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FUZZY MODELING OF THE EFFECTS OF DIFFERENT IRRIGATION DEPTH IN RADISH CROP. PART II: BIOMETRIC VARIABLES ANALYSIS

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KEYWORDS

biometric variables, fuzzy logic, irrigation depth, polynomial regression, neural network.

ABSTRACT

In order to estimate the response of biometric variables in different irrigation depths in radish crop, as well as their relations in the development of the crop, a fuzzy mathematical analysis was carried out from irrigation with depths of different percentages of the crop evapotranspiration (ET_c), using Gaussian pertinence functions for the input variable and triangular for the biometric output variables. Validations were performed using neural network models, smoothing splines and polynomial regression. The relation among the biometric variables was measured applying the Pearson correlation coefficient. The results showed that the fuzzy modeling presented superiority in the crop development estimate over the quadratic polynomial regression model, neural network and smoothing splines, because it achieved an average reduction of errors among the biometric variables, of 7.8% 94.6% and 9.2% for the RMSE in the respective models, as well as a better adjustment of the data with average R² of the variables. The modeling with neural network showed inadequate agronomic behavior in data representation. Regarding biometric variables, the length and diameter of the tuberous root are inversely correlated, and the fresh phytomass of the tuberous root is correlated only with the fresh phytomass of the root.

INTRODUCTION

Radish (*Raphanus sativus*) is a crop that has its biometric parameters highly influenced by external factors. It belongs to the Brassicaceae family and is composed of tuberous roots below ground, and stem and leaves above it (Embrapa, 2012). The tuberous roots are divided into edible parts (where energy is stored) and fixing parts (where it fixes itself to the substrate, nutrients are absorbed, and water and mineral salts are conducted). The edible part can be found in several shapes, from elliptical to elongated or round forms, with diameters ranging between 2 and 5 centimeters. It can also be white, purple, red, or black colored, while its pulp is white (Dantas et al., 2015).

From studies of Filgueira (2007), the radish poor quality and productivity is related to the water stress and the soil temperature and can obtain spongy aspects of the root and cracks. In a study conducted by Bregonci et al. (2008),

the diameter and length reduction of the roots in the two crop cycles was observed.

New structures for verifying information from field experiments allow the use of more advanced techniques. One option is the introduction of mathematical modeling, as it allows, in more advanced processes, to consolidate the results obtained experimentally (Bordin, 2016).

According to Gabriel Filho et al. (2015), the fuzzy logic enables such solidification in a more comprehensive way, because it is applied in vague concepts where it cannot allow the manipulation by traditional logic. By using sets, the fuzzy theory performs its concepts close to the human reasoning in inaccuracies sites (Cremasco et al., 2015, Olivindo et al., 2019).

The use of this tool can be employed in several agricultural areas, such as in studies involving the impacts generated by the irrigation depths in beet crop (Gabriel Filho et al., 2015), in analyzes involving the growth of lettuce crop irrigated with magnetically treated water (Putti,

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2015), effects on tomato crop by the use of saline water (Bordin, 2016), among other studies that need mathematical and computational methods.

Given the above, this study aimed to analyze the efficiency of fuzzy modeling in estimating biometric parameters of the development of radish plants under different irrigation depths, based on crop evapotranspiration, correlating the parameters among themselves.

MATERIAL AND METHODS

Experiment description

The experiment was carried out from September to November 2013, at the Department of Rural Engineering of the School of Agronomic Sciences of UNESP, Botucatu, Brazil (22° 51' S, 48° 26' W, and 786 m altitude). The local climate is defined by Köppen's classification as *Cfa* type, which stands for humid subtropical climate (Köppen & Geiger, 1928).

Crop evapotranspiration was measured using a class-A tank installed in the vicinity of the experimental area. The measurements were performed daily at 08:00 a.m., with an accumulated value of 114.2 mm throughout the cycle.

