



Article The Effects of Winter Cover Crops on Maize Yield and Crop Performance in Semiarid Conditions—Artificial Neural Network Approach

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Abstract: Maize is the most widespread and, along with wheat, the most important staple crop in the Republic of Serbia, which is of great significance for ensuring national food security. With the increasing demand for food and forage, intensive agricultural practices have been adopted in the maize production systems. In this direction, considerable research efforts have been made to examine the effects of different types of cover crops as a green manure on maize productivity; however, no consistent conclusions have been reached so far. Therefore, the objective of the present study is to examine the possibility of predicting the effects of winter cover crops (CC) integrated with different management practices on the morphological traits, yield, and yield components of maize. The experiment was carried out on chernozem soil from 2016 to 2020 as a randomized complete block design arranged as a split-split-plot with three replicates. The pea as a sole crop (P) and the mixture of pea and triticale (PT) are sown as winter CC with the following subplots: (i) CC used as green manure, and (ii) CC used as forage and removed before maize sowing. The artificial neural network is used for exploring nonlinear functions of the tested parameters and 13 categorical input variables for modeling according to the following factors: CC, way of using CC, N fertilization, and year. The computed maximums of plant height, number of leaves, number of internodes, plant density, number of ears, grain yield, 1000-grain weight, hectolitre weight, dry matter harvest residue, harvest index, leaves percentage, stems percentage, and ears percentage are as follows: 232.3 cm; 9.7; 10.2; 54,340 plants ha⁻¹; 0.9; 9.8 t ha⁻¹; 272.4 g; 67.0 kg HL⁻¹; 9.2 t ha⁻¹; 0.52; 18.9%; 36.0%, and 45.1%, respectively. The optimal result is obtained with peas used as green manure, with 50 kg N ha⁻¹ and in the climatic conditions of 2018. Consequently, maize production under subsequent sowing periods can be successfully optimized by adapting selected management options for higher yield accomplishment.

Keywords: cover crops; green manure; maize; yield; crop performance; artificial neural network

1. Introduction

The main challenge for agriculture in the 21st century will be to increase food production with minimal environmental impact [1,2]. Therefore, it is necessary to analyze the current approach to agriculture and gradually introduce new solutions and technologies. Conventional farming over a long time has been proven to lead to soil degradation, reducing soil buffering capacity in the variable environmental conditions [3], and increasing sensitivity to extreme weather events [4]. This coincides with the state of the arable land-use systems in the Pannonian Plain, where significant changes in soil properties have been reported (soil organic matter loss, deterioration of physical and biological properties, salinization, etc.) [5–7]. An additional concern arises from the limited use of manure, which



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Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). is attributed to decreased livestock numbers [8] and narrow crop rotations. The tendency for more efficient use of soil, nutrients, and water has made it increasingly important to adapt current cropping technology. Incorporating cover crops (CC) in crop rotation is one of the solutions for soil conservation and improvement, focusing on the better utilization of agroecological conditions [9,10].

CCs in cropping systems could provide economic and environmental benefits and play an important role in adjusting the cropping systems toward sustainable production [11–15] and climate-smart agriculture. For example, the introduction of CCs may result in the reduction of the use of mineral nitrogen (N) fertilizers due to biologically fixed N [16–18]; preserving soil moisture content and preventing nutrient leaching [19,20]; erosion control [21,22]; maintaining water quality [10]; increasing organic matter content, improvement of soil structure and biological soil properties [23–25]; as well as in the preservation of biodiversity [26], and agroecosystem health in general [12,27].

The selection of suitable cover crop species in semi-arid conditions of the Pannonian Plain is crucial for achieving multiple benefits in sustainable agricultural production. Considering the risk of extremely unfavorable years and the projected increase in the variability of climatic conditions [28], CCs have a great potential to be combined with existing cultivation systems, because during the winter season (November-February), the fields remain bare. Therefore, winter CCs can regulate soil conditions and water accessibility for the subsequent crops [29,30]. In the northeastern U.S. dairy farms, winter CCs that showed higher potential are different types of hairy vetch, clovers, winter wheat, and rye [31]. The same authors point out that winter triticale is increasingly present in production as a CC that can be used as a quality ruminant feed in the spring. Conversely, in Southeastern Europe, Cupina et al. [32] found the lowest yield of silage maize for two consecutive years following triticale due to the higher water consumption. In addition to forage production, winter CCs are increasingly used as green manure [33,34] or as living mulch. The benefits of green manuring are closely related to the C:N ratio in cover crop biomass. Thus, leguminous CCs used as green manure ensure N for the subsequent crop [35], while for increased soil organic matter, priority should be given to grasses because of their higher C:N ratio [36]. Sustainable agricultural practices also favor late spring plowing or reduced tillage, as well as direct maize sowing into living mulch [37]. A meta-analysis based on 268 literature findings showed a 13% increase in maize yields with the CC mixture compared to the control [15]. Therefore, Vojnov et al. [38] suggest that it would be beneficial to include CCs in maize management practice through a strategic concept that would foresee subsidies, which would enable all the positive effects of this important ecological measure on farming in general.

