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APPLICATION OF MULTIPLE LINEAR REGRESSION FOR MULTI-CRITERIA YIELD PREDICTION OF WINTER WHEAT

Summary

The aim of the work was to produce three independent models for prediction and simulation of winter wheat yield, which were marked in the following way: ReWW15_04, ReWW31_05 and ReWW30_06. The produced models enable to make yield forecasts for April 15, May 31 and June 30, directly before harvest in the current agrotechnical season. For the construction of prediction models the Multiple Linear Regression (MLR) method was used. The models are based on meteorological data (air temperature and rainfall) and information on mineral fertilisation. The data were collected from 2008-2015 from 301 production fields located in Poland, in the Wielkopolskie Voivodeship. Evaluation of the quality of forecasts based on MLR models was verified by determining forecast errors using RAE, RMS, MAE and MAPE error gauges. An important feature of the produced prediction model consists in the possibility of making a prediction in the current agrotechnical year on the basis of current weather and fertilizer information.
***Key words**: forecast, multiple regression, MLR, winter wheat, yield prediction*

ZASTOSOWANIE ANALIZY REGRESJI WIELORAKIEJ DLA WIELOKRYTERIALNEJ PROGNOZY PLONÓW PSZENICY OZIMEJ

Streszczenie

Celem pracy było wytworzenie trzech niezależnych modeli do predykcji i symulacji plonu pszenicy ozimej, które oznaczono w następujący sposób: ReWW15_04, ReWW31_05 and ReWW30_06. Wytworzone modele umożliwiają wykonanie prognozy plonu na dzień 15 kwietnia, 31 maja i 30 czerwca, bezpośrednio przed zbiorem w aktualnie trwającym sezonie agrotechnicznym. Do budowy modeli predykcyjnych użyto metody liniowej regresji wielorakiej (MLR). Modele powstały w oparciu o dane meteorologiczne (temperatura powietrza i opady atmosferyczne) oraz informacje o nawożeniu mineralnym. Dane zostały zebrane z lat 2008-2015 z 301 pól produkcyjnych zlokalizowanych w Polsce, na terenie województwa Wielkopolskiego. Ocena jakości prognoz wytworzonych na bazie modeli MLR została zweryfikowana poprzez określenie błędów prognozy za pomocą mierników błędów RAE, RMS, MAE oraz MAPE. Ważną cechą wytworzonego modelu predykcyjnego jest możliwość wykonania prognozy w bieżącym roku agrotechnicznym w oparciu o aktualne informacje pogodowe i nawozowe.
***Słowa kluczowe**: prognoza, regresja wielokrotna, MLR, pszenica ozima, predykcja plonu*

1. Introduction

Wheat is one of the most important plants and is a basic component of food for both humans and livestock. It is grown mainly in Europe, Canada, Russia and the United States. World cereal production in 2016 reached 2,848,661,914 tonnes, including 749,460,077 tonnes of wheat production, which constitutes over 26% of world cereal production. In the European Union, cereal production in 2016 amounted to 298,089,390 tonnes, of which the share of wheat production amounted to 142,652,612 tonnes, which constitutes over 47% of EU production. In this background, the volume of Polish wheat production amounted to 10,827,902 tonnes and represents over 7% of EU production with an average yield of 45.4 dt per hectare of cultivated area. The total area under wheat in Poland in 2016 amounted to 2,384,056 ha [4].

For balanced agricultural management it is important that information on crop yields is provided at the right time and with the highest possible accuracy [11]. This is important for the whole process of planning farm work and risk management [6, 8]. An accurate and timely forecast of yields during the vegetation season is the basis for estimating production volumes during the harvest. Moreover, crop prediction is an important element in estimating potential income [1].

Many factors influence the quantity and quality of yields. One of the most important factors is weather, which is why the constructed models should take into account meteorological data (e.g. air temperature, rainfall, insolation) [16]. Moreover, the following factors should be taken into account in the models under construction: soil properties (pH, structure, organic material content, nutrient levels), soil tillage technologies, plant variety, applied technologies, fertilization level, plant protection, harvesting technology and crop rotation [9].

