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Application of Artificial Neural Networks for Yield Modeling of Winter Rapeseed Based on Combined Quantitative and Qualitative Data

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Abstract: Rapeseed is considered as one of the most important oilseed crops in the world. Vegetable oil obtained from rapeseed is a valuable raw material for the food and energy industry as well as for industrial applications. Compared to other vegetable oils, it has a lower concentration of saturated fatty acids (5%–10%), a higher content of monounsaturated fatty acids (44%–75%), and a moderate content of alpha-linolenic acid (9%–13%). Overall, rapeseed is grown in all continents on an industrial scale, so there is a growing need to predict yield before harvest. A combination of quantitative and qualitative data were used in this work in order to build three independent prediction models, on the basis of which yield simulations were carried out. Empirical data collected during field tests carried out in 2008–2015 were used to build three models, QQWR15_4, QQWR31_5, and QQWR30_6. Each model was composed of a different number of independent variables, ranging from 21 to 27. The lowest MAPE (mean absolute percentage error) yield prediction error corresponded to QQWR31_5, it was 6.88%, and the coefficient of determination R^2 was 0.69. As a result of the sensitivity analysis of the neural network, the most important independent variable influencing the final rapeseed yield was indicated, and for all the analyzed models it was "The kind of sowing date in the previous year" (KSD_PY).

Keywords: winter rapeseed; artificial neural networks; machine learning; yield prediction; yield simulation; MLP (multi-layer perceptron) network; sensitivity analysis; precision agriculture; sustainable agriculture; sustainability

1. Introduction

Vegetable oil obtained from rapeseed is an important element of food and a balanced diet. It is also used for the production of biodiesel, in the form of rapeseed methyl esters (RME) and is also an

essential industrial raw material. These main applications of rapeseed are associated with a high content of protein, carbohydrates, and triacylglycerol (TAG) [1–4]. In view of the above, the cultivated land used for rapeseed must compete between food, industrial, and energy purposes [5,6]. Thus, production planning and forecasting of rapeseed yield is crucial in the whole cultivation process. This is directly related to the financial policy and sales deadline strategy adopted by rapeseed producers.

The 2017 world rapeseed production amounted to 76,238,340 tons, with an average yield of 2.19 t ha^{-1} on the total crop land of 34,740,403 ha. The largest rapeseed producers in the world include Canada (21,328,000 tons), China (13,274,000 tons), India (7,917,000 tons), France (5,200,000 tons), Australia (4,313,230 tons), Germany (4,275,600 tons), and Poland (2,697,265 tons) [7].

There are many factors that influence the size and quality of rapeseed and other crops. These include climatic and soil factors, sowing-cultivation-harvesting technologies, plant variety, and fertilization level [8]. Moreover, the mentioned factors are directly or indirectly related to each other, and their effect on the final crop yield is often not thoroughly studied. Therefore, prediction models supporting decision-making processes throughout the entire plant cultivation stages are increasingly used for data analysis to determine the potential yield before harvest. Such actions are aimed at optimizing production in terms of consumption of all production means which in turn maximize yield and financial profits while minimizing inputs.

In recent years, an increase in the use of prediction models in agriculture has been observed. In particular, tools based on artificial intelligence—artificial neural networks (ANN), giving significantly lower prediction errors than in case of statistical methods—are very popular. Therefore, crop yield models are implemented in computer applications for precision agriculture and are becoming an important element of decision support systems [9–18].

Most often, quantitative data is used for model building, which makes it easier to choose the modeling method. However, there are situations that require a different forecasting approach, which complicates the model building process. The use of combined data (quantitative and qualitative) may in consequence give a better result than in case of only one type of data (only quantitative or only qualitative). Therefore, the authors of this work, encouraged by previous research results [11,19,20], have undertaken the construction and analysis of winter rapeseed yield models based on quantitative and qualitative data. The produced models can be used to simulate the crop in the current agrotechnical season before harvesting. The main assumption is to achieve MAPE (mean absolute percentage error) of up to 7%.

Some of the developed forecasting models predict yields too late, only a few days before harvesting [21]. Al-Gaadi et al. [21] attempted to correlate the final potato tuber yield, i.e., basing on samples taken three days before harvest, with the results of vegetative indices during plant growth. The results of the study showed that the difference between the predicted yield values and actual, observed values was small, as it did not exceed 15%. Of course, crop yield control from air and satellite level is valuable in agricultural production [22], but requires the use of specialized equipment and software. In addition, due to the frequent association of yield with local spectral characteristics of plants, such models can only be used in the region for which they were developed [23].