The artificial neural network (ANN) was recently recognized as an attractive mathematical method for exploring maize production from the subsequent sowing period systems [39–41]. The ANN model does not need concrete model parameters but still embraces a capacity to obtain results from the experimental data, handle the complex system with nonlinearities and elaborate on the synergies between variables [42]. The uses of ANN models cover numerous investigations of agricultural production studies [43]. Agricultural production expenses are not low; therefore, they need to be predicted numerically as much as possible. One of the ways of cost reduction is using fitting tools that predict agricultural production and variations in crop properties through breeding. Moreover, the involved agro-technology level in the cultivation, particularly fertilization with nitrogen, influences crop features and is challenging to prognosticate. The multi-objective optimization (MOO) for adjusting the parameters of agricultural production in order to maximize the yields was presented in the study by [44]. In that study, 13 ANN models coupled with ant colony optimization were developed to optimize the parameters of the biodiesel production process.

In accordance with this study, the MOO analysis combined with ANNs and genetic algorithm (GA) was implemented in the maize production, keeping in mind that there might not be a unique solution due to the contradictory objective functions [39,45,46]. As a

part of this study, the solution of the MOO was estimated by introducing a Pareto optimal method [39].

Based on all of the above, the goal of this study was to examine the possibility of predicting morphological traits, grain yield and yield components, and some crop performance of maize; i.e., the following 13 variables: the plant height (H), number of leaves (NL), number of internodes (NI), plant density (PD), number of ears (NE), grain yield (GY), 1000-grain weight (TGW), hectolitre weight (HW), dry matter harvest residue (DMHR), harvest index (HI), leaves percentage (L), stems percentage (S) and ears percentage (E); as a function of cover crops type (CC), way of using cover crops (WUCC), N fertilization (NF), and year of maize production (YEAR) under semiarid conditions of the experimental site.

2. Materials and Methods

2.1. Experimental Site Description—Location, Climate and Soil Characteristics

The research was carried out in the period from 2016 to 2020, at the Rimski Šančevi experimental station (45°19′ N; 19°50′ E; 80 m a.s.l.) of the Institute of Field and Vegetable Crops in Novi Sad; the National Institute of the Republic of Serbia (in Vojvodina, Northern Province of Serbia), in the typical chernozem zone of the southern part of the Pannonian Plain (Figure 1). According to the WRB classification (2014), the soil type is medium-deep chernozem, formed on loess and loess-like sediments; is classified as Calcareous Chernozem (aric, loamic, pachic), abbreviated as CH-cc-ai.lo.ph.

The climate is characterized as a moderate continental climate with extreme seasonal variability in temperature and precipitation. Based on long-term data (1970–2017), the mean annual air temperature is 11.4 °C and the total annual precipitation sum is 640.5 mm. Monthly precipitation and temperature data were collected from the weather station at Rimski Šančevi experimental field (Figure 1).

Weather Conditions during the Research Period

During the investigated period, temperatures, and precipitation showed differences among investigated growing seasons and deviations from the long-term averages (LTA) (Figure 2). At the beginning of the experiment, from December 2016 to March 2017, the lower precipitation was recorded compared with the LTA (1970–2017). That caused a shortage of water in the soil, and drought continued in summer 2017 (July–August), while in autumn 2017 precipitation increased. Temperatures in the period October–September 2017/18 were higher by 1.4 °C compared with LTA. The amounts of precipitation during the winter period compensated for the lack of soil moisture in 2017 and provided sufficient soil moisture during the spring season of 2018. Total precipitation in the hydrological year 2017/18 (753.4 mm) was above the average values for the experimental site. The small amount of precipitation (7.4 mm) at the beginning of the hydrological year 2018/19 (October) resulted in decreased soil moisture in autumn 2018. In February and March, a period with a lower amount of precipitation continued, and from the spring the precipitation increased, particularly in May (147.6 mm). Total precipitation for the hydrological year 2018/19 was lower by 42.9 mm than the LTA. Based on the meteorological conditions, 2019 was the warmest in the last 50 years, with an average annual temperature of 13.4 °C. During the hydrological year of 2019/20, the amount of precipitation was 72.5 mm higher than LTA. In June and August, the amount of precipitation (163 and 138 mm, respectively) was significantly above the average values. Significant deviations from the monthly temperatures were recorded in November and December 2019, as well as in February 2020. The warmest month in 2020 was August, with an average monthly temperature of 24.1 °C.



Figure 1. Location of the trail and experimental design showing the main analyzed factors: cover crops (CC) type and way of using CC (PT: winter pea + triticale, for green manure and for forage; P: winter pea as a sole crop, for green manure, and for forage; Ø: control treatment-without CC), and N fertilization treatments (N50: with N fertilizer of 50 kg ha⁻¹, NØ: without N fertilizer application).



Figure 2. Long-term average (LTA) and total monthly precipitation (P) and average monthly air temperature (T) for hydrological years (A) 2016-2017, (B) 2017-2018, (C) 2018-2019, and (D) 2019-2020. Bars and left *y*-axis represent precipitation, and right *y*-axis and lines represent temperature data.

