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Artificial Intelligence by Artificial Neural Networks to Simulate Oat (*Avena sativa* L.) Grain Yield Through the Growing Cycle

Osmar Bruneslau Scremin

Exact Sciences and Engineering Department, Regional University of the Northwest of Rio Grande do Sul, Street of Comércio 3000, Universitário, Ijuí/RS – Brazil

ORCID: 0000-0003-0752-378X

E-mail: osmarscremin@hotmail.com

José Antonio Gonzalez da Silva

Agrarian Studies Department, Regional University of the Northwest of Rio Grande do Sul, Street of Comércio 3000, Universitário, Ijuí/RS – Brazil

ORCID: 0000-0002-9335-2421

E-mail: jagsfaem@yahoo.com.br

Ivan Ricardo Carvalho

Agrarian Studies Department, Regional University of the Northwest of Rio Grande do Sul, Street of Comércio 3000, Universitário, Ijuí/RS – Brazil

ORCID: 0000-0001-7947-4900

E-mail: carvalho.irc@gmail.com

Ângela Teresinha Woschinski De Mamann (Corresponding author)

Federal Institute of Education, Science and Technology of Rio Grande do Sul, Street Nelsi Ribas Fritsch, 1111, Neighborhood Esperança, Ibirubá/RS – Brazil

ORCID: 0000-0002-3650-9007

E-mail: angela.mamann@ibiruba.ifrs.edu.br

Adriana Roselia Kraisig

Exact Sciences and Engineering Department, Regional University of the Northwest of Rio Grande do Sul, Street of Comércio 3000, Universitário, Ijuí/RS – Brazil

ORCID: 0000-0002-5495-7700

E-mail: maryshelei@yahoo.com.br

Juliana Aozane da Rosa

Exact Sciences and Engineering Department, Regional University of the Northwest of Rio Grande do Sul, Street of Comércio 3000, Universitário, Ijuí/RS – Brazil

ORCID: 0000-0002-0430-1615

E-mail: juaozane@gmail.com

Cibele Luisa Peter

Exact Sciences and Engineering Department, Regional University of the Northwest of Rio Grande do Sul, Street of Comércio 3000, Universitário, Ijuí/RS – Brazil

ORCID:0000-0003-3376-8211

E-mail: cibele.peter2017@gmail.com

Eduarda Warmbier

Exact Sciences and Engineering Department, Regional University of the Northwest of Rio Grande do Sul, Street of Comércio 3000, Universitário, Ijuí/RS – Brazil

ORCID: 0000-0002-0526-1723

E-mail: eduarda.warmbier@gmail.com

Laura Mensch Pereira

Agrarian Studies Department, Regional University of the Northwest of Rio Grande do Sul, Street of Comércio 3000, Universitário, Ijuí/RS – Brazil

ORCID: 0000-0002-8073-069X

E-mail: lauramensch@gmail.com

Natiane Carolina Ferrari Basso

Agrarian Studies Department, Regional University of the Northwest of Rio Grande do Sul, Street of Comércio 3000, Universitário, Ijuí/RS – Brazil

ORCID: 0000-0002-6538-7299

E-mail: natianeferrari@gmail.com

Cláudia Vanessa Argenta

Agrarian Studies Department, Regional University of the Northwest of Rio Grande do Sul, Street of Comércio 3000, Universitário, Ijuí/RS – Brazil

ORCID: 0000-0003-4462-3384

E-mail: claudia_argenta@yahoo.com

Ester Mafalda Matter

Agrarian Studies Department, Regional University of the Northwest of Rio Grande do Sul, Street of Comércio 3000, Universitário, Ijuí/RS – Brazil

ORCID: 0000-0002-3433-3220

E-mail: estermafaldamatter@gmail.com

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Abstract

Artificial neural networks simulating oat grain yield throughout the crop cycle, can represent an innovative proposal regarding management and decision making, reducing costs and maximizing profits. The objective of the study is to develop biomathematical models via artificial neural networks, capable of predicting the productivity of oat grains by meteorological variables, nitrogen management and biomass obtained throughout the development cycle, making it possible to plan more efficient and sustainable managements. In each cultivation system (soybeans/oats; maize/oats), two experiments were carried out in 2017 and 2018, one for analyzing grain yield and the other for cutting every 30 days to obtain biomass. The experiments were conducted in a randomized block design with four replications for four levels of N-fertilizer (0, 30, 60 and 120 kg ha^{-1}), applied in the stage of the 4th expanded leaf. The use of the artificial neural network makes it possible to predict grain yield by harvesting the biomass obtained at any stage of oat development, together with the handling of the nitrogen dose and meteorological information during cultivation. Therefore, a new tool

to aid the simulation of oat productivity throughout the cycle, facilitating faster decision making for more efficient and sustainable management with the crop.

