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Artificial Intelligence Simulating Grain Productivity During the Wheat Development Considering Biological And Environmental Indicators

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

Tel: +55 (55) 99999-5794 E-mail: angela.mamann@ibiruba.ifrs.edu.br

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

E-mail: jagsfaem@yahoo.com.br

Manuel Osório Binelo

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

E-mail: manuel.binelo@unijui.edu.br

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

E-mail: osmarscremin@hotmail.com

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

E-mail: maryshelei@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

E-mail: carvalho.irc@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

E-mail: lauramensch@gmail.com

Julio Daronco Berlezi

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

E-mail: julio.berlezi28@hotmail.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

E-mail: claudia_argenta@yahoo.com

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Abstract

The artificial neural networks modeling might simulate the efficiency of wheat grain yield involving biological and environmental conditions during the development cycle. Considering the main succession systems in wheat crop in Brazil, the study aimed to adapt an artificial neural network architecture capable of predict the wheat grain productivity throughout the growth cycle, involving nitrogen and non-linearity of maximum air temperature and rainfall. The field experiment was conducted in two successions systems (soybean/wheat and maize/wheat) in 2017 and 2018, the trial design was in a randomize blocs with eight replicate in the level 0, 30, 60, and 120 kg ha^{-1} N-fertilizer doses in the phenological stage of third fully expanded leaves. Every 30 day of the development cycle were obtained the biomass yield, maximum air temperature and accumulated rainfall information. The perceptron multi-layered artificial neural networks with backpropagation algorithm with network architecture 5-8-1 and 5-7-1 in soybean/wheat and maize/wheat system respectively, is able to simulate the wheat grain yield involving the nitrogen dose at top-dressing and the non-linearity of maximum air temperature and rainfall with biomass information obtained during the cycle crop.

Keywords: *Triticum aestivum*, artificial neural networks, maximum air temperature, rainfall, sustainability

1. Introduction

The artificial neural networks (ANN) are computing algorithm that shows a mathematical model inspired by the intelligent organisms whom enable the neural networks humans in the computers systems (Çelebi *et al*., 2017; Dornelles *et al*., 2018). These networks are artificial neurons that can be dispense into several layers and interconnected by connections that store model knowledge and consider the input per each neurons in the network (Vendruscolo *et al*., 2015; Menezes *et al.*, 2015). Therefore, ANN learn by the experience, generalize information and estimate results to not known data (Wasserman, 1989; Silva *et al.,* 2018). Enhancing the optimization processes to make decisions in agriculture. The ANN can be used to elaborate prediction models in complex systems and estimate desired parameters (Huang *et al*., 2010; Silva *et al*., 2014).

There is a need to optimize food production through technologies that ensure yields with lower costs and sustainable to the agroecosystems (Sala *et al.*, 2005; Viola *et al*., 2013). Once, wheat is the most cultivated and consumed cereal all over the world with great importance in human feed (Santos and Medeiros, 2016; Frizon *et al.*, 2017), which requires researches to intensify its production with sustainability. For greater yield in wheat, the nitrogen is an essential element (Teixeira Filho *et al.*, 2010; Prando *et al.*, 2013), however, its management is one of most complex due to the high losses index by leaching and volatilization, increasing the production expenses and generating environmental pollution (Silva *et al*., 2015; Camponogara *et al*., 2016). Furthermore, meteorological elements such as rainfall and air temperature are close related to nitrogen uses or losses by the plant, and related to the wheat productivity expression (Bischoff *et al*., 2015; Santi *et al*., 2017). Those elements are non-linear variable that become difficult its use in the math modeling to predict the productivity. The usage of computational algorithms via ANN can represent a promising tool to aggregate information of biological and environmental variable, with linear or non-linear behavior, allowing it to recognise patterns in the prognosis generation.

The study aimed to adapt an ANN capable of predict the wheat grain productivity throughout the growth cycle, involving nitrogen and non-linearity of maximum air temperature and rainfall, considering the main succession systems in wheat crop in Brazil.