The experiment irrigation used two independent drip systems, with a main line, and secondary lines with drips separated among each other in 0.30 m, with a pressure of 10 m.w.c. and a flow of 1.47 L.h⁻¹. The system efficiency was of 95% and for calculation of the irrigation, time the following equation was used:

$$Ti = 6000 \frac{Kc \cdot Kp \cdot Eca \cdot Sl \cdot Sg \cdot TR}{Ei \cdot Vg} \quad (1)$$

Where:

Kp: the tank coefficient;

Kc: the crop coefficient;

Sl: the spacing between sides (m);

Ei: the irrigation efficiency (%);

Eca: the evaporation of "Class A" tank (mm day⁻¹);

Sg: spacing among drips (m),

Vg: the drips flow (L h⁻¹).

The total irrigation depth was stipulated according to the methodology proposed by Snyder (1992), where it is necessary to use the tank coefficient (*Kp*) defined by the following equation:

$$Kp = 0.0482 + 0.024 \ln(B) - 0.00376 V + 0.0045 UR \quad (2)$$

Where:

B: the border of the vegetation area around the tank (m);

V: the wind speed at 2 meters high (m.s⁻¹);

Kp: the tank coefficient;

UH: the average of relative humidity in percentage.

The values of the irrigation depths applied were 28.6, 57.1, 85.7, 114.2 and 142.8, for 25%, 50%, 75%, 100% and 125%, respectively. As definition for this study, the variables related to the tuberous root are indicating the values regarding the commercialized part of the root of the radish crop.

For the cultivation of radish, sowing was carried out directly in the soil, with pruning on the fourteenth day after the sowing (DAS). The spacing adopted among the crops was of 25 cm by 5 cm, with plots of 4 planting lines in an area of 3.6 m² described by 1.2 m wide and 3 m in length.

To evaluate the development and productivity of the radish crop, biometric variables were analyzed: leaf number (LN), root length (RL), tuberous root diameter (TRD), tuberous root length (TRL), fresh root phytomass (FRP), fresh leaf phytomass (FLP), fresh tuberous root phytomass (FTRP), dry root phytomass (DRP), dry leaf phytomass (DLP), dry tuberous root phytomass (DTRP).

The experiment was conducted in an entirely randomized design (RD), with 5 irrigation depth, where each depth was evaluated with 5 repetitions. The radish crop used in the experiment was Maçarias - Radish No. 19, of Sakata company.

After the harvest, there was the separation of biometric variables to obtain the desired data. The leaves were separated and counted manually. The fresh leaf phytomass was measured with the help of a digital scale graduated at 0.001 g and then maintained in a greenhouse with temperature of 65 °C for 72 hours, performing the dry matter weighing. For measuring the root length, diameter and the tuberous root length, a caliper was used, calibrated in millimeter (mm).

Fuzzy Modeling

Fuzzy models were developed to estimate the biometric variables of radish development and production at harvest point (35 days after transplant). The models were designed according to an agronomic model presented and defined by Putti (2015), which is based on the following function: $f: X \subset \mathbb{R} \rightarrow \mathbb{R}^{10}$; wherein $F(x) = (f_1(x), f_2(x), f_3(x), f_4(x), f_5(x), f_6(x), f_7(x), f_8(x), f_9(x), f_{10}(x)))$, in which x is the irrigation depth (% ETc), with $x \in X = [25, 125]$ and $y = (y_i)$ representing the biometric variables to be assessed.

The fresh root phytomass (FRP) variable was analyzed by several fuzzy models, with details of all possible methodological procedures in Boso et al. (2021).

Figure 1 shows the Fuzzy Rule Based System (SBRF) for radish crop, which is composed of five input variables, namely: *Irrigation depths* (%), indicated as Li , wherein $i = 1, 2, 3, 4, 5$; ten output variables; and a set of five rules for the development of the system. This definition was materialized as the experiment was performed. The irrigation depths were estimated by ETc levels, increasing by 25% from one to another. Biometric variables of crop yield were used as output variables.