Yield predictions based on readily available agronomic and meteorological data made at relatively early and key stages of plant growth and development have a greater contribution to conscious plantation control [20]. During the winter rapeseed vegetation, five critical stages of seed yield formation are indicated, i.e., autumn vegetation, spring re-vegetation, formation of the main and side shoots, flowering, growth of pods, and maturation. While yield prediction in the first two phases may seem too early, the estimation of seed yield after formation of the main and side shoots, flowering, growth of pods and maturation stage, provides interesting, preliminary information about the actual potential yielding of plants in situ.

In the construction of forecasting models, not all available independent variables determining the scale of plant yielding should be taken into account. A big practical problem is combining the vegetation process of plants according to the widely used BBCH scale (Biologische Bundesanstalt, Bundessortenamt und CHemische Industrie) with the dynamically changing production conditions

[24–26]. Operating on the BBCH scale allows for relatively reliable analyses, however precise collection of such data during vegetation is often simply impossible. This would require farmers to regularly observe the plantations and meticulously record the progress of vegetation. Only those farms that manage a small area and cultivate one or two varieties would have a chance to succeed. In the case of cultivating several varieties on a dozen or several dozen areas of fields simultaneously, very accurate monitoring of development phases causes problems. Therefore, in many works, the authors of the models use specific dates of the calendar year, which correspond to key developmental phases in typical years [10,11,20].

2. Materials and Methods

The research place and material was described in [19]. However, additional qualitative data were used to build predictive models (Table 1, Table 2). All field data took into consideration 8 years of research (from 2008 to 2015), from winter rapeseed fields located in Poland, in the central and southwestern part of Greater Poland (Figure 1). In total, data from 328 fields were collected, which were divided into two sets (Table 1). Set A (292 fields) from the first seven years was the basis for model development, while set B (36 fields) from the last year of research was used to validate the constructed models and determine yield prediction errors.

Figure 1. Research area—Greater Poland, Poland (redraw from [19]).

Table 1. The number of productive fields of winter rapeseed divided into two sets, A and B [19].

	Set A							Set B
Year	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Number of fields	32	49	48	50	45	28	40	36

Table 2. Data structure in the neural prediction models.

Symbol	Unit of measure	Variable name	Model QQWR15_4	Model QQWR31_5	Model QQWR30_6	The scope of data
Quantitative data						
R9-12_PY	mm	The sum of precipitation from September 1 to December 31 of the previous year	+	+	+	63–234
T9-12_PY	˚C	The average air temperature from September 1 to	+	+	+	4.9–9.4

R1-4_CY	mm	December 31 of the previous year The sum of precipitation from January 1 to April 15 of the current year	+	+	+	59–185
T1-4_CY	°C	The average air temperature from January 1 to April 15 of the current year	+	+	+	−0.4–4.9
R4_CY	mm	The sum of precipitation from April 1 to April 30 of the current year	−	+	+	8.7–60.4
T4_CY	°C	The average air temperature from April 1 to April 30 of the current year	−	+	+	5.9–12.2
R5_CY	mm	The sum of precipitation from May 1 to May 31 of the current year	−	+	+	14.2–132.5
T5_CY	°C	The average air temperature from May 1 to May 31 of the current year	−	+	+	11.8–16.2
R6_CY	mm	Total precipitation from June 1 to June 30 of the current year	−	−	+	15–121
T6_CY	°C	The average air temperature from June 1 to June 30 of the current year	−	−	+	14.2–19.6
N_LY	kg ha^{-1}	The sum of N fertilization - autumn in the previous year	+	+	+	0–41
N_CY	kg ha^{-1}	The sum of N fertilization - spring in the current year	+	+	+	0–175