2. Materials and Methods

2.1 Crop Area Description

The experiment was developed on field in the 2017 and 2018 agricultural years, located in Augusto Pestana, RS, Brazil (28 °26 '30' S; 54 °00' 58 " W). The growing soil is classified as Oxisol Distroferric Typical and the climate of the region matches to CFA (humid subtropical), with the occurrence of hot summers, no occurrence of prolonged droughts, and cold wet winters, according to Köppen’s classification. The soil analysis was realized ten days before sowing and had the following features chemistry (Tedesco *et al*., 1995): i) maize/wheat system: (pH = 6,5; P= 34,4 mg dm^{-3}; K = 262 mg dm^{-3}; MO = 2,9 %; Al = 0 cmolcdm^{-3}; Ca = 6,6 cmolcdm^{-3}e Mg = 3,4 cmolcdm^{-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 cmolcdm^{-3}; Ca = 6,5 cmolcdm^{-3}e Mg = 2,5 cmolcdm^{-3}). Regardless the agricultural year, the sowing performed on June third week according to the crop recommendation on residual cover with higher and lower C/N relation, maize/wheat system and soybean/oat system respectively.

2.2 Experimental Design

The seed were sown with a seeder-fertilizer in five 5-m-length lines spaced by 0.20 m. The population density was 400 seeds m^{-2} viable seeds. During the study accomplishment was applied tebuconazole fungicide at a dose of 0.75 L ha^{-1}. The weeds were controlled by metsulfuron-methyl herbicide at a dose of 4 g ha^{-1} and hoed when necessary. At the sowing was applied 45 e 30 kg ha^{-1} of P_2O_5 e K_2O based on P and K soil contents to 3000 kg ha^{-1} grain yield expected respectively and 10 kg ha^{-1} of N-starter-fertilizer (except the pattern experimental unity) with the residual to complete the proposal top-dressing N dose in the phenological stage of third fully expanded leaves.

Two experimental studies was performed in each crop condition (soybean/wheat, maize/wheat systems). One to quantify biomass yield through the cutting performed every 30 days until physiological maturity and the other to grain yield estimative. Therefore, at the four experiment the trial design was in a randomize blocs with eight replicate for four N-fertilizer doses (urea) in the level 0, 30, 60, and 120 kg ha^{-1} with the TEC 10 wheat cultivar, total of 128 experimental units. The grain yield was obtained by cutting the three central line 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 (GY, kg ha^{-1}). To quantify biomass yield (BY, kg ha^{-1}) the material plant was harvest 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, total of four cutting.

To estimate biomass yield the plant material were dried in a forced-air oven at 65 ℃ until stabilized weight. The meteorological data of maximum and minimum air temperature and rainfall amount over the wheat growth cycle were obtained through Total Automatic Station installed 500 meters from the experiment.

2.3 Modeling for Artificial Neural Networks

The artificial neural networks (ANN) proposed consist in perceptron multi-layered (PML) by Rosenblatt (1958). These networks are trained using backprogamation algorithm set with optimize algorithm Levemberg-Merquadt (LM), with the ability to treat data no linearly separable, with one input layer, hidden layer (at least) and one output layer (Gonçalves *et al.*, 2010; Perea *et al.*, 2018). The input layer is responsible to receive information, signal, features or mediations that come from the outside. Generally are normalized in relation to the dynamic variation range produced by the activation functions (Silva *et al*., 2010). The hidden layer is composed of neurons with the responsibility to extract related features to the process or the system to infer. On this layer the processing performed per each neuron is defined by the combination of the process realized by the neurons from the previous layers connected to it (Meireles and Cedón, 2010). The output layer generate the production and shows the final network results, that accrue from the neurons processing performed from the previous layers. (Silva *et al*., 2010). The backpropagation algorithm is based on the precept of learning through the error correction, that is, in forward process the input vector spreads out ANN layers producing an output layer with stabilized weight. In the reverse process, the weight are readjusted as follow the learning rule by error correction. (Fleck *et al.*, 2016). The optimize algorithm Levenberg-Merquad require less training period and is automatic interrupt when the generalization minimizes the difference between real and simulated network. It was used the activation function hyperbolic tangent sigmoid.

2.4 ANN Applicability by Environmental and Biological Indicators

The input variables usage by the ANN were: N-fertilizer dose (0, 30, 60 e 120 kg ha^{-1}), growth stages (30, 60, 90 e 120 days), biomass yield (in each growth stages), rainfall and maximum mean air temperature at each stage. The output variable was grain yield, whereas the main cereal succession systems in Brazil (Figure 1).