Yield forecasts can be made using various methods. In agriculture, the frequently used method of Multiple Linear Regression (MLR) [5, 6, 15, 18]. Thanks to it, it is possible not only to create a prediction and simulation model, but also to make a weight evaluation of all independent variables included in the model.

The aim of this work is to build three independent winter wheat yield models based on the basic data held by each agricultural holding, i.e. weather information and fertilisation levels. It is assumed that each model will be based on 13 basic independent variables, while subsequent models will be developed on the basis of additional data in subsequent forecasting dates, i.e. 15th April, 31st May and 30th June. All data were obtained from winter wheat fields and mobile meteorological stations.

2. Materials and methods

Forecast MLR models were constructed on the basis of data collected in 2008-2015 from winter wheat fields located in Poland, in the central and south-western part of Wielkopolskie Voivodeship, and in particular in the poviats of Poznań, Kościan and Gostyń (Fig. 1). In total, data from 301 fields were used for model construction and verification (Table 1). This information formed the basis for the creation of a database for the construction of predictive MLR models, which was divided into two sets, A and B. The set A (255 fields) consisted of information from the years 2008-2014 on the basis of which the models were built. Set B (46 fields) contained information from 2015, which was not involved in the construction of the models, but was only used for their validation.

Table 1. The number of productive fields of winter wheat divided into two sets, A and B
Tab. 1. Liczba pól produkcyjnych pszenicy ozimej z podziałem na dwa zbiory A i 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

Source: own work / Źródło: opracowanie własne

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 MLR predictive models was prepared based on three prediction dates for a calendar year: 15 April, 31 May and 30 June. The models were named respectively ReWW15_04, ReWW31_05 and ReWW30_06.
The models included factors (independent variables) that affect crop yields and are 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 agricultural year.

2.1. Method of construction of the MLR models

Multiple linear regression (MLR) is a statistical method whose main goal is to quantify the connections between many independent variables and a dependent variable. Even if there is no reasonable dependence between variables, one can try to link them by the use of a mathematical equation. This equation may not have a physical sense, but under some assumptions it allows to forecast values determined on the basis of knowledge of other variables. MLR method attempts to model the relationship between two or more interpretive variables (independent) and a response variable (dependent) by fitting a linear equation into the observed data [3, 18, 19].

Multiple regression is preceded by examination of the determination coefficient R^2 for the examined variables. It is

