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Artificial Neural Network Use For Sweet Corn Water Consumption Prediction Depending On Cultivation Technology Peculiarities.

Raisa Anatoliivna Vozhehova¹, Pavlo Volodymyrovych Lykhovyd^{1*},
Sergiy Olehovych Lavrenko², Serhii Vasylovych Kokovikhin¹, Nataliia Mykolaivna Lavrenko²,
Tetyana Yuriivna Marchenko¹, Olena Viktorivna Sydyakina², Tetyana Viktorivna Hlushko²,
and Vasyl Volodymyrovych Nesterchuk¹

¹Institute of Irrigated Agriculture of the National Academy of Agrarian Sciences of Ukraine, Kherson, Naddnyprianske, 73483, Ukraine.

²Kherson State Agrarian University, Kherson, Stritenska Street 23, 73006, Ukraine.

ABSTRACT

The goal of our study was to determine reliability of the artificial neural network method for prediction of the sweet corn water consumption in the irrigated conditions of the South of Ukraine. The field trials were carried out in 2014-2016 in four replications at the drip-irrigated experimental plots of the agricultural cooperative farm "Radianska Zemlia" in Kherson region. The actual water consumption of sweet corn was determined by the field measurements, and was calculated as the sum of consumed soil water, effective rainfall and irrigation water applied to the field. Artificial neural network with the architecture 3-6-1-3-1 was designed on the basis of the gathered field data within JustNN software application. After learning and training of the developed neural network we tested its reliability by the comparison of true values with predicted ones. The analysis proved high accuracy of the prediction, which is approved by the high value of the coefficient of determination (R^2) - 0.937. We conjecture that artificial neural network algorithms are reliable enough to provide forecasts of the crops water consumption depending on the cultivation technology treatments.

Keywords: evapotranspiration, forecasting, irrigation, mineral fertilizers, moldboard plowing, plants density.

**Corresponding author*

INTRODUCTION

Artificial neural networks (further - ANN) is one of the most developing and widely used mathematical modeling method in different branches of modern science. ANN found implementation in natural and life sciences due to the opinion that it is the most accurate and reliable method for modeling of the natural phenomena, which take place in environmental biosystems [2]. In agricultural science and agronomy, ANN is used for prediction of crop yields [3, 9, 15], water quality parameters [13], crops water use [5], reference and total evapotranspiration [11, 20], soil water retention and hydraulic properties [10, 19], landscape changes and lands suitability assessment [22], solar radiation income [6], and other complex agricultural forecasting models. Besides, ANN is used for solving complicated tasks of classification and generalization, simulation of natural processes in artificial mathematical environment by the means of modern computer systems. The main advantages of ANN, in comparison with other conventional mathematical statistical methods, are these [8]:

- high accuracy and reliability in prediction of natural processes peculiarities;
- ability to handle huge data massive and operate with large and complex systems;
- non-linear fuzzy algorithms with the possibility of learning the ANN;
- ability to work with incomplete data sets;
- high flexibility and convenience of use, possibility of ANN to be adjusted to every concrete purpose.

The goal of our study was to assess reliability of ANN method for prediction of the sweet corn water use in dependence to cultivation technology treatments.