Keywords: nitrogen, modeling, biomass, temperature, rainfall, sustainability

1. Introduction

The use of artificial neural networks (ANN) has been growing gradually in the representation of the complex system, mainly in a non-linear variable (Leal *et al*., 2015; Fleck *et al*., 2016). The ANN are mathematical models based on the biological nervous system, formed by neurons that can be distributed in several interconnected layers, which, through training, store knowledge and generalize the information learned, being able to solve complex problems and model the behavior of the variables involved (Saraceno *et al.*, 2010; Azarpour *et al.*, 2015). In agriculture, neural networks can be used to develop prediction models in complex systems and estimate desired parameters, enhancing process optimization and decision making (Huang, *et al*., 2010; Silva *et al.*, 2014).

The implementation of new technologies for the management of agricultural crops has received attention from researchers in the search for a healthy diet. Due to the necessity to optimize food production with cost reduction and sustainability to ecosystems (Nikolla *et al*., 2014; Arenhardt *et al*. 2017). Furthermore, white oats are being used more in the food industry, as flakes, as it is an extremely nutritious and healthy cereal (Gutkoski *et al.*, 2009; Silva *et al.*, 2015).

Nitrogen as fertilizer is the essential element to assure proper oat grain yield requests from the industry (Marolli *et al.*, 2017a; Scremin *et al.*, 2017), but their management is one of the most complex because there are high losses by lixiviation, volatilization, which increase production costs and environmental damage (Brezolin *et al.*, 2017; Marolli, *et al*., 2018). Is highlighted weather elements, the rainfall and air temperature, are strictly linked to the nitrogen gain and losses by the plant, also are the most related to oat grain (Simili *et al*., 2008; Marolli *et al*., 2017b). These elements are non-linear variables, which difficulties the modeling use to predict yield. However, the study of biological processes, the climate and the management all over the growth cycle by ANN, can represent a new technology to make decisions, adding important information to the biological variables and environment, of linear and non linear behavior. It allows the patterns recognition in the generation of prognosis with reduction in production costs and maximizing profits.

The study aimed to develop biomathematics models by ANN, capable of predicting oat grain yield per weather variable, nitrogen management and biomass, obtained all over the development cycle.

2. Method

2.1 Experimental Design Area

The field experiment was carried out in 2017 and 2018, in the municipality of Augusto Pestana, Brazil (28 ° 26 ’30’ ’latitude S and 54 ° 00’ 58’’ longitude W). The soil of the experimental area was classified as Typical Red Latosol and the climate of the region, according to the Köppen classification, of the Cfa type (humid subtropical), with well-distributed rain during the year and the average temperature of the hottest month above 22 ºC. In the study, ten days before sowing, soil analysis was carried out and the following chemical characteristics of the site were identified (Tedesco *et al.*, 1995): i) maize/oat system: (pH = 6,5; P= 34,4 mg dm^{-3}; K = 262 mg dm^{-3}; MO = 2,9 %; Al = 0 $cmol_c dm^{-3}$; Ca = 6,6 $cmol_c dm^{-3}$e Mg = 3,4 $cmol_c dm^{-3}$) and; ii) soybean/oat system: (pH = 6,2; P= 33,9 mg dm^{-3}; K = 200 mg dm^{-3}; MO = 3,0 %; Al = 0 $cmol_c dm^{-3}$; Ca = 6,5 $cmol_c dm^{-3}$e Mg = 2,5 $cmol_c dm^{-3}$). In the two years of experiment, sowing was carried out in the second half of June, according to the cultivation recommendation.

The seeds were sown with a seeder-fertilizer in five 5-m-length lines spaced by 0.20 m, with an experimental area of 5 m^2. The population density was 400 seeds m^{-2} viable seeds, and the cultivar URS-Corona. During the work, applications were made tebuconazole fungicide of the commercial name FOLICUR® CE was applied in the dosage of 0.75 L ha^{-1}, and of the metsulfuron-methyl herbicide of the commercial name ALY® in the dose of 4 g ha^{-1}. In the sowing, 45 and 30 kg ha^{-1} of P_2O_5 and K_2O were applied based on the contents of P and K in the soil in the expectation of grain yield of 3 t ha^{-1} respectively and 10 kg ha^{-1} of nitrogen (except in the unit standard experiment), with the residual to complete the proposal top-dressing dose in the phenological stage of fourth fully expanded leaves.