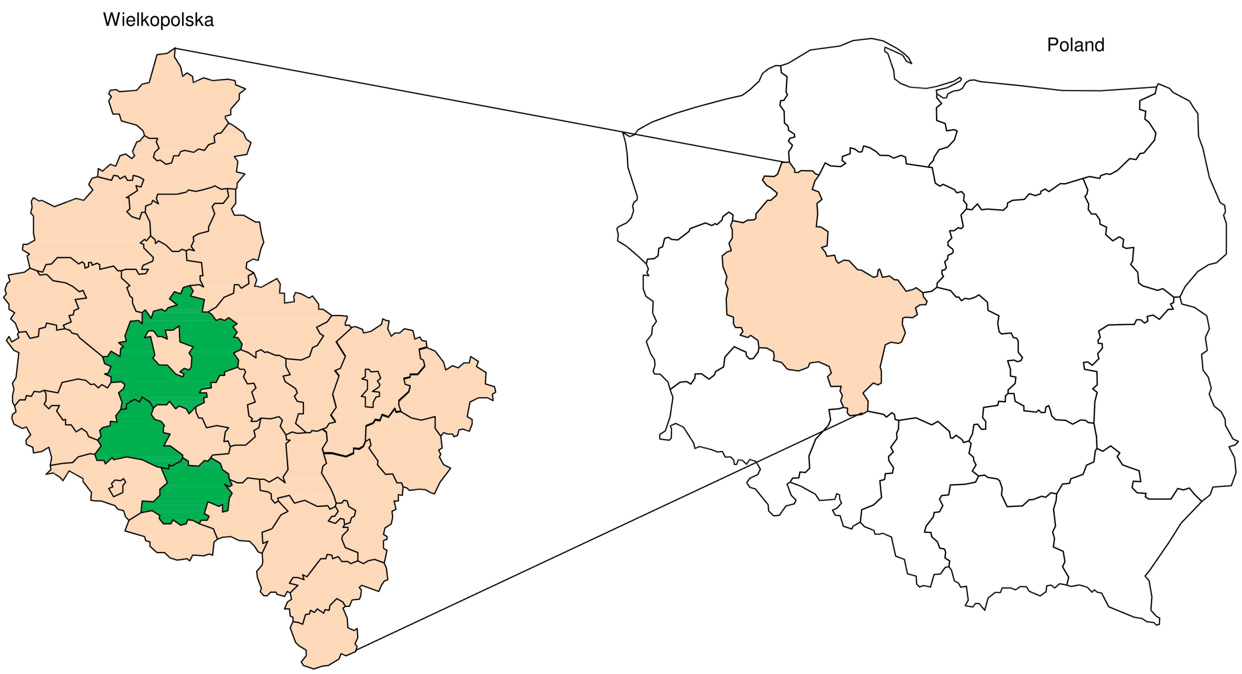

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Fig. 1. Research area – part of Wielkopolska Voivodeship, Poland.
Rys. 1. Obszar badań – część województwa Wielkopolskiego, Polska

Table 2. Data stricture in MLR prediction models
Tab. 2. Struktura danych w modelach MLR

SYMBOL	UNIT OF MEASURE	VARIABLE NAME	MODEL ReWW15_04	MODEL ReWW31_05	MODEL ReWW30_06	THE SCOPE OF DATA
R9-12_LY	mm	The sum of precipitation from 1 September to 31 December of the previous year	+	+	+	63–234
T9-12_LY	^oC	The average air temperature from 1 September to 31 December of the previous year	+	+	+	4.9–9.4
R1-4_CY	mm	The sum of precipitation from 1 January to 15 April of the current year	+	+	+	59–185
T1-4_CY	^oC	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	^oC	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 1 May to 31 May of the current year	-	+	+	14.2–132.5
T5_CY	^oC	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	^oC	The average air temperature from June 1 to June 30 of the current year	-	-	+	14.2–19.6
N_LY	$kg \cdot ha^{-1}$	The sum of N fertilization - autumn in the previous year	+	+	+	0–100
N_CY	$kg \cdot ha^{-1}$	The sum of N fertilization - autumn in the current year	+	+	+	68–359
P2O5_CY	$kg \cdot ha^{-1}$	The sum of P_2O_5 fertilization in the current year	+	+	+	0–82
K2O_CY	$kg \cdot ha^{-1}$	The sum of K_2O fertilization in the current year	+	+	+	0–151
MGO_CY	$kg \cdot ha^{-1}$	The sum of MgO fertilization in the current year	+	+	+	0–46
SO3_CY	$kg \cdot ha^{-1}$	The sum of SO_3 fertilization in the current year	+	+	+	14–115
CU_CY	$g \cdot ha^{-1}$	The sum of Cu fertilization in the current year	+	+	+	10–138
MN_CY	$g \cdot ha^{-1}$	The sum of Mn fertilization in the current year	+	+	+	40–360
ZN_CY	$g \cdot ha^{-1}$	The sum of Zn fertilization in the current year	+	+	+	9–226

Source: own work / Źródło: opracowanie własne

"+" – the variable exists in the model,
„-" – the variable does not exist in the model.

used to evaluate the degree of explanation of the total variability of a dependent variable by an independent variable. It is equal to the square of the multiple correlation coefficient between the analyzed traits. The continuation of the regression analysis is the determination of the probability factor for absolute statistics "t", verified at the level of significance $\alpha = 0.05$ (statistically significant difference). In the final phase of this stage the regression equation is constructed in the form:

$$Y = a + b1X1 + b2X2 + \ldots + bpXp \quad (1)$$

where:
Y – dependent variable (examined feature),
a – constant,
Xp – value of the independent variable,
bp – regression rate.