P2O5_CY	kg ha^{-1}	The sum of P_2O_5 fertilization in the current year	+	+	+	0–104
K2O_CY	kg ha^{-1}	The sum of K_2O fertilization in the current year	+	+	+	0–234
MGO_CY	kg ha^{-1}	The sum of MgO fertilization in the current year	+	+	+	0–298
SO3_CY	kg ha^{-1}	The sum of SO_3 fertilization in the current year	+	+	+	14–115
B_CY	g ha^{-1}	The sum of B fertilization in the current year	+	+	+	0–3.66
CU_CY	g ha^{-1}	The sum of Cu fertilization in the current year	+	+	+	10–487
MN_CY	g ha^{-1}	The sum of Mn fertilization in the current year	+	+	+	70–600
MO_CY	g ha^{-1}	The sum of Mo fertilization in the current year	+	+	+	0–60
ZN_CY	g ha^{-1}	The sum of Zn fertilization in the current year	+	+	+	9–226
DOF_PY	t ha^{-1}	The dose of organic fertilizer in the previous year	+	+	+	0-41
Qualitative data						
KOF_PY	word	The kind of organic fertilizer in the previous year	+	+	+	No, Livestock manure, Chicken manure
LF_PY	word	The liming of a field in the previous year	+	+	+	Yes, No
ST_PY	word	The soil tillage in the previous year	+	+	+	Aggregate cultivator, Shallow tillage, Deep tillage, Ploughing
KSD_PY	word	The kind of sowing date in the previous year	+	+	+	Early, Optimal Tardy

TF_PY	word	The type of forecrop in the previous year	+	+	+	Winter rapeseed, Winter wheat, Winter triticale, Winter barley, Spring barley, Oat, Rye

"+"—the variable exists in the model, "−"—the variable does not exist in the model.

Basic meteorological data was necessary for the construction of predictive models, and the data was obtained from meteorological stations located near fields from which empirical data was collected. Air temperature and atmospheric precipitation were divided into those obtained in the previous year (from September 1 to December 31) and from the current agrotechnical year. Meteorological data for the current year have been additionally divided into shorter periods depending on the model: from January 1 to April 15, from April 1 to April 30, from May 1 to May 31 and from June 1 to June 30.

The neural predictive model construction has been made on the basis of three predicted dates of a calendar year: April 15, May 31 and June 30. They have been named respectively QQWR15_4 (QuantitativeQualitativeWinterRapeseed15_April), QQWR31_5 and QQWR30_6. The prediction dates proposed allow easier control of winter rapeseed yield. They were chosen approximately to the course of key vegetation phases in average years: i.e., April 15—inflorescence emergence, May 31—development and formation of pods, June 30—technical maturity.

The models took into consideration those factors (independent variables) that affect crop yields and are widely available to agricultural producers (Table 2). The following approach for winter rapeseed yield prediction allows forecasting and simulation of estimated yields directly before harvesting, in the same agricultural year.

Tables 1 and 2 present independent variables in qualitative and quantitative research that were the basis for the construction of each of the three neural models. The choice of the network topology was guided by the results of earlier studies [10,11,20]. In addition, the network's ability to approximate and generalize, considering the network error rate, was taken into account. Each constructed neural model QQWR15_4, QQWR31_5, and QQWR30_6 was a result of learning 10,000 networks, one of which was selected with the best parameters. Basic measures of network quality were determined—standard deviation, mean error, deviation error, mean absolute error, quotient of deviation, and correlation. The best model was chosen based on the lowest mean absolute error value and the largest correlation value. Automatic network designer from Statistica v7.1 (StatSoft Inc., Tulsa, OK, USA) was used for neural network building. The 292 data set was divided into three sets: training, validation and test. The sets were divided into 70%-15%-15% proportion (204-44-44 cases in each set).

In the next stage, the obtained neural models QQWR15_4, QQWR31_5, and QQWR30_6 were validated, comparing the results of model prediction with real data from set B (36 cases from 2015). Data from set B were not considered in construction of QQWR15_4, QQWR31_5, and QQWR30_6 neural models. In order to determine the prediction errors of winter rapeseed yields, the difference between the observed and the predicted value was performed. This method is widely described in the literature [20,27–30]. Determination of the quality of predictions was based on the error measures (Equations 1–4):

RAE—relative approximation error;

$$RAE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i)^2}} \quad (1)$$

RMS—root mean square error;

$$RMS = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \quad (2)$$

MAE—mean absolute error;

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (3)$$

MAPE—mean absolute percentage error;

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \quad (4)$$

where
n—number of observations,

y_i —actual values obtained during research,

$\hat{y}_i$ —values given by the model.

