J. Agr. Sci. Tech. (2019) Vol. 21: 51-61

Application of Artificial Neural Networks for Multi-Criteria Yield Prediction of Winter Wheat

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ABSTRACT

Three independent models were constructed for the prediction of yields of winter wheat. The models were designed to enable the prediction of yield at three dates: 15th April, 31st May, and 30th June. The models were built using artificial neural networks with MLP (multilayer perceptron) topology, based on meteorological data (air temperature and precipitation) and information on applications of mineral fertilizer. Data were collected in the 2008–2015 from 301 crop fields in the Wielkopolska region of Poland. The evaluation of the quality of predictions made using the neural models was verified by determination of prediction errors using the *RAE*, *RMS*, *MAE* and *MAPE* measures. An important feature of the constructed predictive models is the ability to make a forecast in the current agricultural year based on up-to-date weather and fertilization information. The lowest *MAPE* error values were obtained for the neural model WW30_06 (30th June) based on an MLP network with the structure 19:19-15-13-1:1, the error was 8.85%. Sensitivity analysis revealed which factors had the greatest impact on winter wheat yield. The highest rank (1) was obtained by all networks for the same independent variable, namely, the mean air temperature in the period from 1st September to 31st December of the previous year (T9-12_LY).

Keywords: MLP network, Neural model, Predictive models, Winter wheat, Yield forecast.

[DOR: 20.1001.1.16807073.2019.21.1.4.3]

INTRODUCTION

The constant increase in global food needs is caused by continuous growth in the human population. Food production has to keep up with the growing demand, at the same time becoming an important part of every country's economy. Wheat is one of the most important plants, producing a basic food ingredient both for people and livestock. It is grown chiefly in Europe, Canada, Russia and the United States. In Poland, in 2014, winter wheat was sown on a total of 1,996,000 ha, and the average yield per hectare was 49.7 deciton (dt) (Central Statistical Office, 2015). Winter wheat is the most commonly grown crop in terms of total area. Polish wheat production in 2013 accounted for 6.6%, in a European Union context, giving the fourth highest place in the share among the 28 member countries (Central Statistical Office, 2015).

Modern technologies are making an ever-increasing contribution to growth in crop yields. This is also associated with the possibility of using crop yield models to make simulations and, consequently, to optimize production processes. Such models may thus lead to the creation of predictive tools which serve as an important element of precision agriculture (Shearer *et al.*, 2000) and the main element of decision-making support systems (Park *et al.*, 2005).

Agricultural production is sensitive to atmospheric conditions, which are directly linked to climate change. Reliable estimates of the effects of climate change require the integration of meteorological and cultivation

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data in constructed models (Nelson *et al.*, 2014). The forecasting of yields during the growing season is a basis for the estimation of the expected size of production at the end of that season (Bussay *et al.*, 2015). Timely and accurate forecasting is essential for crop production, marketing, warehousing, transport, and decision-making, and also supports risk management (Kantanantha *et al.*, 2010; Domínguez *et al.*, 2015).

Crop yields are dependent on a large number of factors, which are often correlated, and which directly or indirectly affect the yields of particular plants. The most frequently encountered factors include soil properties (pH, structure, content of organic material, level of nutrients), weather and climatic factors (air temperature, rainfall, insolation), soil cultivation technology, plant variety, technology and level of fertilization, plant protection, harvesting technology and crop rotation (Niedbała *et al.*, 2007; Khairunniza-Bejo *et al.*, 2014).

In recent years there has been a rise in agricultural applications of artificial neural networks. Analysis by this means often produces better results than traditional statistical methods (Neruda and Neruda, 2002; Mohammadi *et al.*, 2005; Klem *et al.*, 2007; Khashei-Siuki *et al.*, 2011; Khairunniza-Bejo *et al.*, 2014; Khoshnevisan *et al.*, 2015; Safa *et al.*, 2015; Grahovac *et al.*, 2016; Niedbała *et al.*, 2016; Sudhishri *et al.*, 2016).