Two experimental studies was performed in each crop condition (soybean/ oat, maize/ oat systems). One to quantify biomass yield (BY, kg ha^{-1}) through the cutting performed every 30 days until physiological maturity and the other to the grain yield estimative (GY, kg ha^{-1}). Therefore, at the four experiments the trial design was in randomized blocks with four replicates for four N-fertilizer doses (urea) in the level (0, 30, 60, and 120 kg ha^{-1}). The grain yield was obtained by cutting the three central lines of each plot at the harvest maturity, then was threshed and the grain moisture corrected to 13% at the laboratory to the grain yield estimative. To quantify biomass productivity (BY, kg ha^{-1}) the material plant was harvested close to the soil by collecting a linear meter in the three central lines of each plot in 30, 60, 90, and 120 days after emergence, a total of four cuttings.

To estimate biomass productivity the plant material was dried in a forced-air oven at 65 ºC until stabilized weight. The values of maximum air temperature and rainfall, obtained through the Total Automatic Station installed 500 meters from the experimental area.

2.2 ANN Simulation Model

The simulation of the oat grain yield for a development stage was mathematics modeling by ANN, using *Neural Network Toolbox* of Matlab software. These networks are trained using a backpropagation algorithm as activated function of the hidden layer hyperbolic sigmoid tangent, and the training rule Levemberg-Merquadt (LM). The backpropagation is a generalization of the learning algorithm Widrow and Hoff - Least Mean Square (LMS), known as delta rule (Faraco *et al.*, 1998), falls under the category of supervised learning. Network performance is measured by an error function that considers, for each of the different standards *p* on input, the square of the difference between the expected value and the respective calculated output. In other words, the error is the sum of the quadratic errors, defined by the following expression:

$$E = \sum_{i,p} E_i^p = \frac{1}{2}\sum_{i,p}\left(d_i^p - O_i^p\right)^2 \quad (1)$$

E_i^p represents the error of the i-th neural element, for the p-th input,

d_i^p is the output expected on the i-th neural element, for the p-th input and O_i^p is the output produced, is the output produced, defined as:

$$O_i^p = f(a_i^p) = f\left(\sum_j w_{ij} v_j^p - \theta_i\right) \quad (2)$$

v_j^p is the *j*-th input component V^p.

The backpropagation algorithm acts on synaptic weights, minimizing the error function, using the descending gradient technique. In this method, the weight values are modified proportionally to the opposite of the error derivative, according to the following expression:

$$\Delta w_{ij} = \gamma \frac{\partial E_i^p}{\partial w_{ij}} \quad (3)$$

γ, called the learning rate, it controls how big the "step" must be taken.

Defining $d_i^{p,k}$, as output expected in the *i*-th unit of the *k*-th layer, when the *p*-th pattern is presented to the network and,

$$O_i^{p,k} = f(a_i^{p,k}) \quad (4)$$

as the real output is, $a_i^{p,k} = \sum_j w_{ij}^k O_j^{p,k-1} - \theta_i$ e $O_i^{p,0} = v_i^p$, the error function, in the *k* layer, can be describe:

$$E^k = \frac{1}{2}\sum_{i,p}\left(d_i^{p,k} - O_j^{p,k}\right)^2 \quad (5)$$

The weights correction in the output layer K is given by applying the chain rule

$$\Delta w_{ij}^{K} = -\gamma \frac{\partial E^{K}}{\partial w_{ij}^{K}} = -\gamma \sum_{p} \frac{\partial E^{K}}{\partial O_{i}^{p,K}} \frac{\partial O_{i}^{p,K}}{\partial a_{i}^{p,K}} \frac{\partial a_{i}^{p,K}}{\partial w_{ij}^{K}} = \gamma \sum_{p} \delta_{i}^{p,K} O_{j}^{p,K-1} \quad (6)$$

defining itself

$$\delta_{i}^{p,K} = f'\left(a_{i}^{p,K}\right)\left(d_{i}^{p,K} - O_{i}^{p,K}\right) \quad (7)$$

Similarly, it can be shown that in the hidden layers the correction is given by:

$$\Delta w_{ij}^{K} = -\gamma \frac{\partial E^{K}}{\partial w_{ij}^{K}} = \gamma \sum_{p} \delta_{i}^{p,K} O_{j}^{p,K-1} \quad (8)$$

defining itself

$$\delta_{i}^{p,K} = f'(a_{i}^{p,K}) \sum_{j} w_{ij}^{K+1} \delta_{j}^{p,K+1} \quad (9)$$

The sigmoidal function is the most widely used, as it is a monotonic and easily derived function, with its basic model as:

$$O_{i} = f(a_{i}) = \frac{1}{1 + e^{-a_{i}}} \quad (10)$$

a can assume value between 0 and 1 been *i* the active neuron value. Its derivative is:

$$f'(a_{i}) = \frac{e^{-a_{i}}}{\left(1 + e^{-a_{i}}\right)^{2}} \quad (11)$$

Levenberg-Marquardt training is a function that updates the bias weights and values according to Levenberg-Marquardt optimization. It is often considered to be the fastest of the error propagation training algorithms, but it requires more computational memory than the other algorithms. In the Levenberg-Marquardt algorithm, the changes (Δ) in the weights $(\vec{w})$ are are obtained (Lera & Pinzolas, 2002),

$$\alpha\Delta = \frac{-1}{2} \nabla E \quad (12)$$

E is the mean square error of the network,

$$E = \frac{1}{N}\sum_{k=1}^{N} \quad [\vec{y}(x_k) - \vec{d}_k]^2 \tag{13}$$

N is the number of examples, $\vec{y}(x_k)$ is the network output corresponding to the example x_k and $\vec{d}_k$ is the desired output for that example.