The last stage of the research was the sensitivity analysis of the neural network. This analysis gives the opportunity to examine all independent variables in each produced neural model QQWR15_4, QQWR31_5, and QQWR30_6. As a result of this test, the information about the importance (rank) of each measure is obtained. The greater the numerical value of a given feature (error quotient), the greater the impact on winter rapeseed yield. All values below 1 indicate a low impact on the yield of the given independent variable and can be removed from the model.

3. Results

According to the presented methodology of neural model building, 1 of 10,000 models was selected for analysis considering a specific forecast date. These models were chosen based on the best qualitative parameters of the neural network. Detailed information on the quality and structure of selected neural models QQWR15_4, QQWR31_5, and QQWR30_6 are presented in Table 3.

Table 3. The quality and structure of the neural models produced.

	QQWR15_4	**QQWR31_5**	**QQWR30_6**
Neural network	MLP	MLP	MLP
structure	21:33-15-9-1:1	25:37-16-16-1:1	27:39-10-1:1
Learning error	0.0515	0.0914	0.0932
Validation error	0.0898	0.0987	0.0837
Test error	0.1033	0.1042	0.1386
Mean	3.3627	3.3626	3.3626
Standard deviation	1.0703	1.0703	1.0703
Average error	−0.0126	0.0924	0.0205
Deviation error	0.4087	0.5578	0.5548
Mean Absolute error	0.2870	0.4353	0.4118
Quotient deviations	0.3818	0.5211	0.5183
Correlation	0.9245	0.8534	0.8552

MLP—multi-layer perceptron.

The next stage of the analysis was validation of the produced models. The observed yield from set B was compared to the results of prediction of all produced models. For this purpose, formulas (1–4) were applied and the results of model validation are included in Table 4.

Table 4. Measures prediction of analyzed neural models.

Model	RAE (–)	RMS (t ha^{-1})	MAE (t ha^{-1})	MAPE (%)
QQWR15_4	0.098	0.43	0.37	9.87
QQWR31_5	0.068	0.29	0.25	6.88
QQWR30_6	0.076	0.32	0.28	7.69

Network sensitivity analysis

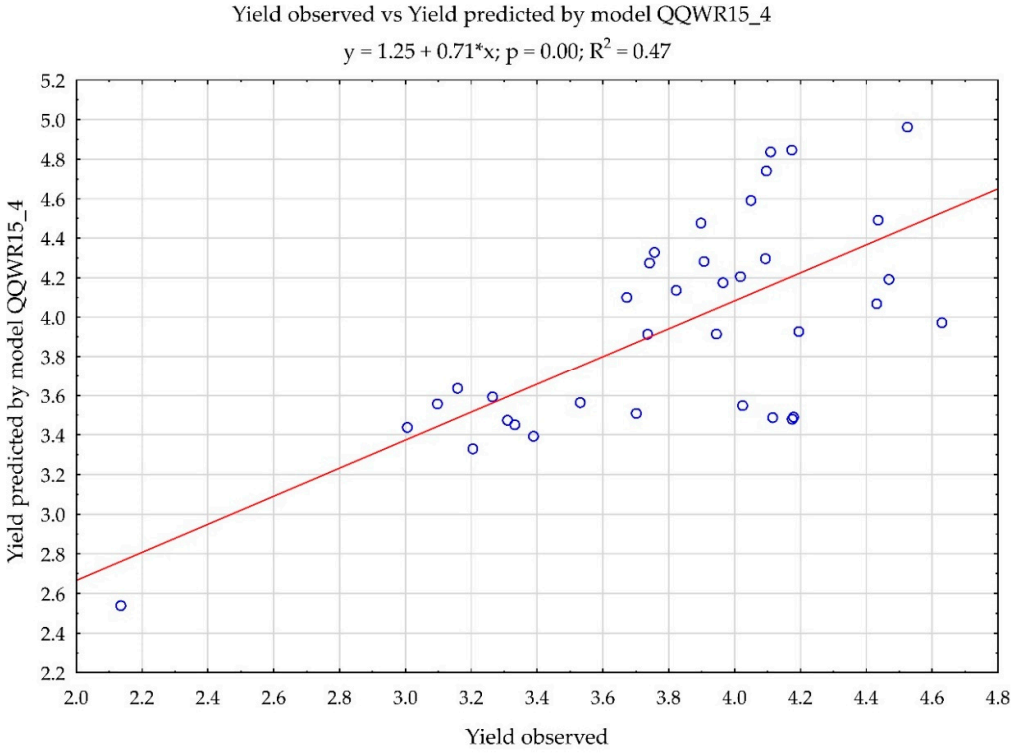
The sensitivity analysis of the produced neural models was the last stage of calculations. For each model QQWR15_4, QQWR31_5, and QQWR30_6 the error quotient and the rank were determined, they are presented in Table 5.