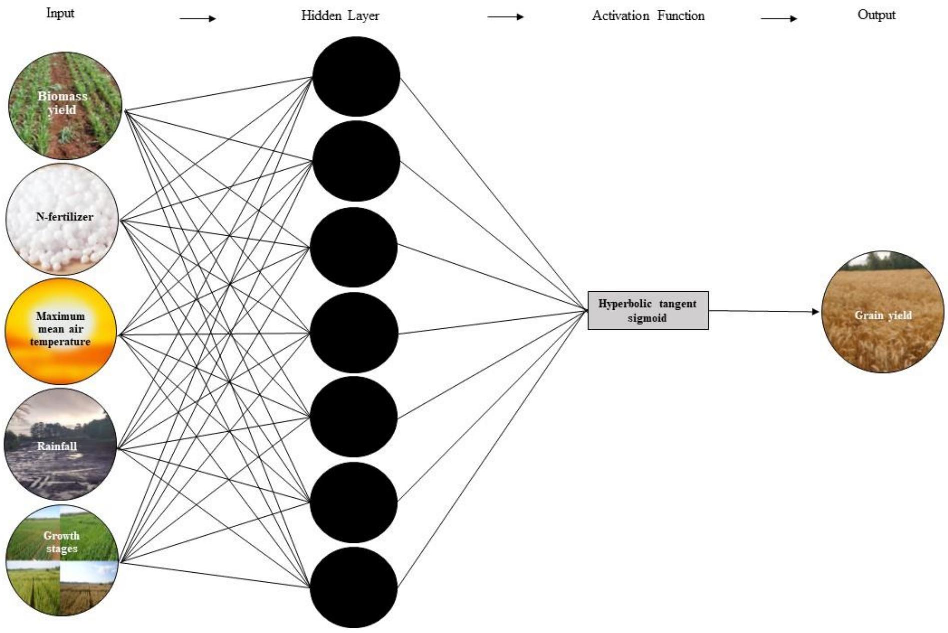

Figure 1. Artificial neural networks by biological and environmental indicators in grain yield simulation of wheat

The training process was begun with weight random values of the variable and this data the output was compared with the real value. The difference between the output network and the real value generate an error signal who adjust the weight and starts a new cycle, to bring the output closer the desired result minimized the error (Vendruscolo *et al*, 2015). It was training 10 ANN with 3 layers (input, hidden and output) The input layer consisted in 5 neurons, the hidden layer had 5 to 10 neurons with increment 1 on 1 and the output layer with 1 neuron. After training each ANN architecture, were choose the lowest mean relative error (MRE) regard the validation data, and the lowest mean squared error (MSE) related to the training data. To represent the ANN architecture were used the signal “NI-NHL-NNO” being NI = input variable numbers, NHL = hidden layer neuron numbers and NNO = output layer neuron numbers. For the ANN architecture, the data (dataset with 128 samples) were random divided in 70% to the training, 15% to test and 15% to validation. To the multilayer ANN training and simulation of wheat grain productivity was used the Neural Network Toolbox MATLAB® software.

To ANN validation chosen in each crop system was consider the behavior and parameters of the polynomial regression obtained from the variable real value on the different nitrogen doses by the bio-experimentation. The quadratic equation (Equation 1) used to estimate the maximum technical efficiency (Equation 2) of nitrogen use, considering the model:

$$GY = b_0 \pm b_1 x \pm b_2 x^2 \quad (1)$$

being, $GY =$ grain yield (kg ha^{-1}) b_0, b_1 e b_2 are the regression model parameters

$$MTE = -\frac{b_1}{2b_2} \quad (2)$$

being, MTE nitrogen maximum technical efficiency (kg ha^{-1}).

In the regression models, determination was use the Excel computing program.

3. Results and Discussion

In the Figure 2 of the wheat crop cycle was observed that the rainfall in 2017 (Figure 2A) and 2018 (Figure 2B) were similar to the historical average last 20 years of 900 mm, however, with different distribution between the years (Figure 2). In 2017, occurred lower rainfall intensity at the cycle beginning with great maximum air temperature, this condition favors the N-fertilizer loses through volatilization. On the other hand, the greater rainfall amount was from half wheat cycle to maturation in 2017 (Figure 2A), this favored minor sunstroke periods that indicated fewer photosynthesis efficiency harming the grain productivity.

