing season, exceeding both 2017 (242 mm) and 2018 (230 mm). This suggests that although heat stress may have been increased, water availability may have mitigated the negative temperature effects (Figure 1).

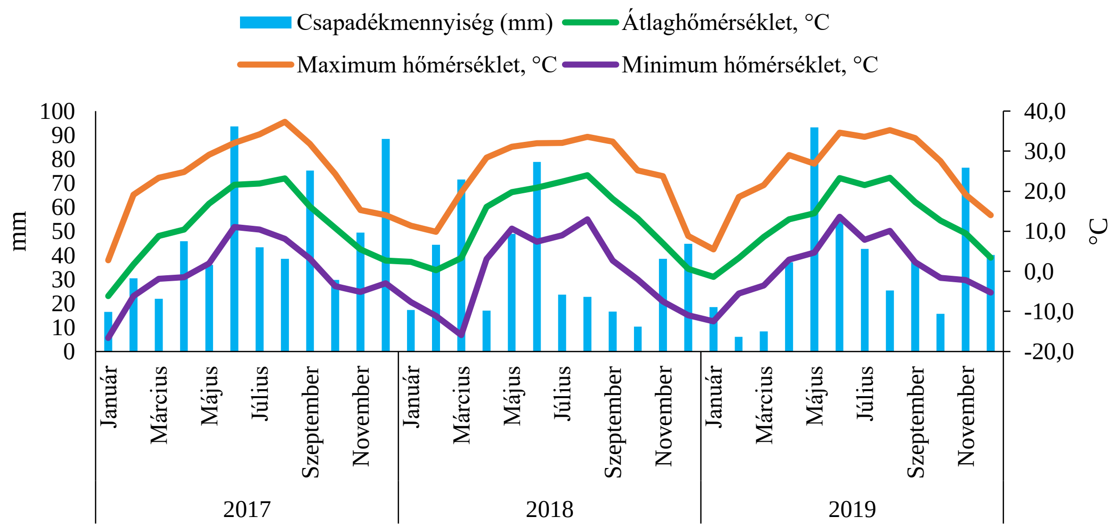

Figure 1 : Temperature and precipitation data in Debrecen between 2017 and 2019 (https://www.ksh.hu/stadat_files/kor/en/kor0071.html)

2.3. Statistical analysis

2.3.1. Descriptive statistical analysis to examine the development of starch content

During the data analysis process, I performed descriptive statistical analysis for each year examined (2017-2019), and then evaluated the data of the three years in a combined manner. In the process, I determined the basic descriptive statistical parameters of the examined variables – maize yield, oil content, protein content, moisture content and starch content, protein yield, starch yield and hl-weight.

2.3.2. Correlation analysis and multivariate statistical tests

I prepared correlation matrices simultaneously with the descriptive statistical analysis, broken down by year and then for the aggregated data of the three years, to map the relationships between the different variables. The calculated correlation coefficients allowed for the evaluation of the direction and strength of the relationship between the paired variables, thereby helping to understand the impact of a change in a given factor on the development of starch content.

2.3.3. Analysis of variance (ANOVA) and least significant difference (LSD) tests

significance of the hypothesized relationships, I performed an analysis of variance (ANOVA) following the methodology of Huzsvai & Balogh (2015). ANOVA provided an effective tool for evaluating the effect of each study factor, allowing us to determine whether the differences between different treatments were statistically significant.

For a more detailed examination of the ANOVA results, the least significant difference (Least Significant Difference (LSD) test was used, which allowed for multiple comparisons.

2.4. Starch yield prediction based on ANN algorithms

During agricultural data processing, I applied machine learning techniques to analyze starch content values from field experiments. I used artificial neural network models (ANN) for the study, with the help of which I examined the impact of various agronomic and environmental factors on the development of starch content, according to four different scenarios.

2.4.1. Analysis objectives and methods

The aim of the research was to reveal the hidden relationships between the variables influencing the development of starch content and to determine the model that gives the best estimate of the starch content value. I used the SPSS 29.0.0.0 statistical software to process the data, which provided the opportunity to compare different machine learning algorithms.

2.4.2. Scenarios and modelling

During the study, I developed four different scenarios that combined the input variables in different ways. I analysed these scenarios independently using the multilayer perceptron (MLP) and radial basis function (RBF) models.