2.2. Experimental Design

The experimental plots were established using a randomized complete block design (RCBD) arranged as a split-split-plot, with 3 replicates (Figure 1). Maize was grown in a 3-year rotation with Sudan grass and soybean. Cover crops (CC) were considered as the main plots, which consisted of the following: (a) the winter pea (Pisum sativum ssp. Arvense L.) (P), (b) the mixture of winter pea + triticale (\times Triticosecale) (PT), and (c) control treatment (Ø, without CC). The CC plots were divided into the following two sub-plots (way of using cover crops, WUCC): in the first sub-plot, winter CC was used as green manure with plowing, while in the second, the cover crops were mowed and forage was taken away. Based on above factors, the trial anticipated 5 treatments as follows: (i) winter pea + triticale (PT) for green manure, (ii) winter pea + triticale (PT) for forage, (iii) winter pea as a sole crop (P) for green manure, (iv) winter pea (P) for forage, and (v) control (Ø)-without CC. All sub-plots were additionally divided into two sub-subplots (N fertilization), namely, with nitrogen fertilizer of 50 kg ha⁻¹ (N50), and without N fertilizer application (NØ). The dimensions of each individual basic plot were 6×4 m, i.e., 24 m². Winter CC was sown in autumn, in the last week of October/beginning of November, and cutting for forage and plowing as green manure was performed in May. After plowing and seedbed preparation, in the first decade of June, maize (hybrid NS-4051) was sown at a distance of 23 cm between plants in a row and 70 cm between rows, with a seeding rate of 62,000 plants ha⁻¹. Nitrogen (Urea, 46% N) was applied in maize vegetative phase BBCH 34, and the harvest was performed in October. The description of field operations by analyzed years is shown in Table 1.

Field/Year	2016–17	2017–18	2018–19	2019–20
Cover Crops				
Winter Pea Winter Pea + Triticale		11 90 -	20 + 30	
Field Operation		Da	ate	
Cover crop sowing Cover crops plowing Maize sowing Fertilization (Urea, 46%) Maize harvest Soil sampling	28 October 5 May 1 June 15 June 26 October 29 October	8 November 18 May 15 June 1 July 18 October 20 October	7 November 22 May 11 June 25 June 23 October 25 October	15 November 18 May 25 May 10 June 16 October 20 October

Table 1. Time of field operations during the season 2016–17, 2017–18, 2018–19, and 2019–20.

2.3. Measurements and Analytical Determination

The disturbed field moist soil samples (1 kg of soil per plot) were collected from the topsoil (0–30 cm) in autumn, after maize harvest (Table 2). The pH value of the soil was determined in the suspension of soil in KCl and H₂O, by Metrel MA 3657 pH meter. Humus content was determined by oxidizing organic matter with potassium bichromate [47]. Calcium carbonate (CaCO₃) content was determined volumetrically using Scheibler calcimeter. Mineral N in the soil was extracted using 2 M KCl (1:4 soil-to-solution ratio, on weight basis) and determined by steam distillation [48]. The available phosphorus (P) and potassium (K) content were measured by the Ammonium-Lactate (AL) method. The concentration of P_2O_5 was measured by spectrophotometry, while the concentration of K₂O was measured by flame photometry [49].

Table 2. Average soil ch	hemical characteristics of	experimental site a	fter maize crop	harvest
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Year	pН	pН	CaCO ₃	Humus	Ν	(mg 100 g^{-1} of Soil)		
	(KCl)	(H ₂ O)	(%)	(%)	(%)	P ₂ O ₅	K ₂ O	
2016 *	7.21 ± 0.10	7.95 ± 0.14	8.57 ± 0.19	2.61 ± 0.19	0.13 ± 0.01	16.65 ± 3.04	20.31 ± 2.01	
2017	7.48 ± 0.06	8.14 ± 0.07	8.96 ± 1.42	2.59 ± 0.08	0.19 ± 0.01	17.13 ± 1.05	23.67 ± 0.52	
2018	7.43 ± 0.10	8.11 ± 0.06	8.68 ± 2.64	2.53 ± 0.15	0.19 ± 0.01	18.41 ± 3.03	23.43 ± 2.21	
2019	7.23 ± 0.03	8.12 ± 0.05	9.48 ± 2.01	2.69 ± 0.19	0.20 ± 0.01	14.54 ± 1.95	23.21 ± 2.05	
2020	7.33 ± 0.05	8.21 ± 0.05	9.11 ± 1.73	2.54 ± 0.13	0.18 ± 0.01	14.62 ± 1.88	23.02 ± 1.53	

* 2016 was taken as initial soli properties before experimental setup. The data in the table represent the mean \pm standard deviation (SD).