MATERIALS AND METHODS

Predictive neural models were constructed using data collected in the years 2008–2015 from productive fields of winter wheat located in Poland, in the central and south-western parts of the Wielkopolska region, specifically in the counties of Poznań, Kościan and Gostyń (Figure 1). In total, data from 301 fields were used to build and verify the models (Table 1). This information formed the basis for the creation of a database was used for the construction of predictive neural models, which was divided into two sets, A and B. Set A (255 fields) consisted of information from the years 2008–2014, which was used to build the models. Set B (46 fields) contained information from the year 2015, which did

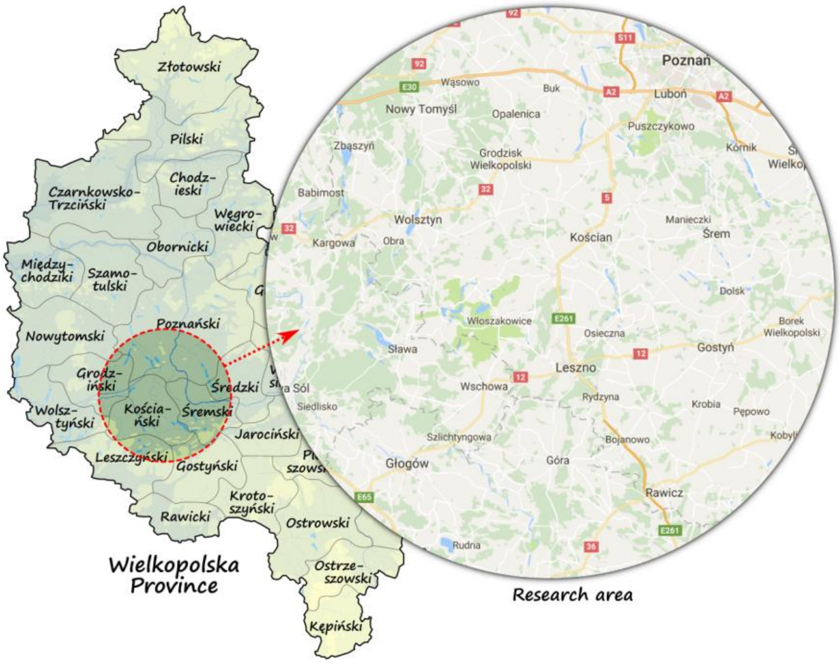

Figure 1. Research area: Wielkopolska region, Poland.

Table 1. The number of productive fields of winter wheat divided into two sets, A and B.

	Set A							Set B
Year	2008	2009	2010	2011	2012	2013	2014	2015
Number of fields	37	34	36	51	15	30	52	46

not play a part in the construction of the models, but was used to validate them.

Meteorological data – air temperature and rainfall for the area and period of the study – were obtained from the stationary and mobile Davis weather stations located closest to the study area, namely, in Kórnik, Gola, Turew, Piotrowo and Stary Gołębin.

The construction of the neural predictive models was prepared on the basis of three prediction dates for a calendar year: 15th April, 31st May, and 30th June. The models were named, respectively, WW15_04, WW31_05 and WW30_06.

The models included factors (independent variables) that affected crop yields and were easily available to agricultural producers (Table 2.).

This approach to the prediction of winter wheat yields enables the making of forecasts and simulation of expected yields directly before harvesting, in the same growing season.

Construction Method of Neural Models

Independent variables for the construction of neural models were selected in such a way that each neural network used a different number of independent variables which are presented in Tables 1 and 2.

In the selection of a network topology and learning method, account was taken of the network's ability to approximate and generalize, based on measures of network quality. Using the Statistica v7.1 software it was possible to test networks with different architectures. For each of the neural models WW15_04, WW31_05 and WW30_06 the number of networks tested was 10,000, with the use of an automated network designer (AND). Network selection was made on the basis of the best parameters determining network quality.