Artificial neural networks are built from three main layers:

- **Input layer** : this is where the agronomic and environmental factors under study are entered into the model.
- **Hidden layer** : this is where data processing and nonlinear relationships are discovered.
- **Output layer** : the network's final prediction of starch content.

To predict starch content I used **two different neural network models** :

1. **Multilayer perceptron (MLP)** – which is capable of identifying **nonlinear relationships** and provides accurate predictions through multi-level processing .
2. **Radial basis function network (RBF)** – which handled larger data sets more efficiently due to its faster learning speed.

2.4.3. Presentation of the composition of scenarios used for machine learning analysis

In the research, I created four different scenarios for machine learning models.
The composition of the scenarios is summarized in Table 1.

Table 1 : Composition of scenarios compiled for machine learning analysis

Scenario	Variables involved	Short justification
SC1	Tillage, irrigation, nutrient treatments, yield, oil content, protein content, moisture content	Tillage, irrigation and nutrient supply directly affect maize growth, yield and content . When included together with other variables, this composition provides a comprehensive picture.
SC2	Year, yield, protein content, moisture content	The goal of the scenario was to explore the role of weather and seasonal parameters, while also including some other variables.
SC3	Year, nutrient, yield, oil content, protein content, HL weight, protein yield, starch yield	It examines the relationships between nutrient supply, yield and quality indicators (protein, oil and Hl mass).
SC4	Year, nutrient treatments, tillage, irrigation, yield, oil content, protein content, Hl weight, protein yield, moisture content, starch yield	The complex model combines crop year effects, agrotechnical factors and content parameters. The goal is to explore the dynamics of the entire system and accurately predict starch content.

Source: own editing

2.4.4. Statistical evaluation of the performance of machine learning models

After running the models, the software evaluated the prediction efficiency and provided the sum of squared errors and relative errors for the given scenario for both the training and testing phases, based on which the primary ranking could be performed. However, for an even more accurate result, I also used additional indicators: Nash - Sutcliffe efficiency (NSE), Pearson 's correlation coefficient (r), the coefficient of determination (r^2) and the root mean square deviation (RMSD). These indicators provided a comprehensive assessment of the performance of the models, taking into account both the accuracy and the reliability of the predictions (Harsányi et al . 2023).

3. RESULTS

3.1. The effect of different nutrient treatments on starch content

During the analysis of the effect of different nutrient treatments, I found that the nutrient dosage had a significant effect on the starch content of maize. Based on the results of the tests, the highest starch content (64.42%) was achieved by the control treatment, which indicates that the lack of nitrogen fertilization had a positive effect on the starch content. In contrast, the lowest starch content (62.61%) was achieved by the 160 kg N/ha + PK nutrient treatment, which indicates that the higher nitrogen dose reduced the starch content. During the statistical analysis, the smallest significant difference between the nutrient treatments was 0.428%, which indicates that the measured differences are statistically significant. Figure 2 clearly illustrates the effect of the different nutrient treatments on the starch content.

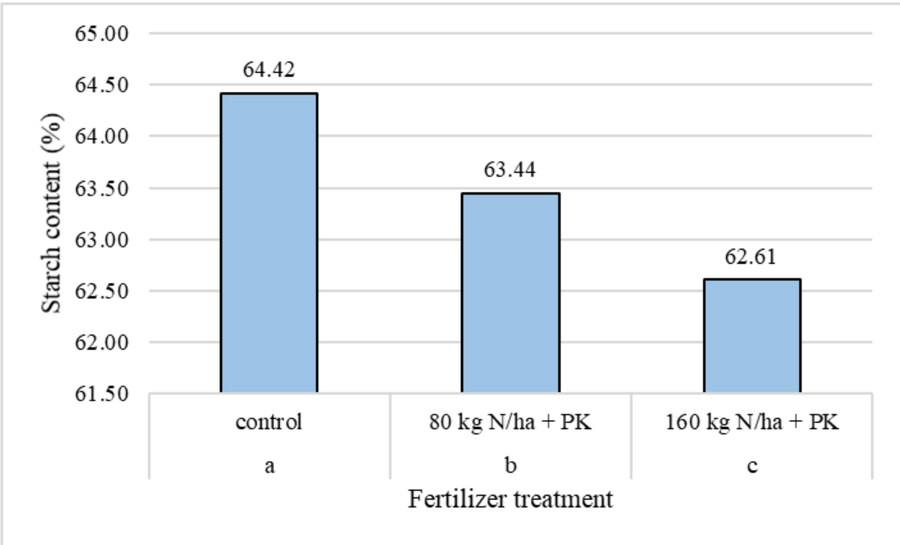

Figure 2 : Effect of nutrient treatments on starch content of maize (Debrecen-Látókép 2017-2019)