Table 5. Sensitivity analysis of neural networks.

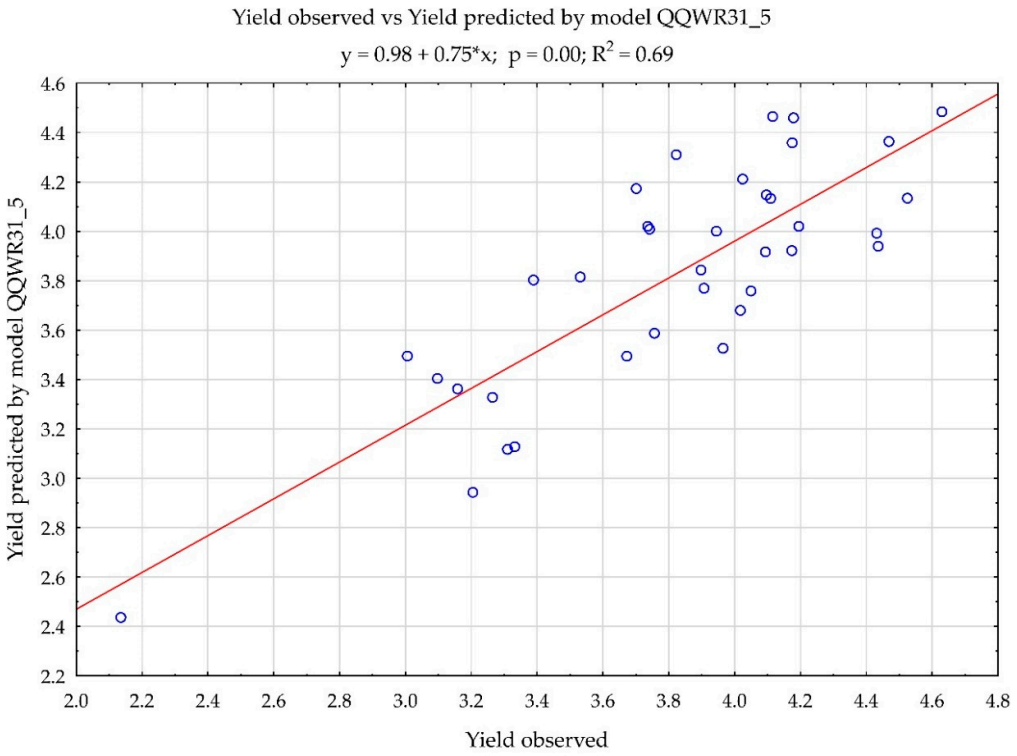
Variable	Model					
	QQWR15_4		QQWR31_5		QQWR30_6	
	quotient	rank	quotient	rank	quotient	rank
R9-12_PY	1.549	4	1.077	5	1.029	10
T9-12_PY	1.224	9	1.007	20	1.027	11
R1-4_CY	1.314	5	1.028	9	1.018	14
T1-4_CY	1.129	13	1.027	10	1.012	20
R4_CY	-	-	1.041	7	1.036	8
T4_CY	-	-	1.012	17	1.021	13
R5_CY	-	-	1.068	6	1.078	6
T5_CY	-	-	1.237	2	1.228	2
R6_CY	-	-	-	-	1.016	17
T6_CY	-	-	-	-	1.012	19
N_LY	1.099	15	1.016	15	1.010	21
N_CY	1.107	14	1.007	19	1.000	26
P2O5_CY	1.027	18	1.013	16	0.989	27
K2O_CY	1.012	21	0.994	24	1.003	25
MGO_CY	1.232	7	1.009	18	1.017	16
SO3_CY	1.081	16	1.038	8	1.018	15
B_CY	1.150	11	1.027	11	1.008	22
CU_CY	1.014	20	1.005	21	1.004	23
MN_CY	1.018	19	0.994	25	1.015	18
MO_CY	1.637	3	1.016	14	1.130	5
ZN_CY	1.078	17	0.999	23	1.003	24
DOF_PY	1.144	12	1.002	22	1.029	9
KOF_PY	1.228	8	1.026	12	1.040	7
LF_PY	1.169	10	1.016	13	1.025	12
ST_PY	1.294	6	1.098	4	1.144	4
KSD_PY	2.273	1	1.251	1	1.435	1
TF_PY	1.846	2	1.204	3	1.150	3