The dry matter yield of aboveground biomass of cover crops (t ha⁻¹) was evaluated before incorporation by cutting the crop to a stubble height of 5 cm. Samples were collected from 1 m² from each basic CC plot and each replicate. Samples were taken from the central part of each plot. The dry matter yield of cover crops was obtained by drying samples to a constant mass at 105 °C in the oven. The morphological traits and yield components of maize were measured at the maize-harvesting time (October) by randomly choosing 15 plants from each plot in 3 repetitions. Grain yield was adjusted to a moisture content of 14%.

The following variables, i.e., performances of maize plants and crops were recorded: plant height (H; cm), number of leaves (NL), number of internodes (NI), plant density (PD; number of plants ha⁻¹), number of ears (NE), grain yield (GY; t ha⁻¹), 1000-grain weight (TGW; g), hectolitre weight (HW; kg HL⁻¹), dry matter harvest residue (DMHR; t ha⁻¹), harvest index (HI), and leaf (L), stem (S), and ear (E) percentage.

2.4. ANN Modelling

A multi-layer perception model (MLP), with three layers (input, hidden, and output) was implemented to construct 13 ANN models for the following output variables: H, NL, NI, PD, NE, GY, TGW, HW, DMHR, HI, L, S, and E; according to the following factors: cover crops type (CC), way of using cover crops (WUCC), N fertilization (NF) and YEAR. This format of the ANN model is approved for its high potential of estimating nonlinear functions [50–53].

Before the ANN model's computation, input and output data should be normalized to enhance the outcome of the ANN [54]. Throughout the ANN model's building, input data are repeatedly inserted in the network [55–57]. The training process of the network was replicated 100,000 times, testing the various structures of the ANN model, including a diverse number of neurons in the hidden and the output layers (1–20), alternative activation functions (such as the following: logarithmic, logistic, tangent hyperbolic, or identity), and with random starting values of weight coefficients and biases. The ANN structure optimization was accomplished by achieving the minimal validation error. The Broyden–Fletcher–Goldfarb–Shanno algorithm (BFGS) was implemented for resolving the unconstrained nonlinear optimization problem throughout the ANNs construction [54].

The maize crop performance database, which was employed for the 13 ANN models, was stochastically segmented into the following: training, cross-validation, and testing data (70%, 15%, and 15% of experimental data, respectively). The training data set was applied during the learning cycle of the ANNs calculation and also used to evaluate the optimal number of neurons in the hidden layer and compute the weight coefficient of individual neurons in the network [58]. The weight coefficients and biases connected to the hidden and output layers of the ANN models were recorded in matrices and vectors W_1 and B_1 , and W_2 and B_2 , individually. The neural network model can be displayed by the following matrix equation:

$$Y = f_1(W_2 \cdot f_2(W_1 \cdot X + B_1) + B_2)$$
(1)

where *Y* is the matrix of the outputs, f_1 and f_2 are transfer functions in the hidden and output layers, respectively, and *X* is the matrix of inputs [59]. The elements of matrices W_1 and W_2 for each ANN model were computed during the learning cycle, in which the elements are constantly introduced applying an optimization method to minimize the disagreement between the data and the models [54,60,61]. The BFGS algorithm was implemented to enhance the evaluation and stabilize the solution's convergence [62]. The coefficients of determination were utilized as parameters to monitor the execution of the achieved ANN model. The ANN model was created to foresee and optimize the following parameters: H, NL, NI, PD, NE, GY, TGW, HW, DMHR, HI, L, S, and E, according to the following treatments (factors): CC, WUCC, NF, and YEAR.

2.5. Global Sensitivity Analysis

The Yoon's global sensitivity formula for the obtained ANN model was exploited to evaluate the relative influence of the input parameters on output variables, based on weight coefficients of the developed ANN models [63].

$$RI_{ij}(\%) = \frac{\sum_{k=0}^{n} (w_{ik} \cdot w_{kj})}{\sum_{i=0}^{m} \left|\sum_{k=0}^{n} (w_{ik} \cdot w_{kj})\right|} \cdot 100\%$$
(2)

where: *w*—weight coefficient in ANN models, *i*—input variable, *j*—output variable, *k*—hidden neuron, *n*—number of hidden neurons, *m*—number of inputs.

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2.6. Error Analysis

The numerical confirmation of the developed model was investigated applying the coefficient of determination (\mathbb{R}^2), reduced chi-square (χ^2), mean bias error (*MBE*), root mean square error (*RMSE*), and mean percentage error (*MPE*). These frequently used parameters can be obtained according to the following equations [64]:

$$\chi^{2} = \frac{\sum_{i=1}^{N} (x_{\exp,i} - x_{pre,i})^{2}}{N - n},$$
(3)

$$RMSE = \left[\frac{1}{N} \cdot \sum_{i=1}^{N} (x_{pre,i} - x_{\exp,i})^2\right]^{1/2},$$
(4)

$$MBE = \frac{1}{N} \cdot \sum_{i=1}^{N} (x_{pre,i} - x_{\exp,i}), \qquad (5)$$

$$MPE = \frac{100}{N} \cdot \sum_{i=1}^{N} \left(\frac{|x_{pre,i} - x_{\exp,i}|}{x_{\exp,i}} \right)$$
(6)

where $x_{\exp,i}$ marks the experimental values and $x_{pre,i}$ present value computed by the model, N and n are the number of observations and constants, accordingly.