3.2. Effect of crop year on starch content

The analysis of the effect of the crop year, which was carried out taking into account climatic effects, clearly showed that the starch content of maize depends significantly on the year of production. During the statistical analyses, the smallest significant difference between the years of production was 0.309% (LSD: 0.309%), which indicates that the differences can be considered significant in terms of starch content. Based on the results of the ANOVA and the LSD test, it can be stated that significant differences can be observed in the starch content of maize between the different years, especially in favour of the year 2018. The year 2018 was outstandingly favourable, while the year 2017 was significantly less favorable in terms of starch content. Figure 13 clearly shows the development of starch content in the three years examined. The bar chart clearly shows the outlier value of the 2018 crop year, as well as the lower, close starch content of the 2017 and 2019 crop years. Significant differences between groups are indicated by the letters (a, b, c) below the bars (Figure 3).

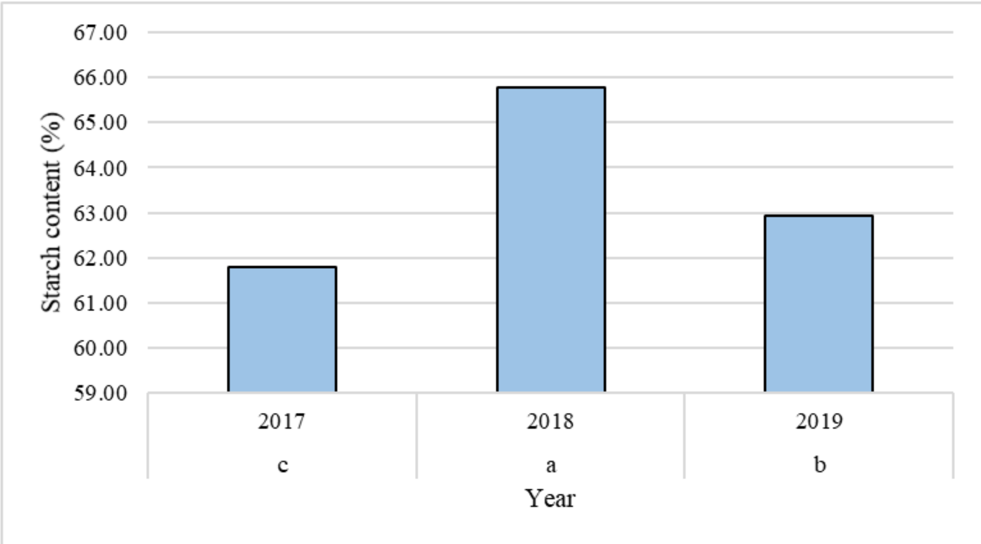

Figure 3 : Effect of crop year on the starch content of maize (Debrecen-Látókép, 2017-2019)

3.3. The combined effect of different tillage methods and crop year on starch content

The effect of tillage and year significantly influenced the starch content of maize, which is an important factor in assessing the efficiency of cultivation technologies. The results of the study showed that the lowest starch content was observed in 2017, especially in the case of strip tillage. In this year, there was no statistically significant difference between winter ploughing and ripping, which suggests that the differences between different tillage methods were less pronounced in this year. In the following year, i.e. in 2018, the starch content of maize was exceptionally high, which supports the previous observations, however, it is important to mention that in this year there was no significant difference between the different tillage treatments, which suggests that environmental factors had a more dominant effect on starch content than tillage technology in this year.

In 2019, significantly lower starch content was observed for all soil cultivation methods tested than in the previous year (2018), however, the starch content was still higher compared to 2017. (Figure 4) .