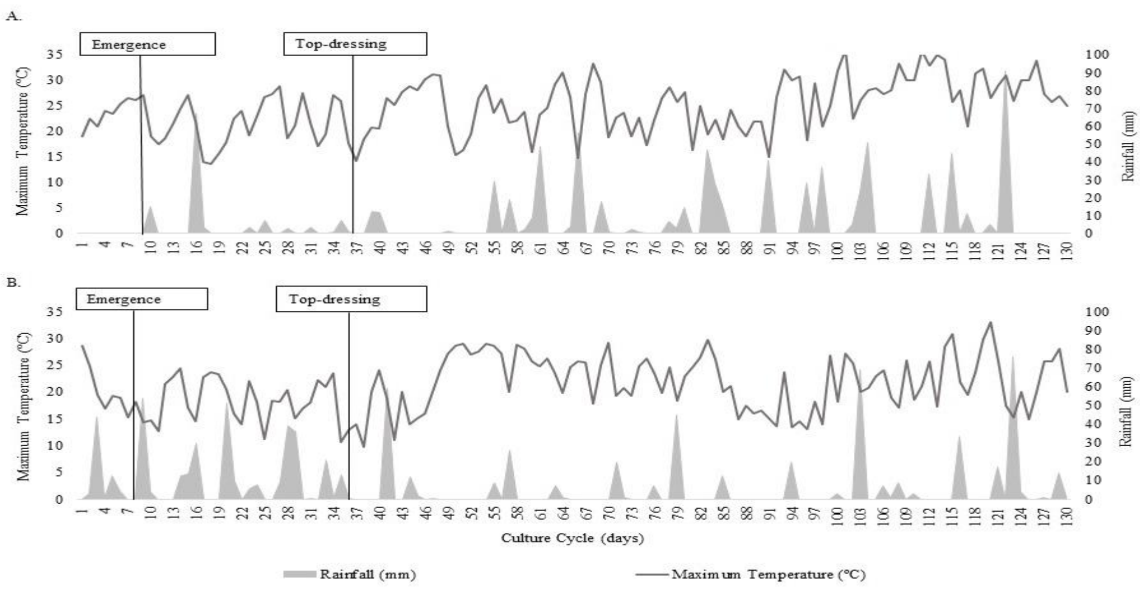

Figure 2. Rainfall and maximum temperature in wheat development. (A) agricultural year 2017 with 1576 kg ha^{-1} grain yield; (B) Agricultural year 2018 with 2246 kg ha^{-1}

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In 2018 (Figure 2B) the greater rainfall was from sowing to 40 days of wheat development and with maximum air temperature lower them registered in 2017. The rainfall had lower intensity and better distribution from the reproductive growth stages to maturity (Figure 2B), facts that gives out the greater grain yield in 2018 in relation to 2017.

Although the technological and scientific advances, the climate still is the most important variable on agriculture (Ayoade, 2010). Being one of the major factors responsible for the cropping variation (Lucena *et al*., 2012). The climate interfere under many agriculture steps as: the ideal conditions of tillage, sowing period, harvest, carriage, storage and others (Cunha, 2013). On it, rainfall and air temperature are the meteorological variable crucial for the yield farming success (Baldisera and Dallacort, 2017). The water shortfall induce the plants stomatal closure leading to reduction transpiration and photosynthesis (Souza *et al*., 2019), committing the productivity and hence the economy and food security (Pohlmann and Lazzari, 2018). Therefore, the rainfall is the decisive variable to comprehend agricultural strategy (Junges *et al*., 2019). Besides, higher temperatures promote biomass yield reduction by the raise respiration rate and stomatal closure, reducing photosynthesis and favours nitrogen losses by volatilization during fertilization (Costa *et al.*, 2018). For instance, as temperature is related to atmospheric humidity, solar radiation, wind speed, rainfall, evaporation and transpiration, can provide valuable information for the crop planning (Ahmadi *et al*., 2018).

In Table 1, regardless the crop system and N-fertilizer dose, in 2017 showed values of biomass productivity upper 2018, until the 60 days after emergence. Although the maximum temperature average had been lower in 2018, which should further the crop, the lowest productivity can be explain due to the rainfall amount, provided large periods without sunlight, limiting the photosynthesis efficiency to biomass yield (Table 1). Stem from the 90 days after emergence, the biomass yield range between the years 2017 and 2018 significantly decreased (Table 1) indicate similarity. In addition, in 120 days after emergence shows a reversal in maize/wheat system, with biomass yield in 2018 upper then 2017.