2.7. Multi-Objective Optimization

The obtained ANN models were employed for multi-objective optimization (MOO) calculation, with the aim to gain the specific set of production parameters, which would extract the maximal values of PD, GY, TGW, HW, DMHR, and HI. The final result of MOO was derived using a Pareto front algorithm, which existed in the case of one objective function improvement without deteriorating the others [39]. The genetic algorithm (GA) was used to find the solutions to the MOO problem by a stochastic method inspired by natural evolution applying the mutation, selection, inheritance, and crossover [65]. For the MOO computation, MATLAB software (version 7.10.0 (2010), The MathWorks Inc., Natick, MA, USA) was used, and gamultiobj algorithm was used for MOO optimization. The primary population is formed by chance and then introduced to a set of points in the design area. The populations of the next generations were determined using distance measures and non-dominated ranking of the particular points within the existing generation [39,45,46]. Modeling, statistical analysis, and multi-objective optimization of the collected data in this study were processed statistically using the software package STATISTICA version 14.0. (TIBCO Software Inc., Palo Alto, CA, USA).

3. Results

3.1. Dry Matter Yield of Cover Crops

The dry matter yield of cover crops differed and depended on a complex interaction of years and CC. Due to favorable weather conditions, the highest dry matter yield of CC was achieved in 2020 with the mixture of PT (4.4 t ha^{-1}) and was higher by 0.9 t ha⁻¹ compared to the sole pea crop (Figure 3). The lowest yield of CC dry matter was achieved in 2017, in the pea crop (1.2 t ha^{-1}), which differed by 0.5 t ha⁻¹ in relation to the mix PT. In the years 2018, 2019, and 2020, the CC yield was higher than in 2017. The yield of PT was higher by 1.7 t ha⁻¹ in 2018, i.e., by 2.7 t ha⁻¹ in 2020 compared to the yield in 2017.



Figure 3. Dry matter yield of different type of CC–winter pea + Triticale (PT) and winter pea (P). Vertical bars on columns represent standard error (SE) of the mean.

3.2. ANN Model

The attained ANN models showed sufficient generalization ability for experimental data prediction. Based on the ANN models' performance, the optimal number of neurons in the hidden layer for calculation of the following selected parameters: H, NL, NI, PD, NE, GY, TGW, HW, DMHR, HI, L, S, and E, the prediction was between 5 and 10 to attain the required high values of R² (in the range from 0.487 to 0.966, for the training period) and as low as possible sum of squares (SS) values (Tables 3 and 4).

Table 3. ANN models summary (performance and errors), for training, testing, and validation cycles.

Variable	Network Name	Performance				Error		Training	Hidden	Output
		Training	Testing	Validation	Training	Testing	Validation	Algorithm	Activation	Activation
Н	MLP 12-7-1	0.966	0.949	0.953	41.583	41.372	41.244	BFGS 179	Tanh	Exponential
NL	MLP 12-9-1	0.487	0.495	0.485	0.124	0.121	0.120	BFGS 127	Logistic	Identity
NI	MLP 12-9-1	0.508	0.501	0.502	0.116	0.114	0.112	BFGS 135	Tanh	Tanh
PD	MLP 12-5-1	0.793	0.796	0.808	397.146	395.384	389.697	BFGS 315	Tanh	Exponential
NE	MLP 12-10-1	0.508	0.515	0.518	0.001	0.001	0.001	BFGS 139	Logistic	Tanh
GY	MLP 12-10-1	0.891	0.902	0.890	0.309	0.305	0.301	BFGS 237	Exponential	Exponential
TGW	MLP 12-7-1	0.838	0.825	0.828	168.655	171.050	168.741	BFGS 122	Tanh	Logistic
HW	MLP 12-6-1	0.713	0.710	0.723	7.391	7.516	7.588	BFGS 248	Logistic	Identity
DMHR	MLP 12-7-1	0.855	0.854	0.841	0.421	0.421	0.414	BFGS 185	Tanh	Logistic
HI	MLP 12-9-1	0.698	0.689	0.694	0.001	0.001	0.001	BFGS 103	Tanh	Tanh
L	MLP 12-5-1	0.855	0.850	0.840	3.489	3.439	3.501	BFGS 383	Logistic	Tanh
S	MLP 12-8-1	0.773	0.764	0.775	3.259	3.214	3.196	BFGS 129	Logistic	Exponential
Е	MLP 12-10-1	0.621	0.628	0.626	8.281	8.370	8.277	BFGS 173	Exponential	Tanh

Table 4. The "goodness of fit" tests for the developed ANN models.