Equation (1) presents a regression model for the predicted trait - winter wheat yield.

2.2. Methodology of evaluation of the created model

The evaluation of the predictive capacity of the produced model is made using indicators of forecast error (*ex post*), comparing data from set B to the results of forecasts created on the basis of set A. These errors are characterised by the fact that they are calculated on the basis of historical data, i.e. on the basis of information on forecasts that have already expired and on the basis of the corresponding realisation of the forecast variable. A forecast error is the difference between the realisation of a forecast variable over time and a forecast realised for the same period [17].

The validation of the produced models was carried out on the basis of data from the year 2015 (set B), which covered 46 fields of winter wheat. These data did not participate in the construction of the model. Methodological methods widely described in literature were used to evaluate the quality of forecasts [3, 8, 10, 12, 13, 17, 18].

– RAE – global relative approximation error;

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

– RMS – root mean square error;

$$RMS = \sqrt{\frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{n}} \quad (3)$$

– MAE – mean absolute error;

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

– MAPE – mean absolute percentage error;

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \cdot 100\ \% \quad (5)$$

where,
n – number of observations,
y_i - actual values obtained during research,
$\hat{y}_i$ - values given by the model.

In order to illustrate better the relations between the real yield and the forecast yield, a graph is made, showing the mutual relations and a linear equation is determined.

3. Results

The produced MLR models are based on 13, 17 and 19 independent variables contained in Table 2. The dependent variable is the yield of winter wheat [t·ha^{-1}]. Table 3 presents the results for the produced models based on MLR.

Table 3. Regression coefficients, standard errors and probability levels for the MLR models
Tab. 3. Współczynniki regresji, błędy standardowe oraz poziomy prawdopodobieństwa dla modeli MLR

Variable	ReWW_15_04			ReWW_31_05			ReWW_30_06		
	Yield: R= 0.7197, R^2= 0.5180 Constant= 6.2838			Yield: R= 0.7372, R^2= 0.5435 Constant= 4.8383			Yield: R= 0.7387, R^2= 0.5457 Constant= 5.8394		
	b	p	significance	b	p	significance	b	p	significance
R9-12_LY	-0.0068	0.0144	*	-0.0062	0.1040	-	-0.0137	0.0896	-
T9-12_LY	0.5737	0.0000	*	0.2465	0.1530	-	0.1012	0.6653	-
R1-4_CY	-0.0114	0.0206	*	-0.0057	0.4612	-	-0.0073	0.3646	-
T1-4_CY	-0.0403	0.4624	-	-0.0833	0.6449	-	-0.2529	0.3279	-
R4_CY	n/a	n/a	n/a	0.0106	0.5572	-	0.0093	0.6270	-
T4_CY	n/a	n/a	n/a	0.1409	0.5959	-	0.2923	0.3664	-
R5_CY	n/a	n/a	n/a	0.0167	0.0046	*	0.0169	0.0042	*
T5_CY	n/a	n/a	n/a	0.0486	0.6728	-	0.1766	0.3919	-
R6_CY	n/a	n/a	n/a	n/a	n/a	n/a	-0.0119	0.2973	-
T6_CY	n/a	n/a	n/a	n/a	n/a	n/a	-0.0615	0.7713	-
N_LY	0.0065	0.1911	-	0.0038	0.4491	-	0.0040	0.4225	-
N_CY	0.0030	0.1997	-	0.0003	0.9042	-	0.0007	0.8141	-
P2O5_CY	-0.0045	0.3982	-	-0.0031	0.5683	-	-0.0032	0.5595	-
K2O_CY	-0.0034	0.2573	-	-0.0038	0.2065	-	-0.0036	0.2303	-
MGO_CY	-0.0693	0.0000	*	-0.0543	0.0022	*	-0.0546	0.0027	*
SO3_CY	0.0180	0.0271	*	0.0118	0.1876	-	0.0123	0.1884	-
CU_CY	0.0238	0.0261	*	0.0209	0.0630	-	0.0174	0.1578	-
MN_CY	-0.0137	0.0000	*	-0.0112	0.0010	*	-0.0104	0.0031	*
ZN_CY	-0.0037	0.4848	-	-0.0060	0.2968	-	-0.0045	0.4537	-