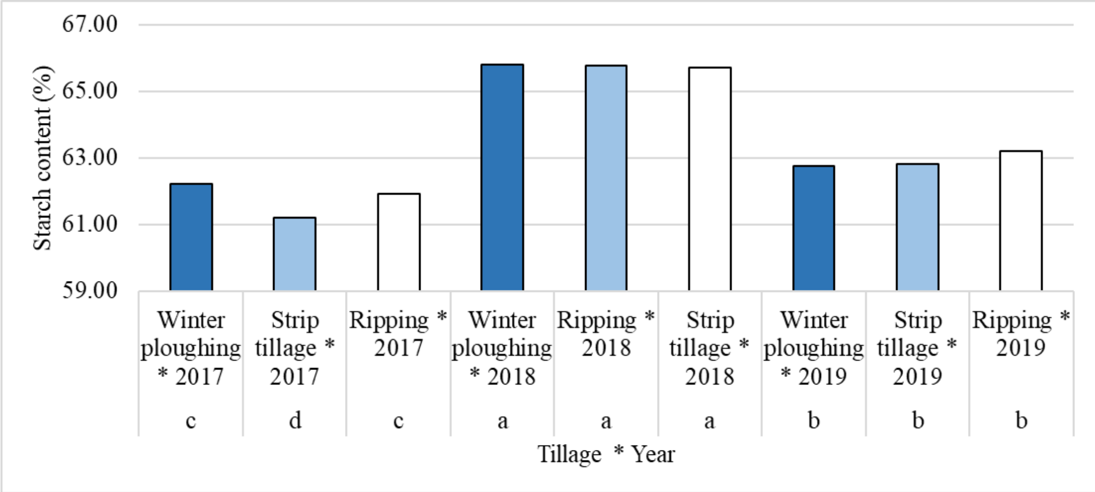

Figure 4 : The effect of primary tillage and crop year on the starch content of maize (Debrecen-Látókép, 2017-2019)

3.4. Combined effect of nutrient treatments and crop year on starch content

The results of the analysis showed that nutrient treatment and crop year had a significant effect on the starch content of the tested maize samples. The examination of crop year effects showed that in 2018 there was no significant difference between the three nutrient treatments, which indicates that favourable climatic conditions dominated the development of starch content in this year. In contrast, in 2019 there was no statistical difference between the nutrient treatments, but the starch content was demonstrably lower in all treatments compared to the previous year. The smallest significant difference between nutrient treatment and crop year was 0.536, which confirms the statistical significance of the differences between treatments. Nutrient treatment and crop year also influenced the starch content of maize together, which showed changes between individual years. The lowest starch content of the studied period was in 2017, when only 60.67% starch content was observed in the 160 kg N/ha treatment . This result again shows that higher N fertilizer doses do not necessarily favor starch formation (Figure 5).

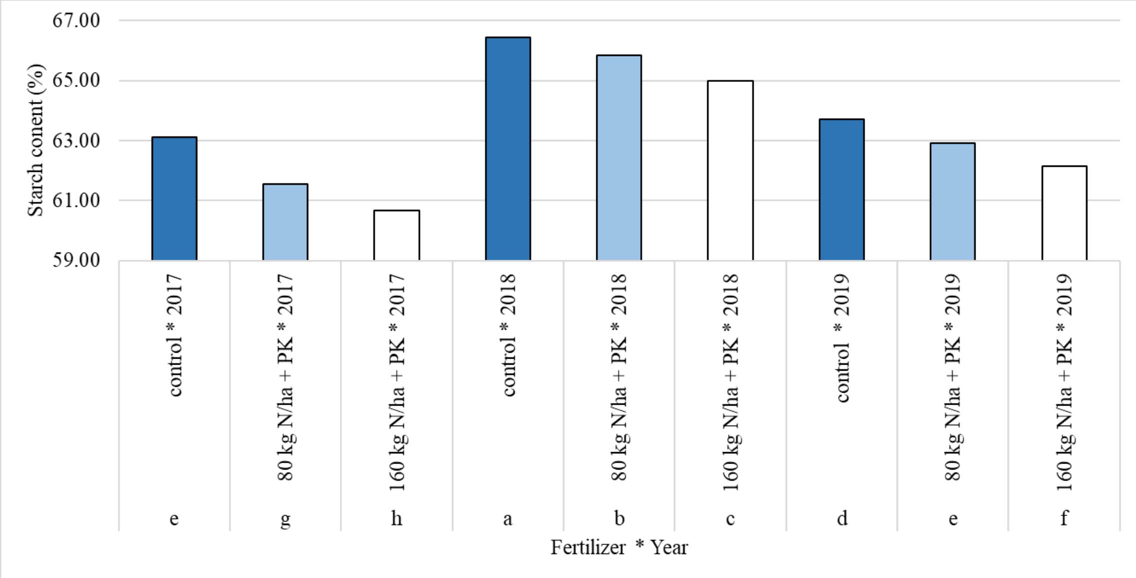

Figure 5 : The effect of fertilization and crop year on the starch content of maize (Debrecen-Látókép, 2017-2019)