The set of empirical data was divided randomly into a learning set, a validation set and a test set. The sizes of the sets were as following: Learning set – 179 cases; Validation set – 38 cases; Testing set – 38 cases. The set was divided in the proportions 70%–15%–15%, taking into account of the number of fields included in the study.

Methodology for Evaluating the Neural Models

Following the construction of neural models using the automate network designer, each model was evaluated on the basis on information obtained from Statistica, namely, the standard deviation, mean error, error deviation, mean absolute error, deviation quotient, and correlation. The best model was selected on the basis on the smallest value of the mean absolute error and the largest value of the correlation.

In the next step, the predictive ability of the constructed neural models was evaluated using *ex post* measures of the prediction error, comparing data from set the B with the results of the predictions made on the basis of set the A. These errors have the property that they are computed on the basis of materials from the past, namely, expired predictions and the corresponding actual values of the predicted variable. The prediction error is the difference between the actual value of the predicted variable at time "t" and the forecast made for the same period (Stańko, 2013).

Table 2. Data stricture in neural prediction models.[a]

Symbol	Unit of measure	Variable name	Model WW15_04	Model WW31_05	Model WW30_06	The scope of data
R9-12_LY	mm	The sum of precipitation from 1 September to 31 December of the previous year	v	v	v	63–234
T9-12_LY	^oC	The average air temperature from 1 September to 31 December of the previous year	v	v	v	4.9–9.4
R1-4_CY	mm	The sum of precipitation from 1 January to 15 April of the current year	v	v	v	59–185
T1-4_CY	^oC	The average air temperature from January 1 to April 15 of the current year	v	v	v	-0.4–4.9
R4_CY	mm	The sum of precipitation from April 1 to April 30 of the current year	-	v	v	8.7–60.4
T4_CY	^oC	The average air temperature from April 1 to April 30 of the current year	-	v	v	5.9 – 12.2
R5_CY	mm	The sum of precipitation from 1 May to 31 May of the current year	-	v	v	14.2–132.5
T5_CY	^oC	The average air temperature from May 1 to May 31 of the current year	-	v	v	11.8–16.2
R6_CY	mm	Total precipitation from June 1 to June 30 of the current year	-	-	v	15–121
T6_CY	^oC	The average air temperature from June 1 to June 30 of the current year	-	-	v	14.2–19.6
N_LY	kg ha^{-1}	The sum of N fertilization - autumn in the previous year	v	v	v	0–100
N_CY	kg ha^{-1}	The sum of N fertilization – spring in the current year	v	v	v	68–359
P2O5_CY	kg ha^{-1}	The sum of P_2O_5 fertilization in the current year	v	v	v	0–82
K2O_CY	kg ha^{-1}	The sum of K_2O fertilization in the current year	v	v	v	0–151
MGO_CY	kg ha^{-1}	The sum of MgO fertilization in the current year	v	v	v	0–46
SO3_CY	kg ha^{-1}	The sum of SO_3 fertilization in the current year	v	v	v	14–115
CU_CY	g ha^{-1}	The sum of Cu fertilization in the current year	v	v	v	10–138
MN_CY	g ha^{-1}	The sum of Mn fertilization in the current year	v	v	v	40–360
ZN_CY	g ha^{-1}	The sum of Zn fertilization in the current year	v	v	v	9–226

[a] "v": The variable exists in the model, "-": The variable does not exist in the model.