The α matrix elements are given by:

$$\alpha_{ij} = (1 + \lambda\delta_{ij}) \sum_{r=1}^{p} \sum_{k=1}^{N} [\frac{\partial y_r(x_k)}{\partial w_i} \frac{\partial y_r(x_k)}{\partial w_j}] \tag{14}$$

p is the number of exits from the network. Starting with the random starting weights, both α and ∇E are calculated by solving Equation 12. The correction for the weight values is obtained by $(\vec{w'} = \vec{w} + \Delta)$, known as the Levenberg-Marquardt learning period. Each iteration with these times reduces the error until it finds a minimum. The λ variable in Equation 14 is the parameter that is adjusted each season according to the evolution of the error.

In each ANN architecture, the data was divided randomly at 70% for training (database with 128 samples), 15% for tests and 15% for validation. The input variables used in the artificial neural network were: N-fertilizer dose (0, 30, 60 e 120 kg ha^{-1}), the oat development stage after emergence (30, 60, 90 e 120 days), the biomass yield, rainfall load and the medium temperature load in each development stage, the output variable of the neural network was oat grain yield. To ensure that the data received equal attention during the training process, thus increasing its efficiency, both the input and output data of the neural network are standardized for the range of -1 to 1, by the data normalization process, expressed by the following equation:

$$pn = \frac{2(p-p)}{p-p} - 1, \tag{15}$$

pn is the normalized, dimensionless value; p is the observed value; p, is the minimum sample value; and p, the maximum sample value. At the beginning of the training, the free parameters are generated randomly and that these initial values can influence the final result of the training, 10 networks of each architecture were trained. Before the ANN architecture training, were chosen the lowest mean relative error (MRE) regard the validation data, and the lowest mean squared error (MSE) related to the training data. Each network was composed of 3 layers (input, hidden and output), in input layer with 5 neurons, the hidden layer varied between 5 to 25 (adding every 5 neurons) and a output layer with 1 neuron. To represent the ANN architecture were used the signal “NI-NHL-NNO” NI = input variable numbers, NHL = hidden layer neuron numbers and NNO = output layer neuron numbers. For the training and validation of ANNs, were used the experimental data obtained in 2017 and 2018 in the field experiment.

3. Results and Discussion

In Figure 1 of the oat cultivation period, it was noticed that the air temperatures were higher in 2017 than in 2018. In addition, in 2017, the rainfall was 813 mm (Figure 1A) and in 2018 it was 785 mm (Figure 1B), they were close to the average of the last 20 years (900 mm), however, with a different distribution between the years. In 2017, the volume of rainfall was low in the vegetative phase, accompanied by a high maximum air temperature. Circumstance that benefits nitrogen losses through volatilization and reduces the stimulus of new tillers, a component directly linked to grain productivity. The most intense rains occurred in the second half of the oat cultivation cycle and extended until close to the harvest in 2017, a condition that indicates less sunstroke and, consequently, reduction in the performance and efficiency of photosynthesis.

In 2018, the largest amount of rainfall was from sowing at 35 days of oat development and with milder maximum air temperature compared to 2017. These conditions favor the maintenance of soil moisture and increase the nitrogen efficiency used by the plant. In addition, from half the cycle to maturation, rainfall volumes were distributed with lesser intensity, improving the oats development conditions, justifying the higher grain productivity obtained in 2018.