Table 1. Meteorological data and biomass yield in wheat phenological stages with nitrogen use

Phenological stages (days)	Year	$\sum Rain$	$\overline{X}_{MaxT}$	soybean/maize BY (kg ha^{-1})	maize/wheat BY (kg ha^{-1})
			0 kg ha^{-1} of N		
30	2017	112	21.3	368	236
	2018	308	18.1	170	130
60	2017	307	23.0	1962	858
	2018	437	20.3	1090	557
90	2017	548	23.1	6546	3685
	2018	570	20.4	5532	2855
120	2017	813	24.7	6765	4651
	2018	736	21.0	6340	5402
			30 kg ha^{-1} of N		
30	2017	112	21.3	335	242
	2018	308	18,1	202	111
60	2017	307	23.0	2880	1036
	2018	437	20.3	1654	665
90	2017	548	23.1	7785	4979
	2018	570	20.4	7838	4019
120	2017	813	24.7	7818	5666
	2018	736	21.0	8071	7535
			60 kg ha^{-1} of N		
30	2017	112	21.3	328	221
	2018	308	18.1	188	116
60	2017	307	23.0	3043	1854
	2018	437	20.3	1813	1234
90	2017	548	23.1	7742	5809
	2018	570	20.4	7445	6380
120	2017	813	24.7	8474	5859
	2018	736	21.0	8844	8685
			120 kg ha^{-1} of N		
30	2017	112	21.3	359	244
	2018	308	18.1	201	110
60	2017	307	23.0	3630	1967
	2018	437	20.3	1804	1521
90	2017	548	23.1	8964	7321
	2018	570	20.4	9117	7750
120	2017	813	24.7	10860	7520
	2018	736	21.0	10533	11033

N - nitrogen; BY- biomass yield; $\sum Rain$ - rainfall sum (mm); $\overline{X}_{MaxT}$ - maximum temperature average (℃)

The results in Table 1 shown complexity action of meteorological condition over yield expression that is direct affect over the development cycle, what justify the need of models more efficient and computational techniques to move on reliable predictions. It is worth highlighting that this information (Table 1) engage the complexity of biological and environmental variables and linear and non-linear effects during the crop. It will be used on artificial neural networks (ANN) training in proposal the simulation of wheat grain yield during the development cycle. This perspective, in Table 2, are shown the mean squared error, mean relative error and variance, observed during the test and validation process for ANN architecture to distinct successions systems.

Table 2. Dimensionless values of the mean squared error to training data, mean relative error and variance to validation data on the training architecture

Architecture NI-NHL-NNO	Mean squared error (training)	Mean relative error (validation)	Variance (validation)
	Soybean/wheat system (2017+2018)		
5-5-1	0.0165	0.0312	0.0206
5-6-1	0.0055	0.0776	0.0182
5-7-1	0.0091	0.0241	0.0170
5-8-1	0.0015	0.0150	0.0180
5-9-1	0.0088	0.0244	0.0196
5-10-1	0.0095	0.0250	0.0175
	Maize/wheat system (2017+2018)		
5-5-1	0.0063	0.0047	0.0777
5-6-1	0.0071	0.0163	0.0256
5-7-1	0.0078	0.0012	0.0276
5-8-1	0.0075	0.0814	0.0300
5-9-1	0.0079	0.0293	0.0159
5-10-1	0.0065	0.0176	0.0221

NI - input variable numbers, NHL - hidden layer neuron numbers and NNO - output layer neuron numbers

To simulated the ANN in wheat grain yield was choose, considering the architecture, whom presented differences between the amount of neurons on the hidden layer and the input layer equal or greater a two and between the lowest mean relative error on the validation and training process. Highlight that the chosen architecture were 5-8-1 to soybean/wheat system and 5-7-1 to maize/wheat system, values that represent the amount of neuron on input layer, hidden layer and output layer, respectively (Table 2). This way, the Figure 3 shows the determination coefficients (R^2) close to one on the training, test and validation process. It allows to confirm the ANN trust in generate algorithm who dimension the real data behavior and generalise the learning to simulation the wheat grain yield, considering the inclusion of biological and environmental variable on the computational process.