Variable	χ^2	RMSE	MPE	SSE	AARD	R ²	Skew.	Kurt.	St.Dev.	Var.
Н	91.419	9.120	3.695	11,975.867	1075.800	0.966	-0.202	0.916	9.151	83.747
NL	0.272	0.497	3.876	35.588	115.667	0.486	0.124	0.176	0.499	0.249
NI	0.255	0.482	3.729	33.452	132.667	0.505	0.269	0.805	0.484	0.234
PD	$8.7 imes10^6$	$2.8 imes10^3$	4.662	$1.1 imes 10^9$	$8.2 imes 10^5$	0.788	-0.127	-0.197	$2.8 imes10^3$	$8.0 imes10^6$
NE	0.003	0.053	3.529	0.400	14.667	0.507	0.075	0.788	0.053	0.003
GY	0.679	0.786	12.653	88.940	184.400	0.885	-0.165	1.726	0.789	0.622
TGW	370.784	18.366	6.015	48,572.767	3704.667	0.835	0.169	0.964	18.430	339.670
HW	16.249	3.845	5.155	2128.660	607.000	0.716	-0.075	1.012	3.858	14.886
DMHR	0.925	0.918	13.658	121.240	105.400	0.854	-0.087	0.632	0.921	0.848
HI	0.002	0.040	6.905	0.228	5.287	0.699	-0.199	0.210	0.040	0.002
L	7.671	2.642	7.517	1004.840	197.867	0.853	2.369	26.149	2.651	7.027
S	7.165	2.553	6.873	938.633	287.467	0.773	0.061	0.959	2.562	6.564
Е	18.206	4.070	6.482	2384.947	356.467	0.621	-1.929	20.442	4.084	16.678

The goodness of fit among experimental computations and model estimated outputs, described as the ANN models' performance (sum of R² within measured and calculated parameters), through training, testing, and validation actions, are displayed in Table 4.

The used ANN models predicted the experimental variables quite well for a wide range of the process parameters (which can be seen in Figures 4 and 5, where the experimentally estimated and predicted values of the ANN models are shown).



Figure 4. Comparison of experimentally obtained values of (**a**) H, (**b**) NL, (**c**) NI, (**d**) PD, (**e**) NE, and (**f**) GY, with ANN predicted values.



Figure 5. Comparison of experimentally obtained values of (**a**) TGW, (**b**) HW, (**c**) DMHR, (**d**) HI, (**e**) L, (**f**) S, and (**g**) E, with ANN predicted values.

The R^2 values within experimental and ANN model outputs for H, NL, NI, PD, NE, GY, TGW, HW, DMHR, HI, L, S, and E, were 0.966; 0.487; 0.508; 0.793; 0.508; 0.891; 0.838; 0.713; 0.855; 0.698; 0.855; 0.773; 0.621, accordingly, throughout the training period.

3.3. Global Sensitivity Analysis—Yoon's Interpretation Method

In this segment, the impact of input variables (i.e., factors CC, WUCC, NF, and YEAR) on H, NL, NI, PD, NE, GY, TGW, HW, DMHR, HI, L, S, and E, throughout the maize production, the Yoon's interpretation method of the generated ANN models were analyzed. The graphical display of the ANN model results is shown in Figure 6.



Figure 6. The relative influence (%) of CC, WUCC, NF and YEAR on (**a**) H, (**b**) NL, (**c**) NI, (**d**) PD, (**e**) NE, and (**f**) GY, determined using Yoon's interpretation method.

As presented in Figure 6a,f, 2017 is the most negatively influential parameter on H and GY, with a relative importance of -40.78% and -23.69%, respectively; while the influence of the year 2018 on the NL was quite the opposite, with a relative influence of +24.23% (Figure 6b). The arid period during the summer months of 2017 (Figure 2a) affected the slow growth and development of maize plants, as well as grain yield. The results show that optimal conditions for maize production can be achieved if winter peas are incorporated into the soil as green manure, along with nitrogen fertilization (50 kg N ha⁻¹), and in years with a favorable precipitation distribution; such as in 2018. NI was mainly influenced by the 2019 year, with a relative importance of -22.64% (Figure 6c), while the year 2020 was the most significant parameter for plant density (Figure 6d), with a relative influence of 30.68%. On the other hand, according to Figure 6e, the number of ears was negatively influenced by the mixture of pea and triticale, using cover crops as green manure, and the year 2020, with a relative importance of -18.36%, -13.11%, and -13.02%, respectively.

The maize yield dependence on the investigated factors is reflected in 1000-grain weight and hectolitre weight. According to Figure 7a,c,f, the year 2017 had a negative effect on 1000-grain weight, dry matter harvest residue, and stem percentage, with a relative importance of -33.48%, -23.02%, and -26.60%, respectively. The year 2019 had a positive impact on the hectolitre weight (+16.55%) and ear percentage (+29.14%), while it showed a negative impact of -23.18% on the harvest index (Figure 7b,d,g). High temperatures affected the 1000-grain weight due to the rapid ripening in dry years such as in 2017. The influence of peas as a cover crop on leaf percentage was negative, with a relative importance of -27.55% (Figure 7e). The result indicates higher effects of the winter pea treatment on the ear and stem percentage, which is made possible by the greater availability of soil moisture and nitrogen.