By considering the results obtained in the previous stages, a decision was made to perform additional analyses and visualizations between the observed yield values and the yield values predicted by the QQWR15_4, QQWR31_5, and QQWR30_6 models. The results of the analyses are presented in Figure 2. The QQWR31_5 model obtained the highest coefficient of determination, the

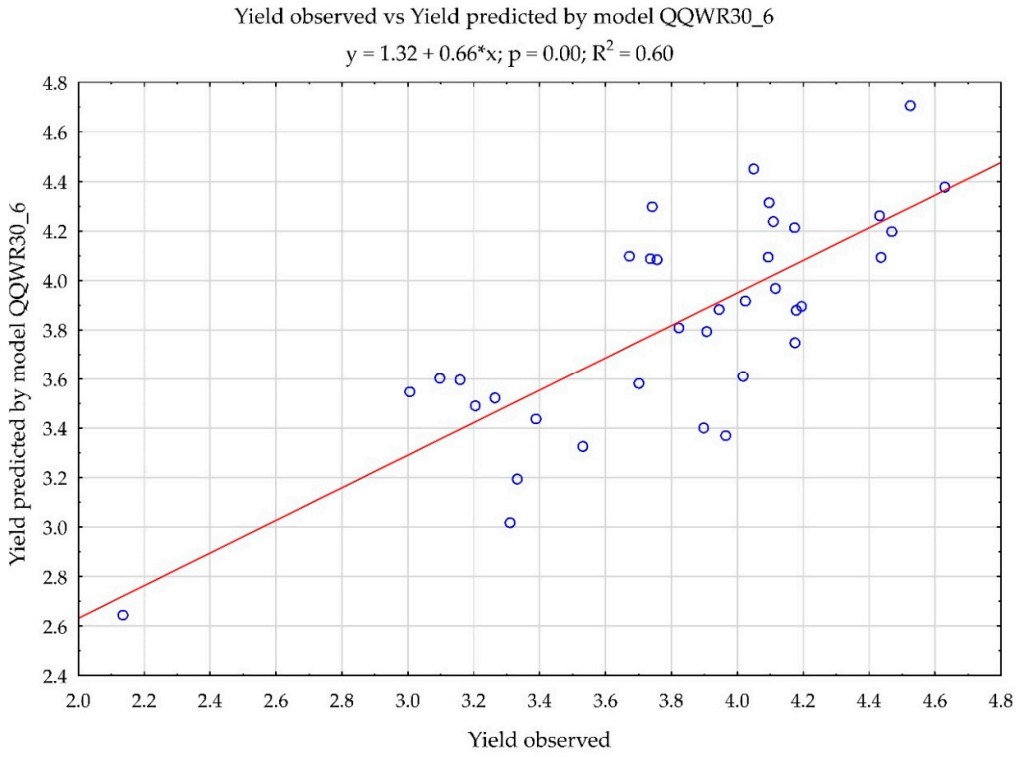
value of which was $R^2 = 0.69$. Slightly lower R^2 values were calculated for models QQWR15_4 and QQWR30_6, which were 0.47 and 0.60, respectively.



(a)



(b)



(c)

Figure 2. Relation between the observed and predicted yield (t ha^{-1}) by model: (**a**) QQWR15_4, (**b**) QQWR31_5 and (**c**) QQWR30_6.