[DOR: 20.1001.1.16807073.2019.21.1.4.3]

Validation of the constructed models was performed on the basis on data from the last year of the study (2015) and covered 46 fields of winter wheat. These data had not played a part in the construction of the neural models. The quality of the predictions was evaluated using a methodology widely described in the literature (Grzesiak *et al.*, 2006; Kantanantha *et al.*, 2010; Parviz *et al.*, 2010; Stańko, 2013; Emamgholizadeh *et al.*, 2015; Khoshnevisan *et al.*, 2015; Safa *et al.*, 2015; Li *et al.*, 2016):

RAE (Global Relative Approximation Error)= $$\sqrt{\frac{\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i\right)^2}} \quad (1)$$

RMSE (Root Mean Square Error)= $$\sqrt{\frac{\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2}{n}} \quad (2)$$

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

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

Where, *n*: Number of observations; y_i: Actual values obtained during research, and $\hat{y}_i$: Values given by the model.

For better visualization of the relations between observed and predicted yield, graphs were plotted showing those relations for each prediction date.

Neural Network Sensitivity Analysis

To test which of the studied independent features make the greatest contribution to explaining the variation in biological yields of winter wheat, analysis of the sensitivity of the constructed neural networks was performed. When a particular input variable (independent feature) is removed from the model, one may observe its effect on the total error of the neural network, making it possible to determine the significance (the impact on the output variable, namely, the yield) of particular independent features.

For this purpose two indicators were used:

Error quotient: This is the ratio of the error to the error obtained when using all independent features; the larger this value is, the greater is the significance of the feature in question. If it is less than 1, the feature in question may be removed from the model to improve its quality, although this is not a compulsory procedure;

Rank: This shows numerically the order of the features by decreasing error, a rank of 1 indicating the greatest significance for the network.

RESULTS AND DISCUSSION

As a result of the analyses, one neural model was selected for each prediction date. Basic information on the quality of the neural models WW15_04, WW31_05 and WW30_06 is given in Table 3. The general structure of the designed neural network model is presented in Figure 2.

To determine the quality of prediction, computations applied for *ex post* methods were performed, using the formulae (1–4). The results are given in Table 4.

In the next step, graphs were plotted showing the relationship between the actual and forecast yield for each prediction date. Figures 3, 4, and 5 show this relationship for the models WW15_04, WW31_05 and WW30_06, respectively.

Network Sensitivity Analysis

In the last step of the computations, network sensitivity analysis was carried out for all of the constructed neural models. The results of this analysis are given in Table 5.

The complexity of the processes taking place during the cultivation of crops, where

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

	WW15_04	WW31_05	WW30_06
Neural network structure	MLP 13:13-13-10-1:1	MLP 17:17-8-2-1:1	MLP 19:19-15-13-1:1
Learning error	0.070648	0.067665	0.083481
Validation error	0.077927	0.071837	0.122100
Test error	0.085406	0.093282	0.128229
Mean	6.785392	6.785392	6.785392
Standard deviation	1.564456	1.564456	1.564456
Average error	0.043649	-0.002061	-0.009340
Deviation error	0.889876	0.873333	0.870046
Mean absolute error	0.698951	0.668304	0.666149
Quotient deviations	0.568808	0.558234	0.556134
Correlation	0.822509	0.830802	0.831277

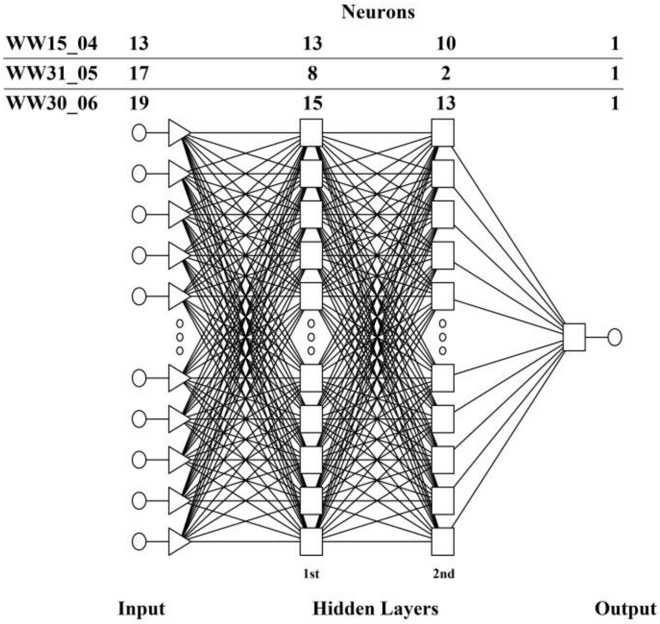

Figure 2. General structure of the neural network.