Source: own work / Źródło: opracowanie własne

Determination of the statistical significance level:
- not significance,
* significance for α = 0.05,
n/a not available in the model.

On the basis of the above results, the multiple linear regressions equations takes the form:

ReWW_15_04 (6)

Yield = 6.2838 − 0.0068□R9-12_LY + 0.5737□T9-12_LY − 0.0114□R1-4_CY − 0.0403□T1-4_CY + 0.0065□N_LY + 0.003□N_CY − 0.0045□P2O5_CY − 0.0034□K2O_CY − 0.0693□MGO_CY + 0.0180□SO3_CY + 0.0238□CU_CY − 0.0137□MN_CY − 0.0037□ZN_CY

ReWW_31_05 (7)
Yield = 4.8383 − 0.0062□R9-12_LY + 0.2465□T9-12_LY− 0.0057□R1-4_CY − 0.0833□T1-4_CY + 0.0106□R4_CY + 0.1409□T4_CY + 0.0167□R5_CY + 0.0486□T5_CY + 0.0038□N_LY + 0.0003□N_CY − 0.0031□P2O5_CY − 0.0038□K2O_CY − 0.0543□MGO_CY + 0.0118□SO3_CY + 0.0209□CU_CY − 0.0112□MN_CY − 0.006□ZN_CY

ReWW_30_06 (8)
Yield = 5.8394 − 0.0137□R9-12_LY + 0.1012□T9-12_LY − 0.0073□R1-4_CY − 0.2529□T1-4_CY + 0.0093□R4_CY + 0.2923□T4_CY + 0.0169□R5_CY + 0.1766□T5_CY − 0.0119□R6_CY − 0.0615□T6_CY + 0.004□N_LY + 0.0007□N_CY − 0.0032□P2O5_CY − 0.0036□K2O_CY − 0.0546□MGO_CY + 0.0123□SO3_CY + 0.0174□CU_CY − 0.0104□MN_CY − 0.0045□ZN_CY

In order to determine the quality of the forecast, the calculations used for the *ex post* methods have been carried out using equations (2-5), with the results shown in Table 4.

Table 4. Measures prediction *ex post* of analyzed MLR models
Tab. 4. Mierniki predykcyjne ex post w analizowanych modelach MLR

Model	RAE [-]	RMS [t]	MAE [$t \cdot ha^{-1}$]	MAPE [%]
ReWW_15_04	0.1301	1.2396	1.0336	13.0143
ReWW_31_05	0.2618	2.3888	2.1629	26.1812
ReWW_30_06	0.3457	3.0034	2.8223	34.5695

Source: own work / Źródło: opracowanie własne

In the next step, a graph of relations between the observed yield and the MLR models forecast was created (Fig. 3) and a linear equations (6-8) was determined based on the results obtained (Fig. 4).

4. Discussion

Three independent models ReWW15_04, ReWW31_05 and ReWW30_06 (equations 6-8) were developed as a result of the analyses. Each model has to make forecasts and simulations on 15th April, 31st May and 30th June, respectively. The models were developed on the basis of 13, 17 and 19 independent variables. In each model the yield is a dependent variable ($t \cdot ha^{-1}$).