3.5. Evaluation of starch content prediction using artificial neural networks (ANN)

, I applied machine learning methods to analyse the experimental data and predict the starch content, namely two artificial neural network (ANN) models, the multilayer perceptron (MLP) and the radial basis function (RBF) model. The MLP is a multilayer neural network that is capable of recognizing complex relationships, while the RBF model is a special neural network that is used to model nonlinear relationships between input data and target variables. The aim of the study was to determine the prediction efficiency of different variables for starch content, based on four predefined scenarios.

Figure 6 shows the network structure and configuration for the MLP_SC4 scenario. The input layer of the model consists of 11 input variables and their subvariables (18 variables in total), which contain all possible agronomic and technological parameters. The inputs include the year, different levels of nutrient treatments, soil cultivation methods, irrigation treatments, as well as the yield, oil content, protein content, hl-weight, protein yield, moisture content and starch yield. The hidden layer of the model contains a total of 5 neurons.

The performance of the MLP_SC4 model was outstanding in both the training and testing phases. In the training phase, the sum of squared errors was only 17.173, while the relative error value was extremely low, 0.038, which clearly indicates that the model fitted the training data set excellently. In the testing phase, the model also showed excellent performance: the sum of squared errors was only 1.179, and the relative error was only

0.006. This indicates that the generalization ability of the model is outstanding and the prediction accuracy was reliably maintained even for samples outside the training data set. Overall, it can be said that the MLP_SC4 model outperformed the previous three scenarios in all respects, thus providing the best prediction performance for the tested MLP and RBF models (Table 2).

Table 2 : Model performance for the MLP_SC4 scenario

Model summary		
Teaching	Sum of squared error	17,173
	Relative error	0.038
	Training time	0:00:00.29
Testing	Sum of squared error	1,179
	Relative error	0.006
Dependent variable: starch content		