Table 4. Measures prediction *ex post* of analyzed neural models.

Model	*RAE*	*RMS*	*MAE* [t ha^{-1}]	*MAPE* [%]
WW15_04	0.1083	0.8493	0.6800	8.97
WW31_05	0.1111	0.8759	0.6802	9.07
WW30_06	0.1103	0.8668	0.6753	8.85

the final result is affected by a combination of anthropogenic, climatic, and geomorphological factors, means that the number of variables required to generate a properly functioning model is very large. Often, models for yield prediction are based on empirical data that are available only in strictly defined experiments (Guérif and Duke, 1998; Vandendriessche, 2000; Domínguez *et al.*, 2015). Such an approach makes it harder for the models to be used and predictions to be made by wider groups of interested persons or institutions.

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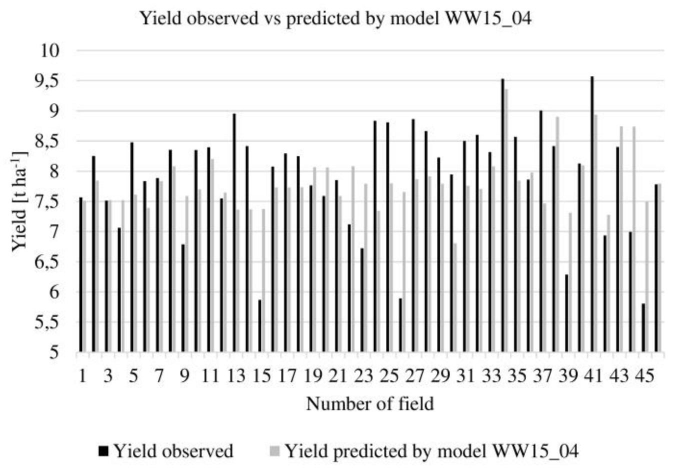

Figure 3. Graphical presentation of the observed and predictive yield: Neural model WW15_04.

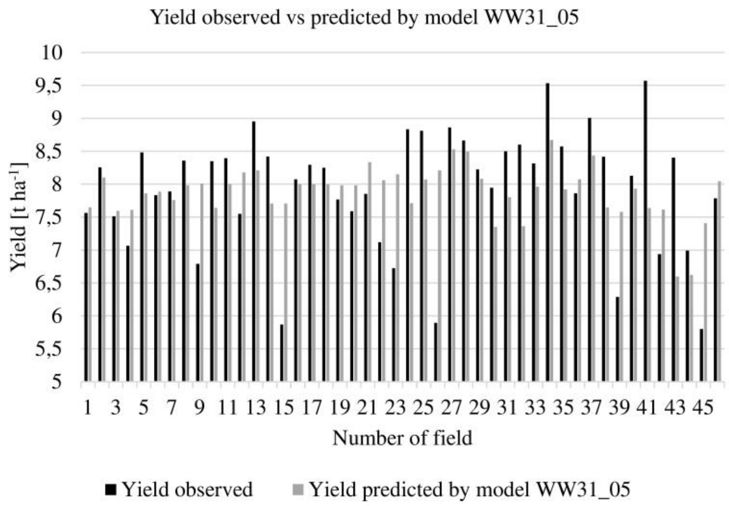

Figure 4. Graphical presentation of observed and predictive yield: Neural model WW31_05.