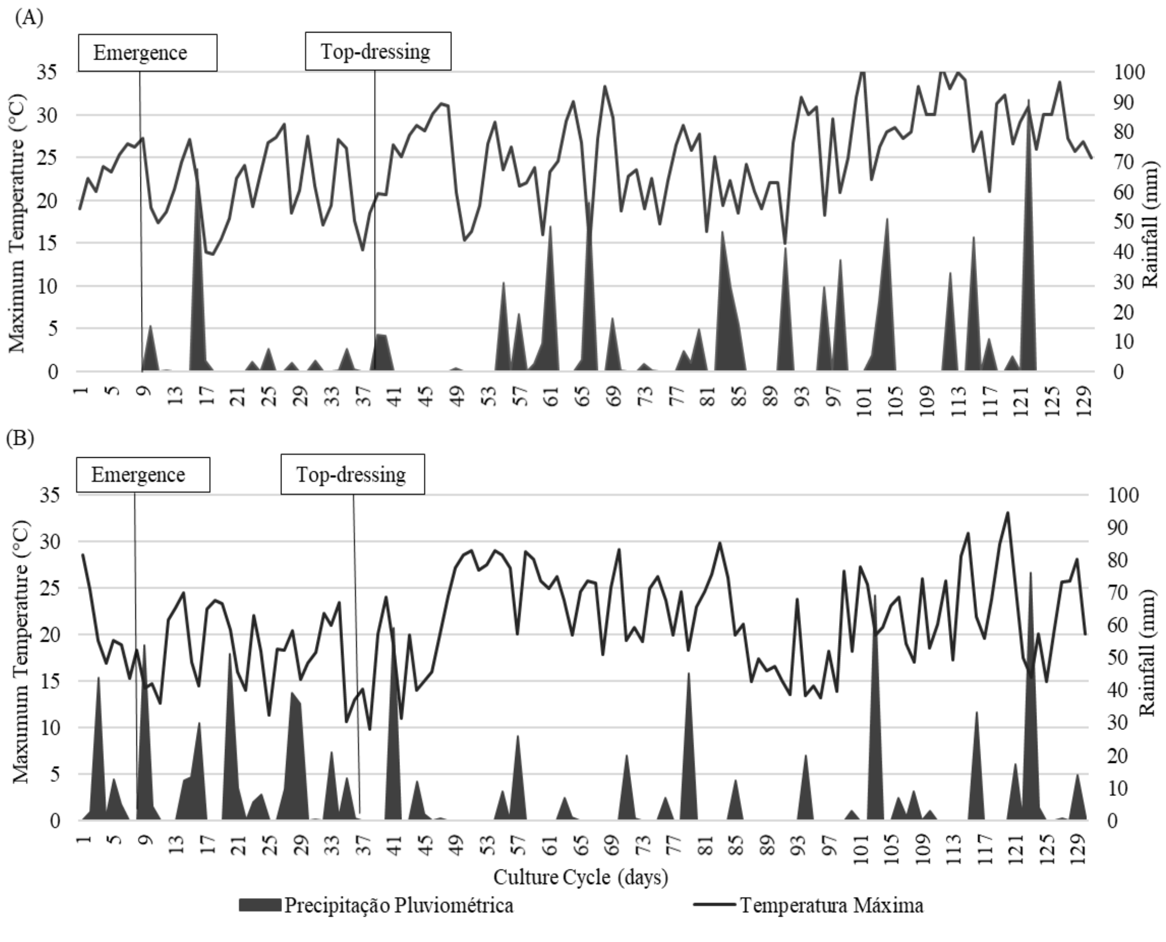


Figure 1. Rainfall and maximum temperature sowing to harvest (A)=2017, (B)=2018

The location and environment are decisive factors for grain yield, with climatic variations throughout the development cycle is the factor that most contributes to the yield changes (Ferrari Neto *et al.,* 2012; Costa *et al.,* 2016). In wheat and oat the crop year condition is defined by the rainfall amount and air temperature (Arenhardt *et al.*, 2015; Marolli *et al.,* 2017a). These affect the rate of organic matter decomposition in contact with the soil and affect the efficiency of nitrogen use by the plant (Acosta *et al.,* 2014). Air temperature is also a determining factor in the yield development, since it acts as a catalyst for biological processes, which is why plants require a minimum and maximum temperature for normal physiological activities (Guarienti *et al*., 2004; Tonin *et al*., 2014a; Tonim *et al.*, 2014b). Arenhardt *et al.* (2015), highlight that longs rainfall season reduce the efficiency of harnessing sunlight and nutrients to photosynthesis, interfering in the development, productivity and quality of grains during harvest (Castro, 2012; Mamann *et al.*, 2017). For oats, the favorable climate is described as milder temperatures with radiation quality, it favors tillering and grain filling, without the occurrence of rainfall in large quantities and intensity. However, it favors an adequate supply of moisture stored in the soil (Castro *et al.*, 2012; Marolli *et al*., 2017b).