MATERIALS AND METHODS

We used the water consumption of sweet corn obtained in the field trials to create, train and test the reliability of ANN in prediction of the crop evapotranspiration. The field experiments were carried out in 2014-2016 by using the split plot design method in four replications at the irrigated lands of the agricultural cooperative farm "Radianska Zemlia" Kherson region, Ukraine; experimental field coordinates are: latitude 46°43'42"N, longitude 32°17'38"E, altitude 42 m). The trials foresaw the study of such cultivation technology elements as: Factor A – soil tillage (moldboard plowing at the depth of 20-22 and 28-30 cm); Factor B – mineral fertilizers doses (no fertilizers applied; N₆₀P₆₀; N₁₂₀P₁₂₀ of active substance applied); Factor C – plants density (35000, 50000, 65000, 80000 plants ha⁻¹). In our trials we used sweet corn cultivar Brusnytsia (standard sweet – su). Sweet corn cultivation began with preparation of the experimental field after harvesting of the fore-crop (winter wheat). Harrowing at the depth of 10-12 cm followed by the moldboard plowing was conducted. Mineral fertilizers (ammonium nitrate and superphosphate) were applied with accordance to the scheme of the trials before plowing. Soil cultivations at the depth of 8-10, and 5-6 cm were conducted during the spring period. Sweet corn was sown at the depth of 5-6 cm with the inter-row spacing of 70 cm. The time of the crop sowing varied from year to year and was: 1st of May in 2014, 22nd of May in 2015 and 21st of May in 2016, respectively. Herbicide Harnes (*Acetochlor*, 900 g L⁻¹ of the active substance) was applied before sowing of the crop in the dose of 2.0 L ha⁻¹. Karate Zeon insecticide (*Lambda-cyhalothrin*, 50 g L⁻¹ of the active substance) was applied at the stage of 3-5 leaves of the crop in the dose of 0.2 L ha⁻¹. Master Power herbicide (*Foramsulfuron*, 31.5 g L⁻¹, *Iodosulfuron*, 1.0 g L⁻¹, *Tienecarbazon-methyl*, 10 g L⁻¹, *Cyprosulfamide* (antidote), 15 g L⁻¹ of the active substances) was applied at the stage of 7-8 leaves of the crop in the dose of 1.25 L ha⁻¹. Koragen insecticide (*Chlorantraniliprole*, 200 g L⁻¹ of the active substance) was used at the beginning of the panicle earing period in the dose of 0.1 L ha⁻¹ dose. Soil moisture during the crop vegetation period was maintained at the level of 80% of the field water holding capacity by the means of drip irrigation system. Soil moisture was assessed by the balance-drier methodology in the laboratory of Kherson State Agrarian University [21]. Amounts of the effective rainfall were accounted by using the rain gauge. Irrigation water was applied to the field in such amounts: in 2014 – 10 times by 5 mm until the 7-8 leaves stage of the crop and 12 times by 10 mm during the rest of the vegetation period; in 2015 – 6 times by 5 mm until the 7-8 leaves stage of the crop and 9 times by 10 mm during the rest of the vegetation period; in 2016 – 8 times by 5 mm until the 7-8 leaves stage of the crop and 12 times by 10 mm during the rest of the period. The actual water consumption of sweet corn was calculated as the sum of consumed soil water, effective rainfall and irrigation water applied to the field [21].

We used JustNN software application to perform mathematical processing of the experimental data and creation of the ANN with the architecture 3-6-1-3-1, which contains three hidden layers of neurons. The

software uses a standard sigmoid activation function type, which can be simply described by the equation 1 [14]:

$$S = \frac{1}{1 + e^{-x}} \tag{1}$$

where e is a mathematical constant, and x is a free argument.

We used the coefficient of determination (R^2) value to compare the ANN predicted level of sweet corn water consumption with the actual ones. The coefficient of determination was calculated by using the equation 2 [4]:

$$R^2 = 1 - \frac{V(yx)}{V(y)} \tag{2}$$

where $V(yx)$ is the dispersion of the dependent argument.

RESULTS AND DISCUSSION

The ANN created within JustNN software application was trained and learned by using the data set, which was previously built on the basis of the results of the field trials with sweet corn. As a result of the training process we obtained the values of the training errors, which are represented in the Table 1.

Table 1: Training errors of the artificial neural network

Type of the training error	Average value of the error, mm	Standard deviation, mm
The minimum	0.000011	0.000057
Average	0.009913	0.000080
The maximum	0.044620	0.001982

Besides, the designed ANN provided us with information on the significance of the inputs, which were used for training, learning and forecasting of the crop water consumption. The significance was given in the absolute expression. Additionally, we conducted a calculation of the inputs value in percentage. So, it was determined that the strongest influence on sweet corn water consumption was caused by the factor of plants density. The least effect on the studied index had the depth of moldboard plowing (Table 2).

Table 2: The input significance of the studied factors in sweet corn water consumption (average for 2014-2016)

The factor	Absolute significance, points	Standard deviation, points	Percentage
Plants density	7.28	0.23	41.25
Doses of mineral fertilizers	6.33	0.43	35.86
Moldboard plowing depth	4.04	0.80	22.89

The results of the ANN prediction for the crop water consumption are represented in the Table 3.