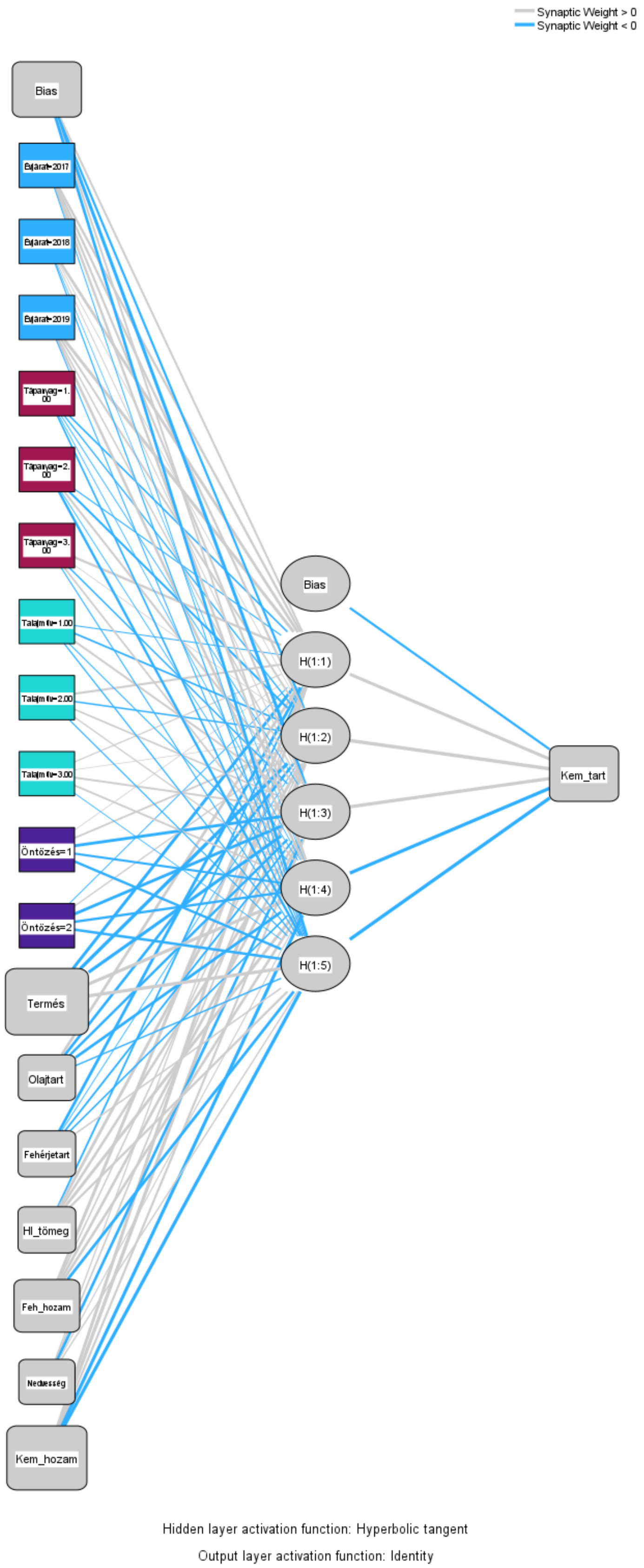

Figure 6. Structural structure of the MLP_SC4 scenario model

the predicted and actual starch content values of the MLP_SC4 model is illustrated in Figure 7. Based on the scatter plot, it can be clearly seen that the predicted values are almost exactly along the actual data, which shows that the model performs exceptionally well. The standard deviation is extremely low even at higher starch content values, which shows the stability and accuracy of the MLP_SC4 model.

The raincloud diagram shows that the distributions of the estimated and actual starch content overlap almost completely, demonstrating the exceptional predictive power of the model. The shape of the distributions and the almost complete agreement of the mean values indicate that the MLP_SC4 model produced the best fit in the tests so far.

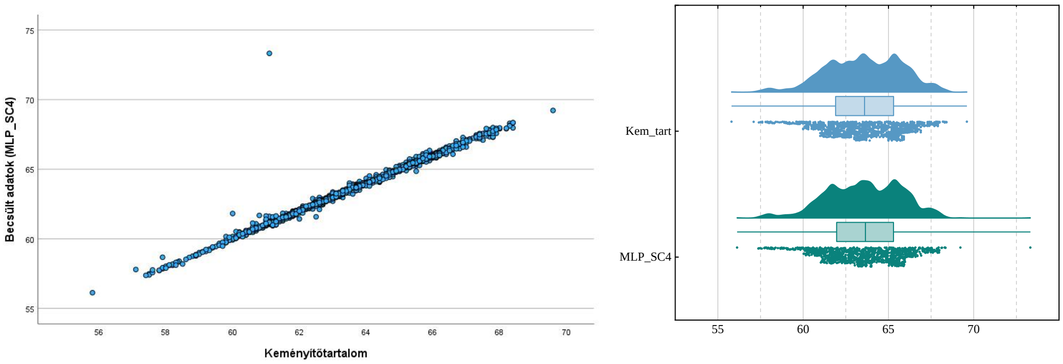

Figure 7 : Scatterplots and raincloud plots of estimated values of MLP_SC4

In previous studies, I evaluated the performance of MLP models based on the sum of squared errors and the relative error. These indicators clearly illustrated the prediction accuracy in both the training and testing phases, but if we want to get an even more comprehensive picture of the overall performance and reliability of the model, it is necessary to examine additional performance indicators that more accurately demonstrate the differences between the scenarios. To this end, I calculated four indicators for each scenario, as shown in Table 3.

Table 3 : Performance of MLP model scenarios based on additional performance indicators

	Model performance indicators			
	r	r^2	RMSD	NSE
MLP_SC1	0,961	0,923	0,611	0,923
MLP_SC2	0,928	0,861	0,820	0,861
MLP_SC3	0,945	0,894	0,718	0,894
MLP_SC4	0,986	0,972	0,368	0,972

Based on the above, it turned out that the MLP model performed better than the RBF model in all cases. In addition to the best performing combination being MLP_SC4 and the worst being RBF_SC1, the least efficient scenario of the MLP model also outperformed the best RBF scenario. Table 4 summarizes the efficiency indicators of each scenario.