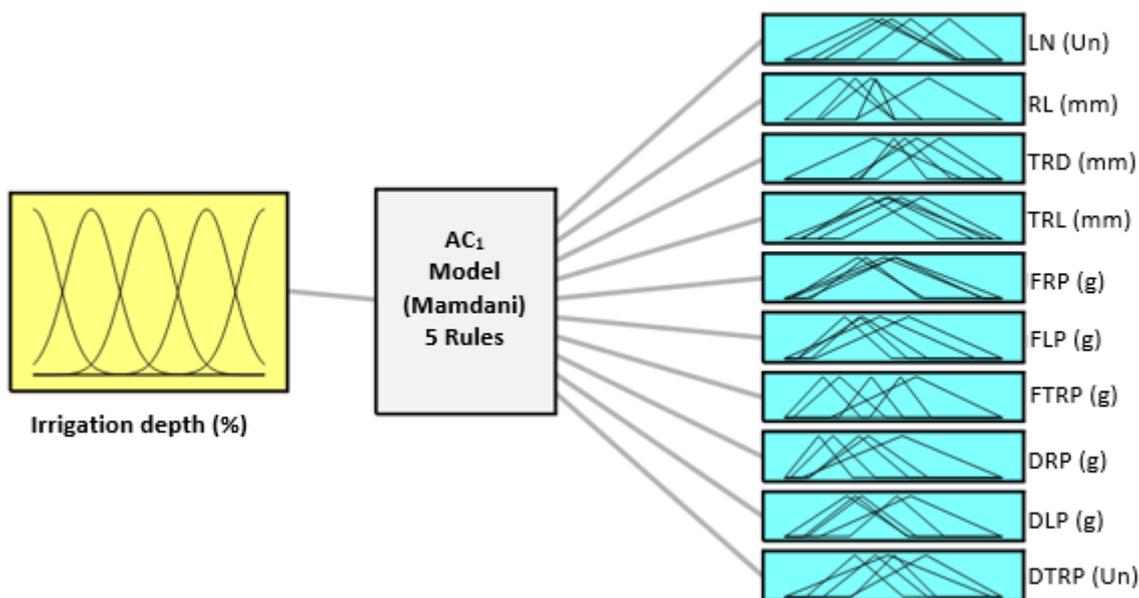


FIGURE 1. Fuzzy rule-based system for estimating radish crop yield, with Gaussian membership functions for the input variable (irrigation depth in % of ETc) and triangular membership functions for the output biometric variables and 5 rules. Output variables: leaf number (LN), root length (RL), tuberous root diameter (TRD), tuberous root length (TRL), fresh root phytomass (FRP), fresh leaf phytomass (FLP), fresh tuberous root phytomass (FTRP), dry root phytomass (DRP), dry leaf phytomass (DLP), dry tuberous root phytomass (DTRP).

Figure 2 shows the Gaussian pertinence functions adopted for the fuzzy sets of the input variable “Irrigation Depth”, which points with pertinence degree equals 1 represent the adopted depths, namely 25%, 50%, 75%, 100% and 125% of the ETc.

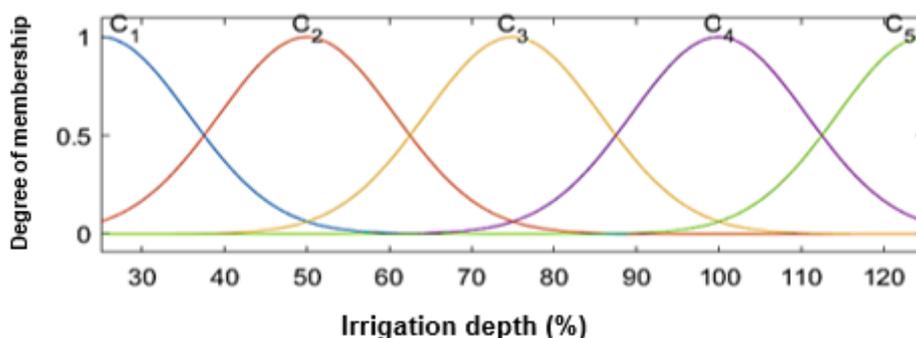


FIGURE 2. Gaussian pertinence functions for the input variables (irrigation depth), of the FRBS, related to the fuzzy sets C_1, C_2, C_3, C_4 and C_5 , concerning the irrigation depths 25%, 50%, 75%, 100% and 125% of the ETc, respectively, with pertinence degree points varying between 0 and 1.