Table 3: Comparison of the true and predicted values of sweet corn water consumption (average for 2014-2016)

Doses of mineral fertilizers	Plants density	Sweet corn water consumption, mm ± standard deviation		
		True values	Predicted values	Residuals
Moldboard plowing at the depth of 20-22 cm				
No fertilizers	35000	258.3±3.42	261.5±3.88	-3.2±1.13
	50000	261.6±3.40	262.4±4.33	-0.8±0.95
	65000	265.7±4.71	264.7±5.75	+1.0±1.07
	80000	266.8±5.17	269.1±8.29	-2.3±3.21

N ₆₀ P ₆₀	35000	262.4±4.48	262.9±4.65	-0.5±1.50
	50000	268.1±6.81	266.0±6.66	+2.1±0.17
	65000	271.4±7.34	270.9±8.78	+0.5±1.50
	80000	274.0±1.096	274.6±8.51	-0.6±2.58
N ₁₂₀ P ₁₂₀	35000	267.1±6.45	267.9±7.76	-0.8±1.42
	50000	270.7±6.31	272.8±8.96	-2.1±2.65
	65000	277.1±9.22	275.7±8.35	+1.4±0.92
	80000	277.6±9.00	276.7±7.97	+0.9±1.25
Moldboard plowing at the depth of 28-30 cm				
No fertilizers	35000	259.5±3.20	262.1±3.96	-2.6±0.85
	50000	262.3±3.84	263.5±4.11	-1.2±0.75
	65000	266.2±5.14	266.6±4.31	-0.4±1.85
	80000	267.5±5.36	270.8±5.06	-3.3±0.55
N ₆₀ P ₆₀	35000	263.3±3.64	264.1±4.27	-0.8±0.86
	50000	268.6±4.26	267.7±4.47	+0.9±1.47
	65000	271.7±4.26	272.0±5.40	-0.3±1.33
	80000	274.8±7.48	274.9±6.70	-0.1±1.59
N ₁₂₀ P ₁₂₀	35000	267.6±5.60	269.1±4.74	-1.5±1.68
	50000	271.4±5.42	273.3±5.95	-1.9±0.78
	65000	277.5±7.48	275.6±7.09	+1.9±0.40
	80000	278.6±7.19	276.5±7.55	+2.1±0.36

The average amplitude of fluctuation of the water consumption residuals is only -3.3...+2.1 mm. So, this is just slightly more (the difference is 0.4 mm) than one minimum irrigation norm, which was 5.0 mm in our field trials. Therefore, it cannot be considered a high enough value to make the crop suffer from water stress. Such a little water deficit or over-watering will not cause any significant deterioration of yields qualities or lead to yield losses. Besides, with accordance to the results of correlation analysis we determined that the coefficient of determination (R^2) between the true and predicted by the ANN water consumption values is 0.937, and such a high value tells us about a strong correspondence between them. Therefore, we conclude that ANN method for prediction and mathematical assessment of possible crop water consumption is quite a reliable one, and can be used in agricultural practice. And some other scientific works agree with the above-mentioned statement [1]. Besides, other previously conducted scientific studies proved high efficiency of ANN technologies application in such fields of agricultural water management as: forecasting irrigation water demands with accordance to irrigation schedules, regimes, and water distribution, etc. [17, 18]; prediction of the reference crop evapotranspiration and weekly evapotranspiration from the fields [12, 23]; forecasting groundwater level [16]; prediction of the water quality [7, 13]. So, ANN should be thoroughly and carefully studied for further adjustment and implementation for the needs of agricultural water management, because this mathematical instrument is one of the most powerful and provides incredible range of possibilities for significant improvement and rationalization of the water use.

CONCLUSIONS

The results of the study proved that ANN is a reliable and accurate mathematical tool for prediction of sweet corn water consumption with accordance to the crop cultivation treatments. The statement is approved by the high value of the coefficient of determination (0.937), and the low amplitude of the predicted index fluctuation in the ANN model - 5.4 mm, which is just about the one minimum irrigation norm of 5.0 mm.

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