Table 4 : Summary of model performance

Model	Scenario	Teaching		Testing	
		Sum of squared errors	Relative error	Sum of squared errors	Relative error
MLP	SC1	36,536	0,081	14,948	0,069
	SC2	59,893	0,132	27,611	0,156
	SC3	42,323	0,095	26,979	0,131
	SC4	**17,173**	**0,038**	**1,179**	**0,006**
RBF	**SC1**	**280,262**	**0,611**	**144,479**	**0,638**
	SC2	95,621	0,212	43,717	0,214
	SC3	256,587	0,558	98,352	0.488
	SC4	156,305	0.341	51,767	0.307

Finally, the Taylor diagram shown in Figure 8 summarizes the forecasting performance of the MLP model scenarios.

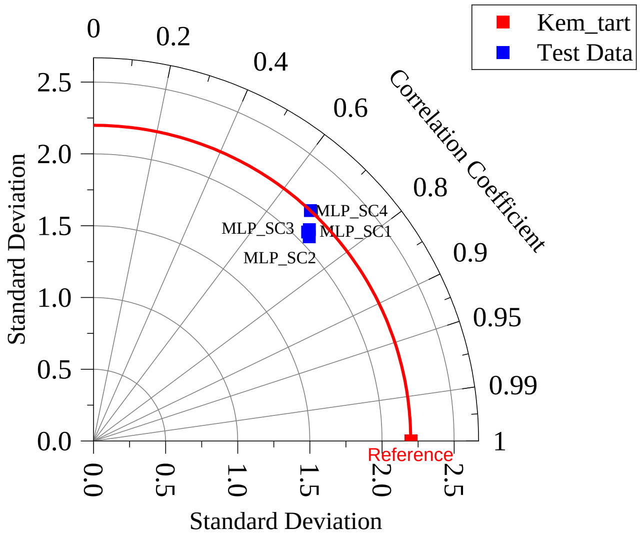

Figure 8. Representation of the efficiency of the scenarios used in the MLP model using a Taylor diagram

the artificial neural network (ANN) algorithms - the multilayer perceptron (MLP) and the radial basis function (RBF) - in predicting starch content, I applied the ridge line method shown in Figure 9. When examining these graphs, it becomes obvious that the predictive output generated by the MLP algorithm shows a higher degree of similarity with the observed measurements. In contrast, the predictive ability of the RBF algorithm is less accurate in this context.

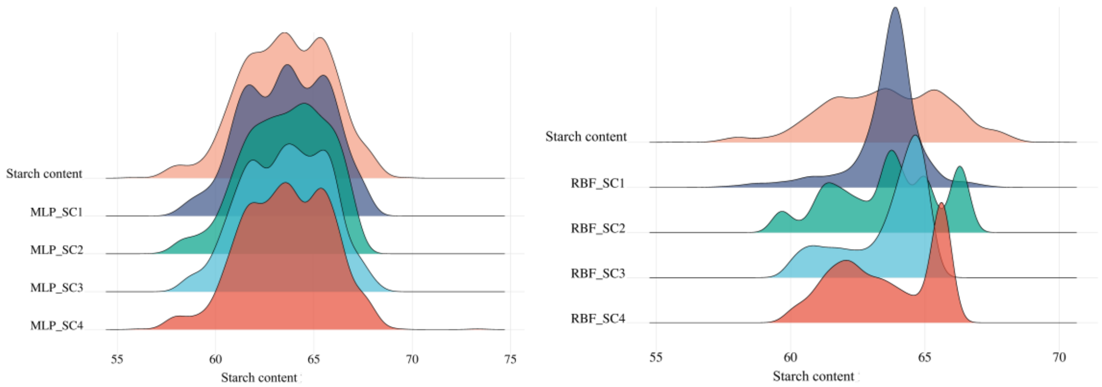

Figure 9. Ridge line plot of observed and ANN-MLP predicted values for the scenarios examined.

4. NEW SCIENTIFIC RESULTS

1. The effect of year significantly influenced starch content. Based on ANOVA and LSD tests, it was demonstrated that the starch content of maize grain showed significant differences between years. The average starch content measured in 2018 (65.76%) was significantly higher than in both 2017 (61.78%) and 2019 (62.93%) (LSD $p < 0.01$), confirming the prominent role of year-specific conditions in shaping grain composition at the studied site and period.

2. Increasing fertilizer doses reduced starch content during the studied years. A statistically significant difference was observed in starch content among the three nutrient treatments (control, 80 kg N ha^{-1}, 160 kg N ha^{-1}). The average starch content was 65.01% in the control treatment, while at the highest nitrogen level it decreased to 60.67% (LSD $p < 0.001$). This result demonstrates that under the given experimental conditions and years, higher N doses lead to a reduction in starch content; however, since they increase yield, they exert a positive effect on the specific starch yield.