The rule base was developed from the argument: “If Depths is C_i then the output variable is $C_{k_i}, i = 1,2,3, 4, 5$ ” where the input variable is the antecedent and the output variable is the consequent. Five rules were created with the input (*water depths*) and output variables the biometric variables (LN, RL, TRD, TRL, FRP, FLP, FTRP, DRP, DLP, DTRP).

The fuzzy rules construction was performed with the combinations among the mentioned variables, according to the pertinence degree that are associated to the input fuzzy sets (C_i), and to the output fuzzy set (C_{k_i}). Table 1 describes the combination of the input and output variables for the formation of the FRBS rule base.

TABLE 1. FRBS rules base, for radish culture, in the estimate of the biometric variables in the harvest point, with 5 input fuzzy sets, 5 output fuzzy sets and 5 rules. Output sets: LN (leaf number); RL (root length); TRD (tuberous root diameter); TRL (tuberous root length); FRP (fresh root phytomass); FLP (fresh leaf phytomass); FTRP (fresh tuberous root phytomass); DRP (dry root phytomass); DLP (dry leaf phytomass); DTRP (dry tuberous root phytomass).

Rules	Input Sets	Output Sets									
		LN	LR	TRD	TRL	FRP	FLP	FTRP	DRP	DLP	DTRP
1	1	5	4	2	4	5	4	3	4	5	4
2	2	4	3	5	3	3	3	1	5	4	3
3	3	3	5	4	1	4	5	4	3	3	5
4	4	2	2	3	2	2	1	5	2	2	2
5	5	1	1	1	5	1	2	2	1	1	1

The construction and development of the fuzzy modeling, was initially analytical and subsequently structuring it mathematically with the aid of electronic spreadsheets (Excel software) and by the Fuzzy Logic Toolbox, present in Matlab® software. Similar systems can be found in Cremasco et al. (2010), Cremasco et al. (2015) Gabriel Filho et al. (2011, 2015, 2016), Pereira et al. (2008), Putti et al. (2014, 2017a, 2017b), Viais Neto et al. (2019a, 2019b), Martínez et al. (2020) and Góes et al. (2021).

Model validation

The efficiency of fuzzy models was analyzed by a polynomial regression of second degree. According to Sousa & Alves (2016), regression analyses aim to predict possible relationships between dependent and independent variables in experimental data by mathematical models developed.

In order to realize and emphasize the efficiency of fuzzy modeling, it has also developed the smoothing spline modeling and neural network. According to Helwig (2017) splines is a set of flexible functions capable of smoothly modeling data. The analyzed data are called nodes, where these are in the spline interval. For each pair of nodes, the spline function assumed a polynomial of n degree. The Smoothing Spline is defined for the parameter *p* and weight *W_i*. The non-definition of weights presupposes 1 for all analyzed data and the *p* value is defined between values 0 and 1. The Smoothing Spline is defined by the minimizer (Boor, 2001):

$$p \sum_i W_i (Y_i - f(x_i))^2 + (1 - p) \int \left(\frac{D^2 f}{Dx^2} \right)^2 Dx \quad (3)$$

For Teramoto et al. (2020), neural networks are made up of neurons capable of processing information efficiently. Using a data set and a training program, the algorithm allows estimating values closer to reality. For the data of the present study, 10 hidden neurons and the Levenberg-Marquardt algorithm were used. This algorithm is based on the least squares method, seeking to find the most appropriate adjustment for a given set of data, minimizing residues between the real data and the adjustment curve. Its resolution is given by the following equation (França et al., 2009):

$$(J^T(x_k)J(x_k) + \lambda_k I)d_k = -J^T(x_k)R(x_k) \quad (4)$$

Where:

J is the Jacobian matrix;

I is the identity matrix, and

λ_k is a determinable parameter.