Table 1 shows the mean square error in the training process and the mean relative error and variance, verified in the development of the artificial neural network. In the soybean/oat system the network architecture of 5-5-1 to 5-20-1 showed closest value of mean relative error next, but when variance is observed in the validation process, the architecture 5-5-1 showed minor value from the other. It represents that the error for all the data training decreased, but there will not necessarily be a reduction on the validation values. However, since it exhibits low value of variance, it does not express low mean relative error for the validation data (Table 1), in addition to presenting the relationship between the number of training samples and the number of hidden connections greater than 2, as indicated by Masters (1993). Besides, must be careful that networks with many neurons on the hidden layer can memorize training padrons instead of extracting generalizing characteristics (produce suitable outputs to inputs that were not present in the training (Braga *et al.*, 2000; Teodoro *et al.*, 2015). Thus, following the interpretation proposed by Masters (1993) and Braga et al., (2000), for this crop system the network architecture of 5-10-1, because it showed better capacity to predict oat grain yield.

Table 1. Mean quadratic error value, for all the training, mean relative error and variance for the data validation, in the training architecture

Architecture NI->NH->NO	Mean quadratic error (training)	mean relative error (validation)	Variance (validation)
	soybean/oat system		
5-5-1	5.54E-3	1.01E-2	7.82E-3
5-10-1	5.51E-3	7.76E-3	1.42E-2
5-15-1	5.83E-3	6.29E-3	2.32E-2
5-20-1	5.64E-3	7.85E-3	2.32E-2
5-25-1	6.81E-3	1.44E-2	1.96E-2
	maize/oat system		
5-5-1	6.31E-3	4.77E-3	7.77E-3
5-10-1	6.75E-3	8.44E-3	6.37E-3
5-15-1	5.89E-3	5.69E-3	7.78E-3
5-20-1	6.39E-3	1.78E-2	8.32E-3
5-25-1	3.42E-3	9.62E-3	1.68E-2

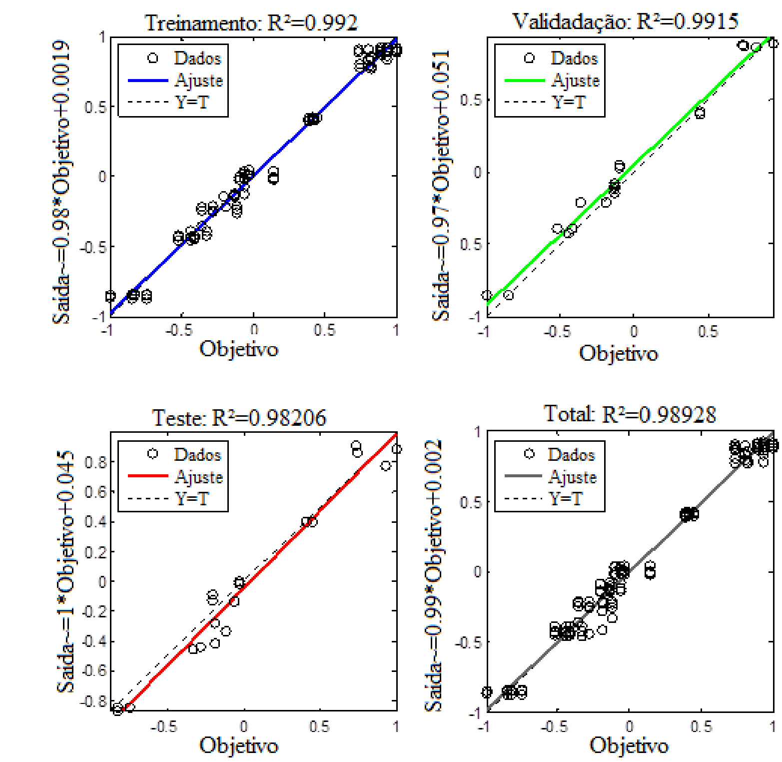
NI= Number of input layer neurons; NH= Number of hidden layer neurons; NO= number of output layer neurons

In the maize/oat system (Table 1), the minor mean quadratic error was observed in the 5-25-1 architecture, but, with more validation variation. Then, following the precept on choosing the soybean/oat system, was selected to maize/oat system the 5-15-1 structure, to represent lower mean quadratic error than the other structure and to have lower mean relative error.

The results found in the 10 and 15 neurons configuration in the hidden layer showed there is not the need for complex structures, because the hidden layer does not represent linearity between the data (Soares *et al*., 2015; Dornelles *et al*., 2018) and, in this case, there is not more complexity on the structure to understand yield tendency by climate condition, and the biomass manager in oat. Braga *et al*. (2007) and Bullinaria, (2016) indicated simpler configuration to apply ANN, avoiding overfitting occurrence and making the research process and configuration optimization easier to a certain task.

In Figure 2, the determination coefficients of training (70% data), validation (15% data), test (15% data) and total network (100% data) of the soybean/oat and maize/oat system. The determination coefficients of the chosen networks demonstrate the reliability and confirm that the generated algorithm scales the behavior of the actual data obtained, effectively, presenting values close to 1, that is, 100%.