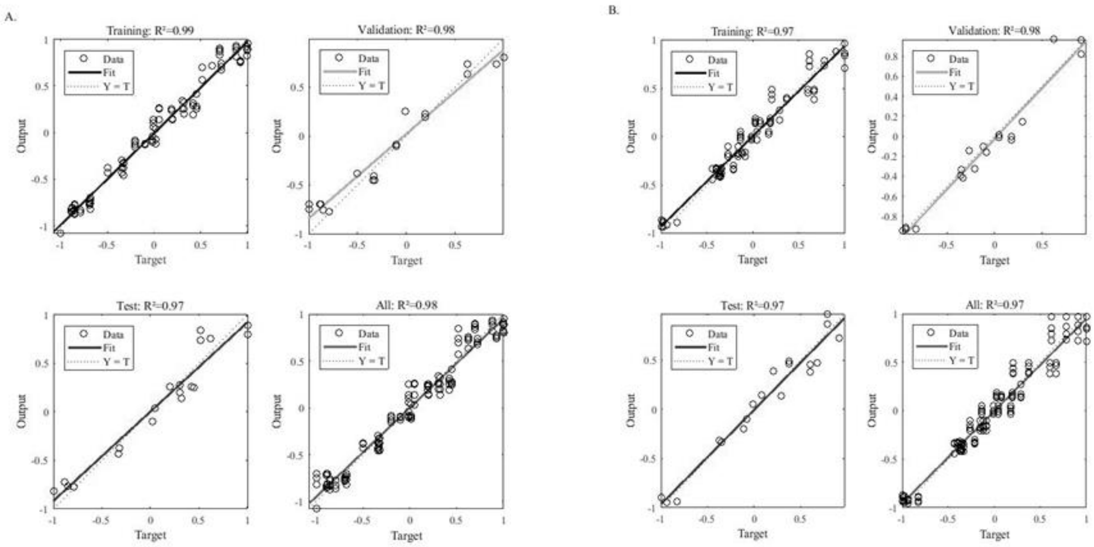

Figure 3. Determination coefficient of training, test, validation, and all neural artificial networks. (A) Architecture 5-8-1 to soybean/wheat system; (B) Architecture 5-7-1 to maize/wheat system

In Table 3, shown the average comparison of wheat grain yield observed and simulated through ANN for each crop system. Stands out, the grain yield increased due to the nitrogen dose rise, evidencing a quadratic behavior (Figure 4). This same pattern also was recognized by the ANN since the simulation on 30 days after the emergence, regardless the crop system. To illustrate, in soybean/wheat system highlight the nitrogen 120 kg ha^{-1} condition with average 2728 kg ha^{-1} wheat grain yield, and the ANN simulation shown on the 30 days after emergence the average 2801 kg ha^{-1} grain yield. These results differs (AE) in just 73 kg ha^{-1} grain, which confirm the high ability of ANN to prediction. Thus, stands out that the greater AE were under 200 kg ha^{-1} wheat grain (Table 3), fact that vouch the ANN validation on predictability grain yield.

Table 3. ANN simulation in wheat grain yield in distinct phenological stages with nitrogen use

N (kg ha^{-1})	phenological stage (days)	Soybean/wheat system			Maize/what system		
		GYs	$\overline{X}GYo$ (2017+2018)	AE	GYs	$\overline{X}GYo$	AE
0	30	1421	1381	40	959	880	79
	60	1391		10	860		20
	90	1434		53	957		77
	120	1372		9	916		36
30	30	2358	2167	191	1439	1468	29
	60	2245		78	1450		18
	90	2263		96	1450		18
	120	2283		116	1381		87
60	30	2724	2542	182	1740	1716	24
	60	2559		17	1765		49
	90	2550		8	1791		75
	120	2604		62	1626		90
120	30	2801	2728	73	2126	1948	178
	60	2766		38	2102		154
	90	2780		52	1890		58
	120	2843		115	1769		179

N - nitrogen; GYs - simulated grain yield (kg ha^{-1}); $\overline{X}GYo$ - observed grain yield average (kg ha^{-1}); AE - absolute error (kg ha^{-1})

The Figure 4, regardless the crop system, evidence the quadratic behavior for wheat grain yield on crop field and simulated in ANN. For quadratic behavior in soybean/wheat system (Figure 4A), the maximum technical efficiency of nitrogen use by the real data was with 100 kg ha^{-1}. The quadratic equation obtain through ANN simulation shown maximum technical efficiency in 93 kg ha^{-1} nitrogen, a slight variation of 7 kg ha^{-1} that would not modify the productivity on real cropping.