From the generated models, we sought to measure their efficiency using the coefficient of determination (*R*²) and the root mean square error (RMSE). The values of the deviation from the root mean square error (RMSE) indicate the uncertainty of the model according to the size of the error generated. The smaller the error presented, the better the model is adjusted (Santos et al., 2014; Meskini-Vishkaee & Davatgar, 2018). The determination coefficient (*R*²) consists of validating the quality of the model in representing real data, in a range between 0 and 1, indicating as a percentage (Grácio & Oliveira, 2015).

As a way to evaluate the influence of a variable in the development of another biometric variable of the studied crop, the correlation coefficient (*r*) was used, which indicates the linear association degree among the two variables and its direction measure. This association is expressed by a correlation coefficient, in a numerical way, by clouds of dots in a dispersion diagram (Martins & Rodrigues, 2014).

The correlation coefficient has values understood between -1 and 1, where the negative demonstrates that the variables are inverse, and the positive value demonstrates that the variables are direct. The higher the coefficient, the higher will be the association degree of the analyzed variables (Lordelo et al., 2018)

The yield estimation data for radish crop generated by the fuzzy model and by polynomial regression were statistically assessed by the Minitab software.

RESULTS AND DISCUSSION

Based on data of biometric parameters of radish yield, fuzzy models were employed by Gaussian pertinence functions for input variables (irrigation depths, in %ETc) and triangular functions for output values (biometric variables).

Gaussian pertinence functions were chosen for Input variables because they produce smoother curves and better phenomenon presentation, from an agricultural point of view. However, by allowing function points to coincide with data averages and better results with fewer errors, a triangular pertinence function was used for output variables. Figure 3 shows triangular pertinence functions of the output variables, and Table 2 their delimiters.