Figure 7. The relative influence (%) of CC, WUCC, NF, and YEAR on (**a**) TGW, (**b**) HW, (**c**) DMHR, (**d**) HI, (**e**) L, (**f**) S, and (**g**) E, determined using Yoon's interpretation method.

3.4. Multi-Objective Optimization (MOO) of the Outputs of ANN

One of the main goals of this research was to optimize PD, GY, TGW, HW, DMHR, and HI throughout different field management practices and years, synchronously, employing the ANN models and varying input variables. These numerical assignments were solved for the ANN models by applying the MOO computation in Matlab. The MOO method was set to obtain the best combinations of different parameters by maximizing the output variables in the ANN models. The optimization method's constraints were used in the experimental series of parameters. The number of generations achieved was 723 for the ANN models, while the population dimension was set to 200 for all input variables. Thus, the number of points on the Pareto front was 69 for the ANN models. The computed maximums of H, NL, NI, PD, NE, GY, TGW, HW, DMHR, HI, L, S, and E were the following: 232.3 cm; 9.7; 10.2; 54.340 plants ha⁻¹; 0.9; 9.8 t ha⁻¹; 272.4 g; 67.0 kg HL⁻¹; 9.2 t ha⁻¹; 0.52; 18.9%; 36.0%, and 45.1%, respectively. The optimal result was obtained with the following parameters: peas used as green manure, with an application of 50 kg N ha⁻¹, and in the climatic conditions of 2018.

4. Discussion

Our study showed that climatic conditions significantly modified overall cover crop performance while increasing the sensitivity of the main crop to weather conditions (Figure 3). This is particularly noticeable in 2017, when the lack of precipitation (first during the winter period, and later during the spring) suppressed their growth, and decreased the yield. During the four years of research, the average dry matter yield of cover crops was higher in the mixture of pea and triticale $(3.4 \text{ t h}a^{-1})$ compared to peas as a sole crop (2.1 ha⁻¹) (Figure 3). Similar to our results, Ref. [66] states that mixed cover crops have a higher forage yield and a better nutrient balance for ruminant feed than sole cropping. On the other hand, the plowing of a cereal/legume mixture results in a larger amount of dry matter incorporated into the soil as green manure [67], which affects the soil's physical properties and soil air regime [68].

The selection of proper cover crops and timely incorporation of winter CCs can increase or adversely affect the crop yield of the subsequent crop in rotation. Chen et al. [69] registered an increased maize yield from 1.60 to 2.43 t ha^{-1} following CC, which is consistent with the results of our study. Increased maize yield was also obtained in the research of [70], in which a mean increase of grain yield was 78, 91, and 66% with the inclusion of cowpea, pigeon pea, and hemp, compared with the fallow system. On the contrary, Ref. [71] reported a decrease in the yield of cash crops (maize and sunflower) by 0.5-3.0 t ha⁻¹. In our study, the sowing of maize was performed after the recommended date to give CCs more time to produce higher biomass. Currently, there is a lack of information on crop cultivation in the subsequent sowing period in the temperate conditions of Vojvodina province. Nevertheless, the assumption is that hybrids of shorter FAO maturity groups can be established significantly later than the optimal term with acceptable risks. Mahama et al. [70] confirm that the sowing delay of main summer crops is related to the necessity to provide time for winter CCs growth and higher biomass production, and in the case of legumes, to accumulate N. However, in this study, it was shown that this practice could be successfully implemented for the winter cover crops. Out of four years of research; only in 2017 arid periods were recorded in July and August with 29.4 mm of precipitation (90 mm less than the LTA).

Consequently, the yield components of maize were lower and affected the yield accomplishment. In conditions with uncertain amounts of precipitation necessary for the plants' growth and development, it is essential to make a trade-off between the benefits provided by CCs and the possibility of obtaining a reduced yield of the main crop. Given that the average maize yield in our experiment is not considerably lower than the average grain yield of the recommended sowing dates, this approach could be a crucial point in designing future cropping systems in semiarid conditions.

ANN models can help predict maize behavior under our experimental setup. In most cases, the predicted values were approaching the desired R^2 value for the ANN models. The SS achieved by the ANN models is of the same order of magnitude as experimental errors for H, NL, NI, PD, NE, GY, TGW, HW, DMHR, HI, L, S, and E, which were also observed in similar studies [54,62,72]. The ANN protocols are challenging (71–141 weights-biases) due to the high nonlinearity of the studied system [54,73]. Neverthe the character of the ANN models fit as observed in Table 4, where χ^2 , *MBE*, *RMSE*, and MPE were lower [64]. The residual analysis of the developed model was additionally conducted to provide insight into maize response to key variables and the limitations of ANN analyses. In addition, skewness was used to estimate the deviation of the distribution from regular symmetry. Skewness showed different values for some variables (NI, L, H, HI, E, etc.), indicating asymmetrical distributions, although normal distributions are ideally symmetrical. Accordingly, these indicators are developed as a consequence of complex interactions between the observed parameters. The data set was checked for kurtosis (the "peakeness" of a distribution). In our study, leaf and ear percentages are distinct in kurtosis values compared with other parameters, indicating heavier tails than normal distribution, with high peaks and outliers. This can be explained by the occurrence

of smaller maize plants in which sudden maturation occurs in specific years. A high R² is suggestive that the variation was estimated, and that the data fitted satisfactorily to the suggested model [74,75]. Marcillo and Miguez [15] in a meta-analysis of maize yield dependence on intercrops, concluded that CC from the *Poaceae* family neither positively nor negatively affected maize yield, while leguminous plants and their mixture showed a significant impact. Similar results were observed in our experiment as CC and years showed positive effects on the yield of subsequent maize crops.