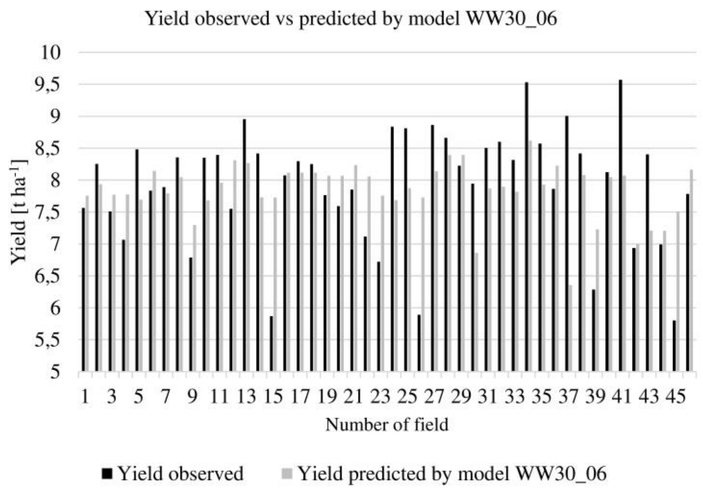

Figure 5. Graphical presentation of observed and predictive yield: Neural model WW30_06.

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Table 5. Sensitivity analysis of neural network.

Variable	Model					
	WW15_04		WW31_05		WW30_06	
	Quotient	Rank	Quotient	Rank	Quotient	Rank
R9-12_LY	**1.242**	**2**	1.152	4	1.1002	7
T9-12_LY	**1.389**	**1**	**1.647**	**1**	**1.4923**	**1**
R1-4_CY	1.1	6	1.056	10	1.053	11
T1-4_CY	1.21	4	**1.523**	**2**	1.1525	5
R4_CY	-	-	1.069	7	1.076	9
T4_CY	-	-	1.104	5	**1.207**	**2**
R5_CY	-	-	1.074	6	1.189	3
T5_CY	-	-	1.17	3	1.101	6
R6_CY	-	-	**-**	-	1.1821	4
T6_CY	-	-	**-**	-	1.074	10
N_LY	1.044	12	1.058	9	1.028	12
N_CY	1.099	7	1.018	15	0.999	17
P2O5_CY	1.059	11	1.03	13	0.995	19
K2O_CY	1.09	10	1.032	12	0.997	18
MGO_CY	1.024	13	1.035	11	1	16
SO3_CY	1.11	5	1.062	8	1.006	14
CU_CY	1.232	3	1.024	14	1.025	13
MN_CY	1.099	8	1.003	17	1	15
ZN_CY	1.092	9	1.013	16	1.092	8

The present work made a comprehensive approach to the construction of predictive models of winter wheat yields at three dates, based on the use of artificial neural networks possible. An additional advantage of these models is that they can be used in the current agricultural year, prior to harvesting. The models were constructed using weather data and information on fertilizer application, which are relatively easy to obtain. It was expected that the correct functioning of the constructed models would be verified by comparison of the predictions obtained with the actual wheat yields in the final year of the study.

A frequent problem in the prediction of crop yields using neural models is the selection of an appropriate network topology. According to literature reports (Niedbała *et al.*, 2007), the network most frequently used for predictive purposes is the multilayer perceptron (MLP). In the present work, the three models WW15_04, WW31_05 and WW30_06 were constructed on the basis on that network type.

A good model ought to describe the behavior of a system adequately (Li *et al.*, 2016). This means that the model should be similar to the studied empirical system from which data are taken for studies, analyses, and computations. As Stańko (2013) points out, in analyzing a predicted phenomenon, one may mistakenly evaluate the nature of patterns over time, the interdependencies existing and the factors influencing the changes, and this leads to prediction errors. Errors in the output data may result from incorrect preparation of the information, excessive aggregation or improper computations. In building a predictive model, one may sometimes oversimplify and inappropriately describe the studied reality.