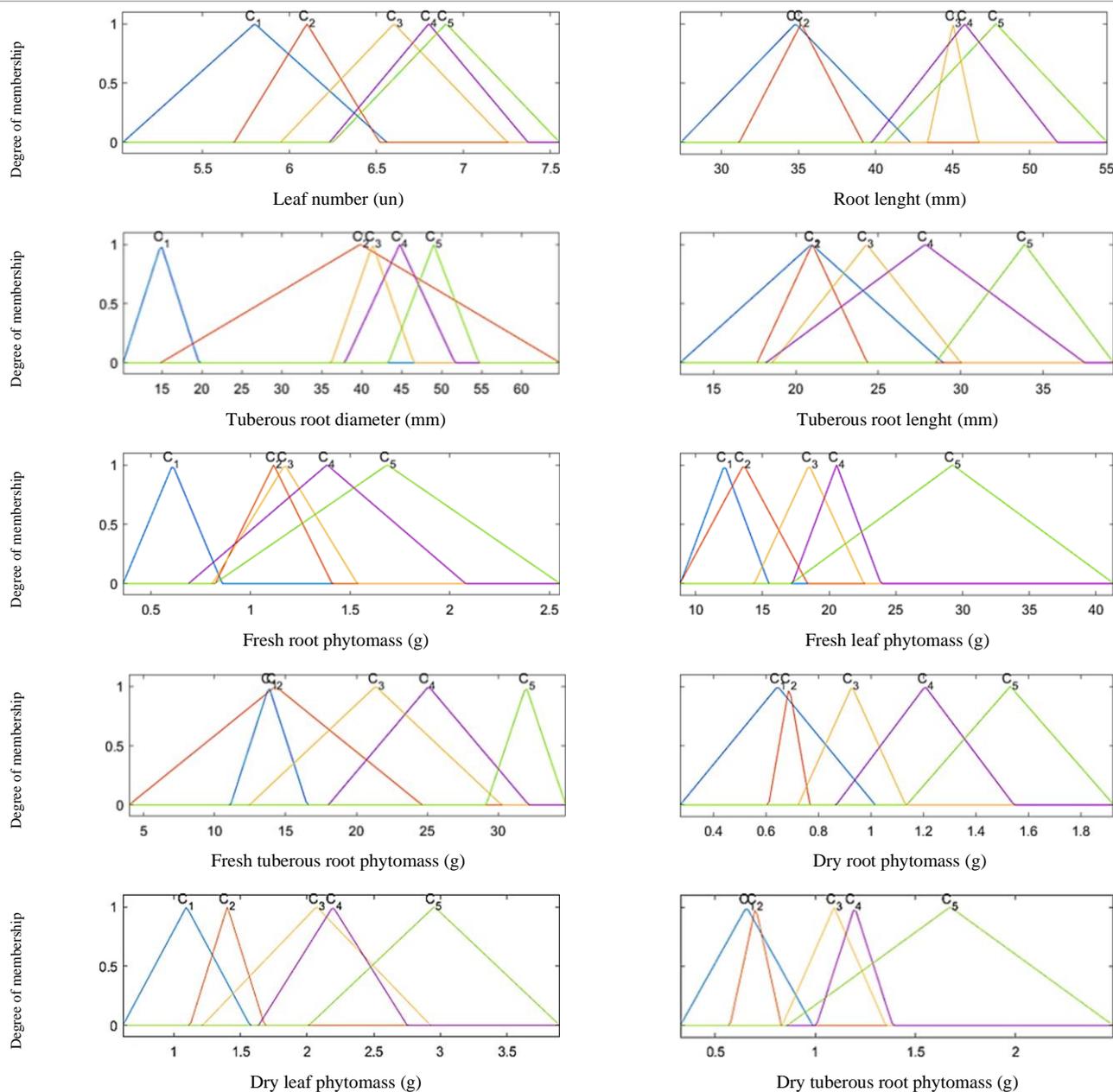


FIGURE 3. Triangular pertinence functions of the fuzzy sets C_1, C_2, C_3, C_4 and C_5 of the biometric (output) variables of the radish culture.

TABLE 2. Delimitators of the triangular pertinence functions of the fuzzy sets $C_1, C_2, C_3,$ and C_5 of the biometric output variables, concerning the irrigation depths 25%, 50%, 75%, 100% and 125% of the ETC, respectively. Output sets: LN (leaf number); RL (root length); TRD (tuberous root diameter); TRL (tuberous root length); FRP (fresh root phytomass); FLP (fresh leaf phytomass); FTRP (fresh tuberous root phytomass); DRP (dry root phytomass; DLP (dry leaf phytomass); DTRP (dry tuberous root phytomass).

		Degree of membership				
		C1	C2	C3	C4	C5
Output Variables	LN	[5.04 5.8 6.6]	[5.7 6.1 6.5]	[5.9 6.6 7.3]	[6.2 6.8 7.4]	[6.2 6.9 7.6]
	RL	[27.4 34.8 42.3]	[31.2 35.2 39.2]	[43.4 45.0 46.7]	[39.7 45.8 51.8]	[40.6 47.8 55.0]
	TRD	[10.2 14.9 19.6]	[14.8 39.8 64.8]	[36.2 41.4 46.5]	[37.9 44.8 51.7]	[43.4 49 54.6]
	TRL	[12.9 20.9 28.9]	[17.6 20.9 24.3]	[18.6 24.3 30.0]	[18.1 27.9 37.5]	[28.5 33.9 39.3]
	FRP	[0.4 0.6 0.9]	[0.8 1.12 1.4]	[0.8 1.5 1.5]	[0.7 1.4 2.1]	[0.8 1.7 2.6]
	FLP	[8.8 12.2 15.5]	[8.8 13.6 18.4]	[14.4 18.5 22.6]	[17.2 20.6 23.8]	[17.2 29.3 41.3]
	FTRP	[11.1 13.8 16.5]	[3.9 14.3 24.6]	[12.5 21.3 30.2]	[18.0 25.1 32.1]	[29.1 31.9 34.8]
	DRP	[0.3 0.6 1.0]	[0.61 0.7 0.8]	[0.7 0.9 1.]	[0.90 1.2 1.5]	[1.1 1.5 1.9]
	DLP	[0.6 1.1 1.6]	[1.1 1.4 1.7]	[1.2 2.1 2.9]	[1.6 2.2 2.8]	[2.0 2.9 3.9]
	DTRP	[0.3 0.7 0.9]	[0.6 0.7 0.8]	[0.8 1.1 1.4]	[1.0 1.2 1.4]	[0.9 1.7 2.5]