4. Discussion

Many different modeling methods are applied to predict crop yield. Regardless of the method chosen, it is necessary to collect empirical data from the past. It is assumed that the models will have a lower forecast error as the number of years and the number of data on which they are based increase [10]. A large number of factors affecting crop yields determine the choice of the optimal method of analysis. Many of the independent variables can only be obtained from specialized tests. Apart from data availability, another problem in modeling is their format and structure. While quantitative data are most often used, available qualitative data are often difficult to implement in produced models. Therefore, the decision was made to integrate quantitative and qualitative data. Each model produced as part of the following research work, i.e., QQWR15_4, QQWR31_5, and QQWR30_6 is based on both types of data and allows making yield forecasts in the current agrotechnical year before harvesting. In addition, it was assumed that a good model will have a low MAPE and will be up to 7%. Artificial neural networks, which are non-linear modeling methods, were used to implement the assumed prediction error. As a rule, they give better forecast results than classical mathematical models and enable combining quantitative and qualitative data. Most often, MLP (multi-layer perceptron) topology network is used in forecasting, which was implemented to build three models QQWR15_4, QQWR31_5, and QQWR30. Each model is based on 21, 25, and 27 independent variables, respectively, which include 5 qualitative variables (Table 2).

Validation of produced neural models for predicting winter rapeseed yields is based on determining the quality of forecasts using four measures, i.e., RAE, RMS, MAE, and MAPE. The error values for all produced neural models are shown in Table 4. However, the most commonly used indicator for determining the forecast error is MAPE. The lowest error values of this indicator were obtained only for the QQWR31_5 neural model based on the MLP network with the structure 25: 37-16-16-1: 1, which was 6.88%. The same time period (January–May) obtained the lowest error in

prediction of winter wheat yield in work [20]. In the following work, the MAPE error rate was assumed to be up to 7%. This means that the other two models QQWR15_4 and QQWR30 did not achieve the assumed error rate because their MAPE was higher and amounted to 9.87 and 7.69, respectively.

The network sensitivity analysis was another element of performed calculations. It took into account all neural networks produced. The independent variable "The kind of sowing date in the previous year" (KSD_PY) (Table 5) obtained the highest rank 1 in each network, which is consistent with literature sources [31–34]. In the QQWR31_5 model, the error quotient was 1.2510. Interestingly enough, the independent variable, "The average air temperature from May 1 to May 31 of the current year" (T5_CY) came second in this model, which took a lower value of 1.2367. A similar situation was also observed in QQWR30 model. As it was investigated in [20], the dominant influence of atmospheric factors in predicting winter wheat yield did not correspond completely to prediction of winter rapeseed yield. In the QQWR15_4 model, the independent feature "The type of forecrop in the previous year" (TF_PY) came second. However, as indicated earlier, QQWR15_4 and QQWR30 did not achieve the assumed MAPE rate. Despite the differences in the results of individual models, it can be explicitly indicated that qualitative data had a dominant impact on the forecast of winter rapeseed yield. Other authors studying this species [35–37] have also confirmed that sowing date is a very important feature. Rapeseed is very sensitive to date of sowing, because its dynamic development takes place at a temperature exceeding 12°C. In the area studied, such temperatures usually occur at the turn of the second and third decade of August. Sowing that is too late, taking place in September or October, causes lower aboveground matter development in plants. Their growth cone contains insufficient buds of future generative organs. On the other hand, too early sowing poses the risk of excessive outgrowth before winter, which is characterized by a large above-ground matter, susceptible to damage and freezing. Failure to meet the proper sowing date is almost always associated with poorer wintering of plants. The maximum delay in sowing, which does not influence reduction in yield, is 5–7 days.

Comparing the predicted yield to observed yield (Figure 2), the best fit was for QQWR31_5 model, with $R^2 = 0.69$. This confirms the right assumption of the maximum MAPE of up to 7%.

5. Conclusions

The results of the present work clearly indicate the possibility of using neural models to predict the yield of winter rapeseed in practice, basing on quantitative and qualitative data. For this purpose, particularly useful is the QQWR31_5 model, whose MAPE is 6.88% and its determination coefficient R^2 is 0.69. It is the only model that met the assumptions of the work regarding the maximum MAPE of up to 7%. In addition, neural network sensitivity analysis revealed that "The kind of sowing date in the previous year" (KSD_PY) had the greatest impact on winter rapeseed yield. Such result was obtained for all analyzed models. The neural models presented in the paper can be applied in precision agriculture as a key factor in decision making systems.

Further research should be aimed at optimizing the produced neural models in two directions. As part of the first direction, independent variables should be reduced while simultaneously maintaining the MAPE rate. The second direction is to obtain more empirical data from regions with different soil and climatic conditions. Such actions will aid in expanding the field scope of model practical application and should positively affect the accuracy of forecast.

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