With this in mind, in the following work, four *ex post* measures of error were used, namely, the global Relative Approximation Error (RAE) of a model, the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE). These were used in determining the quality of the models and the errors in the predictions of winter wheat yields.

Table 4 contains *ex post* error values for all constructed models. One of the most often used indicators characterizing the values of prediction errors is the *MAPE* (Zhang *et al.*, 1998; Niedbała *et al.*, 2007; Kantanantha *et al.*, 2010). The lowest *MAPE* error values were obtained for the neural model WW30_06 based on an MLP network with the structure 19:19-15-13-1:1, the error was 8.85%. Having in mind the critical *MAPE* level of up to 10%, in cases that remain under significant influence of random effects (Stańko, 2013), the results for all models are highly satisfactory, lying in the range 8.85–9.07%.

Following the completion of all computations, a network sensitivity analysis was performed for all of the constructed neural models. The highest rank (1) was obtained by all networks for the same independent variable, namely, the mean air temperature in the period from 1 September to 31 December of the previous year (T9-12_LY). This is consequently the factor that has the greatest impact on the yield of winter wheat. This implies that the process of soil fertilization was well-adapted to the nutritional needs of winter wheat and was based on the actual level of microelements and macroelements in the soil. In the model WW30_06, which has the lowest MAPE value, the second-ranked factor was the average air temperature in April of the current year (T4_CY).

In summary, the analyses described here indicate that the prediction of winter wheat yields using artificial neural networks produces good prediction results. Nonetheless, the optimization of the models requires further research, in which data will be taken from a larger number of fields and further analysis will be made of the number of independent factors in the models.

ACKNOWLEDGEMENTS

The authors would like to thank all those who made it possible to collect weather data and information about fertilization in selected locations. Without them, the work could not be carried out.

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کار برد شبکه های عصبی مصنوعی برای پیش بینی عملکرد چند معیاری گندم زمستانه

گ. نیدبالا، و ر. ج. کوزلوزکی

چکیده

در این پژوهش ، سه مدل مستقل برای پیش بینی عملکردهای گندم زمستانه ساخته شد. این مدل ها به گونه ای طراحی شده بود که پیش بینی عملکرد را در سه تاریخ ۱۵ آوریل، ۳۱ ماه مه، و ۳۰ ژوئن ممکن می ساخت.در ساختن این مدل ها از شبکه مصنوعی با توپولوژی MLP(multilayer perceptron) بر پایه آمار هواشناسی (درجه حرارت هوا و بارندگی) واطلاعات مربوط به مصرف کودهای معدنی استفاده شد . داده ها در سال های ۲۰۱۵–۲۰۰۸ از ۳۰۱ مزرعه در منطقه Wielkopolska لهستان برداشت شد. کیفیت پیش بینی ها ی به دست آمده از شبکه عصبی مصنوعی با تعیین خطاهای پیش بینی با استفاده از سنجه های RAE، RMS،MAE و MAPE ارزیابی شد. در مورد این مدل های پیش بینی، یک جنبه مهم این است که می توان بر مبنای آمار به روز هواشناسی و اطلاعات مصرف کود، عملکرد را در سال زراعی جاری پیشگویی کرد. در این پژوهش، کمترین مقدار خطای MAPE در شبکه عصبی مدل (30 June) WW30_06و بر مبنای شبکه MLP با ساختار 19:19-15-13-1:1 برابر ۸/۸۵٪ بود. تحلیل حساسیت داده ها آشکار ساخت که کدام عوامل بیشترین تاثیر را روی عملکرد گندم زمستانه داشت. بالاترین رتبه (۱) در تمام شبکه ها به طور یکسان به متغییر مستقل با نام میانگین درجه حرارت هوا از ۱ سپتامبر تا ۳۱ دسامبر سال قبل(T9-12_LY) تعلق داشت.

[DOR: 20.1001.1.16807073.2019.21.1.4.3]