(A)



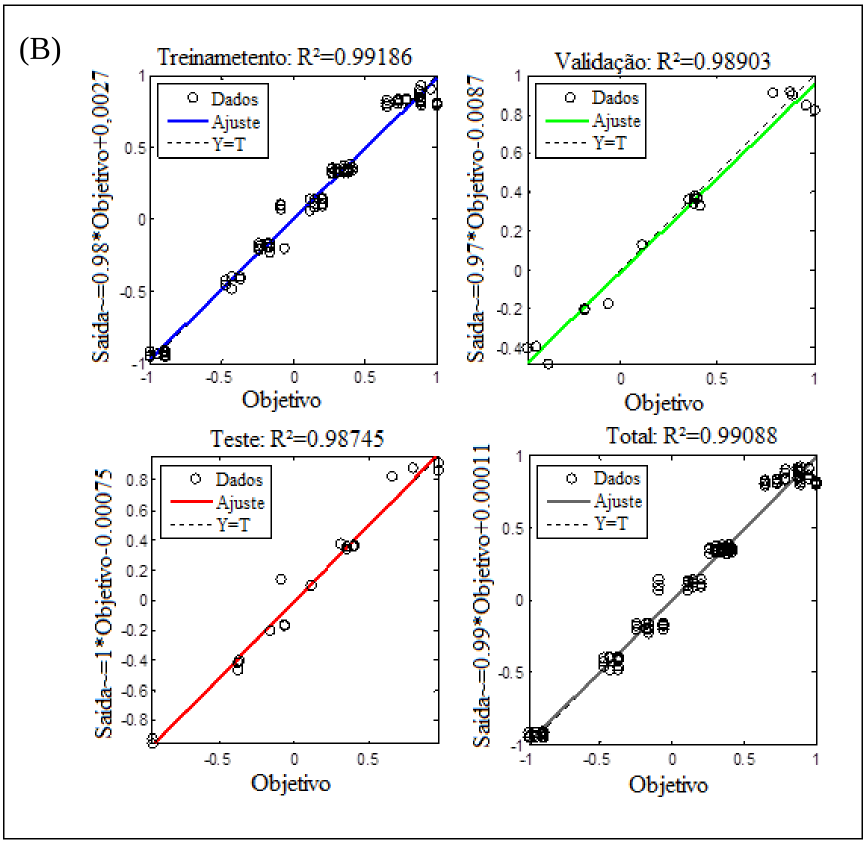


Figure 2. training coefficient determination, test, validation and all (training, test, validation) Of the ANN. (A)= Architecture 5-10-1 to soybean/oat system; (B)= Architecture 5-15-1 to soybean/maize system

To verify the performance of the ANN chosen for each crop system, in the 2 and 3 Table, the architecture 5-10-1 and 5-15-1 of the soybean/oat and maize/oat system, were compared the grain yield value obtain by the cumulative effect of the years 2017+2018 with the estimated value of ANN. To the input values of the artificial neural network were used the doses of N-fertilizer, the oat development stages, the biological yield, the accumulated rainfall mean and the maximum temperature mean accumulated in each stage of oat development (Figure 2).

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Table 2. Values comparison of the grain oat yield obtained in the validation of ANN with architecture 5-10-1 and in the field experiment in the soybean / oat system

N	Cycle (days)	Year	YB (kg ha^{-1})	$\sum_{rain}$ (mm)	$\overline{T}_{max}$ (°C)	GY (kg ha^{-1}) (2017+2018) Simulation/ANN	GY (kg ha^{-1}) (2017+2018) trust interval
0	30	2015	288	337	18.4	2322	L_i =1987
		2014	345	112	21.3		
	60	2015	1317	480	20.0	2260	$\overline{X}$ = 2220
		2014	1430	307	23.0		
	90	2015	4117	565	20.2	2320	L_s=2420
		2014	4594	548	23.1		
	120	2015	9919	785	20.7	2215	
		2014	5044	813	24.7		
30	30	2015	327	337	18.4	3179	L_i =2750
		2014	370	112	21.3		
	60	2015	2188	480	20.0	3188	$\overline{X}$ = 3035
		2014	1722	307	23.0		
	90	2015	5059	565	20.2	3183	L_s=3278
		2014	8266	548	23.1		
	120	2015	11972	785	20.7	3059	
		2014	8857	813	24.7		
60	30	2015	320	337	18.4	3444	L_i =2872
		2014	359	112	21.3		
	60	2015	2250	480	20.0	3481	$\overline{X}$ = 3342
		2014	3131	307	23.0		
	90	2015	8611	565	20.2	3485	L_s=3745
		2014	9681	548	23.1		
	120	2015	12051	785	20.7	3452	
		2014	11012	813	24.7		
120	30	2015	304	337	18.4	3171	L_i =3061
		2014	369	112	21.3		
	60	2015	3234	480	20.0	3244	$\overline{X}$ = 3192
		2014	3398	307	23.0		
	90	2015	9531	565	20.2	3161	L_s=3663
		2014	11295	548	23.1		
	120	2015	14864	785	20.7	3159	
		2014	11939	813	24.7		