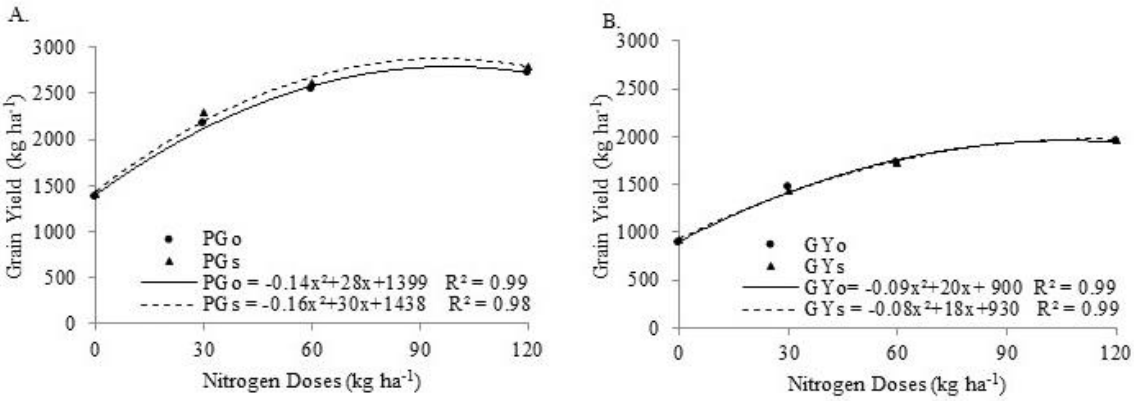

Figure 4. Behavior and parameters of grain yield regression equation observed and simulated by artificial neural network. GYo – grain yield observed (kg ha^{-1}); GYs – grain yield simulated (kg ha^{-1}); R^2 – determination coefficient; (A) soybean/wheat system; (B) maize/wheat system

In maize/wheat system (Figure 4B), the maximum technical efficiency of nitrogen use with real crop field data was 111 kg ha^{-1}. The equation created with simulated values by ANN shown maximum technical efficiency 113 kg ha^{-1} nitrogen. Also on this condition, the slight variation observed was 2 kg ha^{-1} who ensure the technique quality in proposition to ally biological and environmental indices to simulate wheat grain yield over the development cycle. Therefore, is possible to validate the ANN use on grain yield predictability in each wheat phenological stage, in different condition of nitrogen use on distinct succession systems, regard to the non-linearity of maximum air temperature and rainfall with biomass information obtained during the crop cycle.

The ANN allows complex systems modeling who has properties as: function capacity, linear and non-linear multiple variables with unknown interactions and good generalization capacity (Demuth *et al*., 2014). These models are able to quickly process a large data amount and recognise patterns based on self-learning (Teodoro *et al.*, 2015). Therefore, the ANN has been awakening the agricultural interest due to the simulation ability and process optimization. On this perspective, detaches the studies conducted with the optimization of oats seeding rate with grain yield forecast (Dornelles *et al.*, 2018), eucalypt volume simulation considering biological different parameters of the specie (Bhering *et al*., 2015), tree height simulation with different growth conditions (Campos *et al.*, 2016). Soybean yield simulation with agronomic features, growth habits and population density (Alves *et al.*, 2018). In maize, Soares *et al*. (2015) had used morphological variable to simulate the crop grain yield using multilayer ANN with backpropagation training algorithm. Reis *et al.* (2018) also used this ANN model to project a diametrical distribution in Amazônia.

4. Conclusion

The multilayer artificial neural networks with the backpropagation learning algorithm and with the network architecture 5-8-1 and 5-7-1 on soybean/wheat and maize/wheat, respectively, is able to simulate wheat grain yield with the nitrogen dose at top-dressing and non-linearity of the maximum air temperature and rainfall with biomass information obtained during the crop cycle.

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