The determination coefficient R^2 in the produced models ranged between 0.5180 and 0.5457. This means an average adjustment of the model between the independent variables and the dependent variable. On the other hand, the statistical significance of particular factors, at the significance level of α=0.05 was differed. In the ReWW15_04 model, the indicated significance level reached eight independent variables: R9-12_LY, T9-12_LY, R1-4_CY, MGO_CY, SO3_CY, CU_CY, MN_CY. The first group includes weather factors (temperature and precipitation) from the autumn-spring period. The second group consists of fertilizer factors - magnesium, sulphur, copper and manganese. The results of significance α=0.05 mean that these factors had the greatest influence on the shaping of yield in the period from 1st September to 15th April. In model ReWW31_05 the indicated level of significance reached three independent variables: R5_CY, MGO_CY, MN_CY. Two variables overlapped with the previous model, while the analysis additionally indicated the importance of precipitation levels in May (R5_CY). Therefore, it can be assumed that in the period from 1st April to 31st May, it was these factors that determined the yield to a large extent. In model ReWW30_06 the indicated importance level reached three independent variables, which were also indicated in model ReWW31_05: R5_CY, MGO_CY, MN_CY. This means that in June the same factors determined the yield as in May.

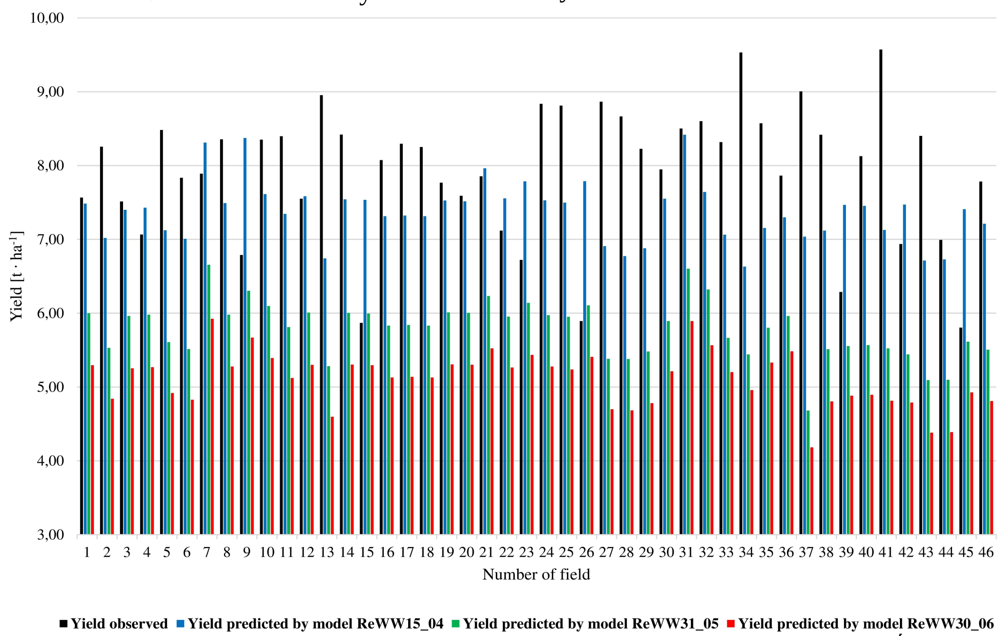

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Fig. 3. Observed and predicted yield of winter wheat in MLR model
Rys. 3. Rzeczywisty i prognozowany przez model MLR plon pszenicy ozimej