In our study, the smaller number of ears of maize can be explained by the soil's lower moisture content on the plots with the combined sowing of winter peas and triticale. However, this is contrary to the study of [76], who determined higher soil moisture after legume CCs compared with the mixture with cereal, while the lowest moisture content was in the soil after triticale. As shown in Figure 6, nitrogen fertilization had the lowest impact on the plant height, number of leaves and internodes, plant density, number of ears, and grain yield, while years were the most influential. The assumption is that fresh biomass mineralization can be sufficient for the N-demand of latter-sown maize. Refs. [77,78] found that plant density (the number of plants per unit area) is a decisive factor in maize production, but the optimal plant density is not always the same, but rather varies depending on the year. In recent decades, maize grain yield has become increasingly dependent on climatic conditions during plant growth and development [79]. Therefore, predicting optimal plant density represents a challenging task. The maize yield in the subsequent sowing directly depends on the water spent by the winter CCs and precipitation distribution during subsequent crop cultivation [80,81]. According to [82], CCs may have a more significant potential to reduce drought stress in maize after longterm use in systems with less soil disturbance. Rosa et al. [83] found that CCs in semi-arid conditions did not contribute to the increase in maize grain yield, and most CC types are associated with a reduction in maize yield. The same authors relate this consequence to the lack of soil moisture and nitrogen availability during the maize growing season. Despite many benefits, ref. [84] points out that the benefits of CCs in practice are still limited because the effects on productivity and economic return are variable. In addition to that, for conclusive CCs assessment and compliance with main crops, it requires multi-location trials and ideotype selection of both CC and crop sequence. In the work of [85], ANN was used to predict the role of individual nutrients on various parameters of rice plants. Contrary to our results, the authors determined that nitrogen is the most limiting nutrient among the studied nutrients in terms of obtaining the maximum grain yield of rice, regardless of the season and variety. They observed an improvement in plant height, number of tillers, and dry matter, indicating an important role of N in vegetative growth. According to Figure 2, there are differences in the amount of precipitation and their distribution during the growing period of maize, with 2018 and 2020 being higher in precipitation for the period June-September. The authors [85,86] point out that environmental variables, such as air temperature, total precipitation, insolation, and soil properties, significantly influence plant parameters and crop performance prediction using ANN models.

The main limitations of this and similar studies are that, although each of the analyzed treatments (factors) in ANN models has a specific role in the growth and development of plants, complex interactions among them often make it difficult to understand the separate actions of individual factors. Moreover, it is almost impossible to fully assess the individual effects of input parameters on the final performance of plants and crops. This is particularly pronounced in field conditions, where crop performance is subjected to a very complex environment, with sudden variations in climatic parameters such as temperature, precipitation, relative air humidity, etc. In addition, statistical models are often criticized for failing to provide a scientific understanding of the processes being studied.

5. Conclusions

This study indicates that empirical artificial neural network models could be successfully utilized to predict plant-examined parameters. The prediction of those variables using parameters such as cover crops, way of using cover crops, N fertilization, and year showed high accuracy in estimating with the artificial neural network model. The obtained models provided a good fit to experimental data and were adequate to predict the output variables successfully, showing a reasonably good predictive capability (overall R^2 for plant height, number of leaves, number of internodes, plant density, number of ears, grain yield, 1000-grain weight, hectolitre weight, dry matter harvest residue, harvest index, leaf percentage, stem percentage, and ear percentage were 0.791; 0.791; 0.878; 0.960; 0.818; 0.700; 0.843; 0.691, accordingly). The computed maximums of plant height were 232.3 cm, number of leaves 9.7, number of internodes 10.2, plant density 54,340 plant ha⁻¹, number of ears 0.9, grain yield 9.8 t ha^{-1} , 1000-grain weight 272.4 g, hectolitre weight 67.0 kg HL^{-1} , dry matter harvest residue 9.2 t ha⁻¹, harvest index 0.52, percentage of leaf 18.9%, stem 36%, and ear 45.1%, respectively. Our study implies that subsequent maize production in rainfed conditions can be performed with winter pea cover crops used for green manure, supplementary nitrogen addition of 50 kg ha⁻¹, and under a rainfall amount of >330 mm (June-September). The developed mathematical models give satisfactory accuracy for potential practical application in maize production and enable the proper selection of cropping management for the farmers. Given the scope of this work, it would be essential to suggest cover crops as necessary agroecological measures that would amplify the positive outcomes of other field management practices in field crop production.

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