$\sum_{rain}$ = rainfall summation; $\overline{T}_{max}$ = maximum mean temperature; N= N-fertilizer (kg ha^{-1}); BY= biological yield; GY= grain yield; ANN= Artificial neural network; L_i= inferior limit; $\overline{X}$ = mean; L_s= superior limit

In Table 2, soybean/oat system, the simulation showed high capacity to predict for oat grain yield, the values simulated by the ANN were between the truste interval of cumulative effects in the year 2017 and 2018. In the maize oat system (Table 3), the simulation also stayed between the truste interval. The ability to understand exemples and generalize information is the main problem solution by ANN, (Wasserman, 1989; Martins *et al.*, 2016). The generalization that is associated with the network's ability to learn from a small set of examples and subsequently provide coherent responses to unknown data is a demonstration that a ANN go beyond simply mapping input and output relationships (Soares *et al.*, 2014). These results show that the use of the network enables the predictability of grain yield at any OAT development stage, in any condition of use of the N-fertilizer and in different succession systems, becoming a tool to aid decision making regarding the management of culture.

One thing to regard is that the Neural Network can accept different input data. Thus, data collected in the field, such as topographic conditions and measures, edaphic parameters, phytomass values, stage of development of agricultural crops, etc., can also be used as a source of definition and context for a specific target, important in the task of memorization thematic feature (Bucene & Rodrigues, 2004; Depiné *et al.*, 2014; Dornelles *et al.*, 2018).

Table 3. Values comparison of the grain oat yield obtained in the validation of ANN with architecture 5-15-1 and in the field experiment in the maize / oat system

N	Stage (days)	Year	BY (kg ha^{-1})	$\sum_{rain}$ (mm)	$\overline{T}_{max}$ (°C)	GY (kg ha^{-1}) (2017+2018) Simulation/ANN	Trust interval
0	30	2015	324	337	18.4	1458	L_i =1240
		2014	195	112	21.3		
	60	2015	854	480	20.0	1524	$\overline{X}$ = 1551
		2014	1029	307	23.0		
	90	2015	4370	565	20.2	1522	L_s=1818
		2014	4462	548	23.1		
	120	2015	7524	785	20.7	1517	
		2014	4657	813	24.7		
30	30	2015	326	337	18.4	2384	L_i =2163
		2014	230	112	21.3		
	60	2015	1484	480	20.0	2430	$\overline{X}$ = 2476
		2014	1305	307	23.0		
	90	2015	4991	565	20.2	2431	L_s=2745
		2014	6564	548	23.1		
	120	2015	9515	785	20.7	2584	
		2014	8490	813	24.7		
60	30	2015	294	337	18.4	2840	L_i =2451
		2014	268	112	21.3		
	60	2015	1857	480	20.0	2897	$\overline{X}$ = 2902
		2014	1968	307	23.0		
	90	2015	5587	565	20.2	2852	L_s=3289
		2014	7845	548	23.1		
	120	2015	10628	785	20.7	3030	
		2014	10282	813	24.7		
120	30	2015	272	337	18.4	3032	L_i =2778
		2014	300	112	21.3		
	60	2015	2668	480	20.0	3126	$\overline{X}$ = 3094
		2014	2685	307	23.0		
	90	2015	6353	565	20.2	2997	L_s=3364
		2014	9803	548	23.1		
	120	2015	12111	785	20.7	3181	
		2014	11179	813	24.7		

$\sum_{rain}$ = rainfall summation; $\overline{T}_{max}$ = maximum mean temperature; N= N-fertilizer (kg ha^{-1}); BY= biological yield; GY= grain yield; ANN= Artificial neural network; L_i= inferior limit; $\overline{X}$ = mean; L_s= superior limit

Despite the promising results of using a neural network system to predict oat yield throughout the development stages, there is a need to qualify this technique for future data analysis, with a greater number of predictor variables, both for the plant and the ground. Therefore, it is suggested to test different configurations of neural networks, in order to obtain a greater relationship between productivity data, soil attributes, plant attributes, management and climate, thus obtaining greater accuracy in the estimates of variables of interest in crops.

4. Conclusion

The use of the artificial neural network makes it possible to predict grain yield by harvesting the biomass obtained at any stage of oat development, together with the handling of the nitrogen dose and meteorological information during cultivation. Therefore, a new tool to aid the simulation of oat productivity throughout the cycle, facilitating faster decision making for more efficient and sustainable management with the crop.

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