3. A strong negative correlation was observed between maize starch content and protein content. According to Spearman's correlation analysis, when data were pooled, a correlation coefficient of –0.72 was found between starch and protein content. This result confirms the initial hypothesis regarding the above-mentioned negative correlation under the studied period and experimental conditions. Furthermore, this finding is supported by the normalized importance values obtained from the ANN analyses (particularly in the best-performing MLP_SC4 scenario), where protein content played a prominent role as an important influencing factor in the estimation of starch content.

4. The multilayer perceptron (MLP) model estimated starch content with outstanding accuracy. In the machine learning analysis, the MLP_SC4 model achieved a relative error of 0.006, a Pearson correlation coefficient of 0.986, and a Nash–Sutcliffe efficiency of 0.972 in the testing phase, indicating an extremely precise fit to the actual values. The performance of this model surpassed all RBF-based models and other scenarios, confirming the superior efficiency of the MLP model in predicting agricultural quality traits. Thus, in small-plot field maize experiments with diverse data

types, one of the initial assumptions of the research was fulfilled, namely that the MLP model would provide more effective estimations than the RBF model.

5. PRACTICAL RESULTS

The results revealed during the research can contribute to the practical development of modern maize production in many ways. For decisions aimed at shaping starch content – as a content indicator of high industrial and feed importance – it is crucial to know which environmental and agrotechnical factors have a measurable effect on it.

Based on the results of several years, it is clear that reducing the intensity of nitrogen fertilization can significantly improve starch content . When the highest nitrogen dose was applied, the starch content decreased by more than 4% compared to the control, which has a direct impact on industrial processability and storability. This suggests that maximizing yield does not always lead to improved quality , and in order to optimize the content , it is advisable to plan the nutrient supply strategy in a differentiated and targeted manner.

Among the tillage methods, ripping proved to be the most favourable for starch yield, especially in drought years. This suggests that exploring deeper root zones may improve water utilization , which indirectly helps stabilize starch content.

The MLP-type machine learning models used in the research achieved outstanding accuracy in predicting starch content. This may provide a basis for the development of precision decision support systems that can predict content values in real time based on production location, technology, and crop year data.

Based on my results , producers, processors and breeders may be able to influence starch content in a targeted, data-driven manner , thereby increasing the economic and quality efficiency of maize production.

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7. PUBLICATIONS ON THE TOPIC OF THE THESIS

DEBRECENI EGYETEM

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Nyilvántartási szám: DEENK/146/2025.PL
Tárgy: PhD Publikációs Lista

Jelölt: Fejér Péter
Doktori Iskola: Kerpely Kálmán Doktori Iskola
MTMT azonosító: 10084000

A PhD értekezés alapjául szolgáló közlemények

Magyar nyelvű tudományos közlemények hazai folyóiratban (1)

1. Ferencsik, S., Rátonyi, T., **Fejér, P.**, Harsányi, E.: A kukorica talajművelési rendszereinek összehasonlító elemzése réti csernozjom talajon.
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2. Zagyi, P., Tamás, A., Rácz, D., **Fejér, P.**, Radócz, L., Horváth, É.: Correlation analysis of relative chlorophyll content and yield of maize hybrids of different genotypes.
Agrártud. Közl. 1, 211-214, 2022. ISSN: 1587-1282.
DOI: http://dx.doi.org/10.34101/actaagrar/1/10393

3. Huzsvai, L., **Fejér, P.**, Illés, Á., Bojtor, C., Bojté, C., Horváth, É., Demeter, C.: Analysis of sweet corn nutritional values using multivariate statistical methods.
Agrártud. Közl. 1, 103-108, 2021. ISSN: 1587-1282.
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8. **Fejér, P.**, Széles, A., Horváth, É., Rátonyi, T., Ragán, P.: Effects of some agronomic practices on the quality of starch content of maize grains.
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További közlemények

Magyar nyelvű tudományos közlemények hazai folyóiratban (1)

20. Harsányi, E., **Fejér, P.**, Kutasiné Nagy, I., Rátonyi, T.: A vidékiség értelmezése és a földhasználat helyzete Magyarországon.
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Idegen nyelvű absztrakt kiadványok (2)

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