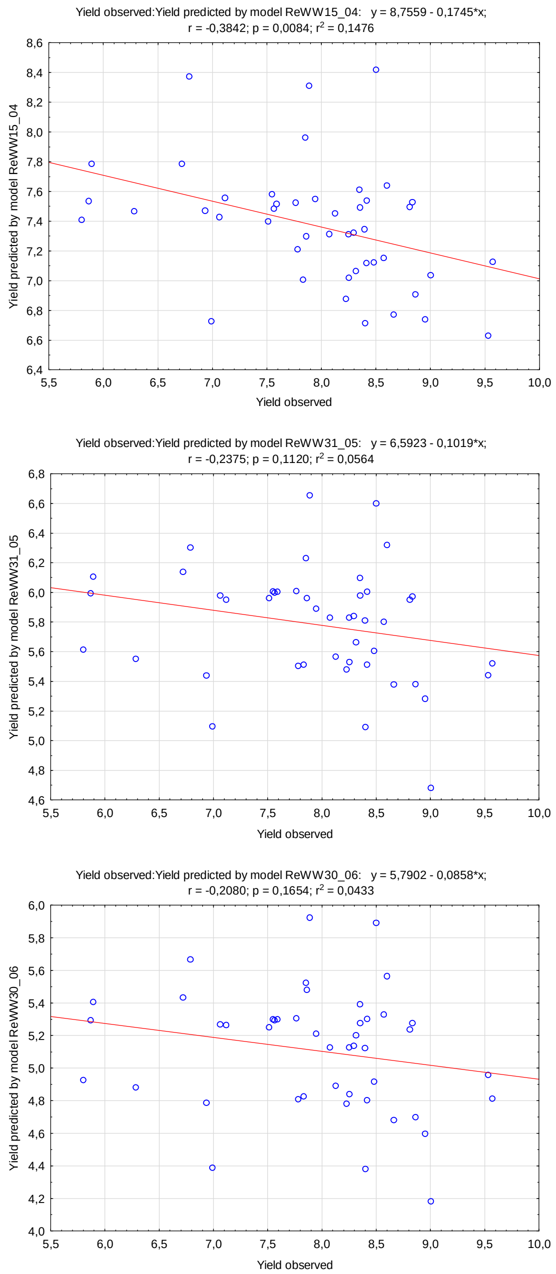

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Fig. 4. Relation between observed and predicted yield with linear equation

Rys. 4. Relacja pomiędzy plonem rzeczywistym i prognozowanym wraz z równaniem liniowym

The MLR yield models are based on empirical data, which are generally available to every farmer. The advantage of the models consists in the possibility of simulation in the current agrotechnical year, before harvest. Available forecast dates for each models are 15th April, 31th May and 30th June. In the literature one can find information about models which are built on the basis of specialised field research [2, 7, 20]. Unfortunately, this approach to modelling has two major disadvantages. First, such tests are cost- and time-consuming. Secondly, models based on such information can only be used by a narrow group of specialists.

It was assumed that the proper functioning of the models developed in the work will be verified by comparing the obtained forecasts with the actual value of winter wheat yield in the last year of the study.

In view of the above, four *ex post* error measures were used in this paper: relative approximation error (RAE), root mean square error (RMS), mean absolute error (MAE), mean absolute percentage error (MAPE). They were applied to determine the quality of the model and to determine the errors in the forecast of winter wheat yield.

Table 4 shows the error values for the models produced. To the most commonly used indicators characterizing the values of prediction errors belongs MAPE, which is easy to interpret [5, 8, 14]. The minimum MAPE error value for the ReWW15_04 model was 13.01%. The maximum MAPE error value for the ReWW30_06 model was 34.56%. Considering a critical MAPE error rate of up to 10%, in cases that are significantly affected by random conditions [17], the results are unsatisfactory.

It should be noted that the RAE, RMS, MAE, MAPE error value increases with the dates on which the models are based (Table 4). In addition, it should be noted that as the number of independent variables in the model increases - the yield prediction error also increases. These situations are well illustrated in Fig. 3.

For this reason, further work should be undertaken in order to reduce the prediction error by selecting another set of independent variables or changing the method of building the predicting model.

5. Conclusion

1. Application of the MLR method to produce prediction and simulation models of winter wheat yield allows for possible application in agricultural practice of the ReWW15_04 model only.
2. The lowest MAPE forecast error of 13.01% was obtained for the ReWW15_04 model, which is an acceptable value.
3. The created models are based on empirical data which are easily accessible and do not require specialised research to gather them.
4. Further work should be undertaken on the optimisation of models, i.e. the selection of an appropriate number of independent variables influencing winter wheat yields.
5. The construction of models based on a larger number of fields, a broader time horizon and a wider territorial coverage should be considered.

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