After defining the output pertinence functions, the efficiency of the models for each biometric variable was verified by statistical tests. Table 3 shows the statistical results obtained for the validation of the models.

TABLE 3. Validations for the biometric output variables of the radish culture, with information of the determination coefficient (R^2), root mean square error (RMSE) of the fuzzy model, smoothing splines, neural network and polynomial regression. Variables: RL (root length); LN (Leaves Number); DTR (Diameter of the tuberous root); TRL (tuberous root length); FRP (fresh root phytomass); FLP (fresh leaf phytomass); FTRP (fresh tuberous root phytomass); DRP (dry root phytomass); DLP (dry leaf phytomass); DTRP (dry tuberous root phytomass). All R^2 values have $p < 1\%$.

Variable	Index	Fuzzy Model	Polynomial regression	Smoothing Splines	Neural Network
LN	R^2	0.37	0.36	0.37	0.36
	RMSE	0.56	0.56	0.62	0.34
RL	R^2	0.53	0.41	0.48	0.59
	RMSE	5.20	5.81	5.90	26.05
TRD	R^2	0.54	0.52	0.53	0.49
	RMSE	11.21	11.25	12.11	156.39
TRL	R^2	0.38	0.34	0.37	0.02
	RMSE	6.14	6.34	6.67	448.10
FRP	R^2	0.34	0.27	0.32	0.33
	RMSE	0.49	0.52	0.54	0.25
FLP	R^2	0.46	0.21	0.35	0.52
	RMSE	6.37	7.46	7.29	33.92
FTRP	R^2	0.50	0.10	0.45	0.52
	RMSE	6.89	8.81	7.49	42.04
DRP	R^2	0.59	0.43	0.55	0.59
	RMSE	0.28	0.32	0.31	0.08
DLP	R^2	0.54	0.52	0.51	0.49
	RMSE	0.60	0.61	0.66	0.41
DTRP	R^2	0.41	0.26	0.37	0.48
	RMSE	0.42	0.46	0.46	0.15
Mean	R^2	0.47	0.34	0.43	0.44
	RMSE	3.82	4.21	4.21	70.77

According to the statistical analysis of the models, the fuzzy model stood out for all biometric parameters of radish yield when compared to the polynomial regression models. Fuzzy modeling promoted an average reduction of errors among biometric parameters by 7.83% for RMSE as well as better data fitting with average correlation coefficient of biometric parameters (25.9%), thus showing its efficiency for estimating crop yield of radish.

Such fuzzy logic superiority over second-degree polynomial regression for MRSD was also observed by Silva et al., (2014), who analyzed wheat yield with nitrogen fertilization, as well as that by Putti (2015) when analyzing lettuce development when irrigated with magnetically-treated water.

Fuzzy models proved to be more suitable than smoothing splines and neural networks for data analysis. Smoothing splines had an average value of 4.2 of the RMSE error, while that of the fuzzy model was 3.8 for the analyzed parameters. Such a difference shows an average error reduction by 9.2%, thus confirming the efficiency of fuzzy modeling. Neural networks had R^2 values higher than the other models for some biometric parameters. However, the RMSE values (on average, 70.77) of the neural network model demonstrated its unsuitability for such analyses.

To represent a comparison of the model developed for each biometric parameter, Figure 4 graphically demonstrates a comparison between the fuzzy model and statistical model, highlighting the efficiency of each one.

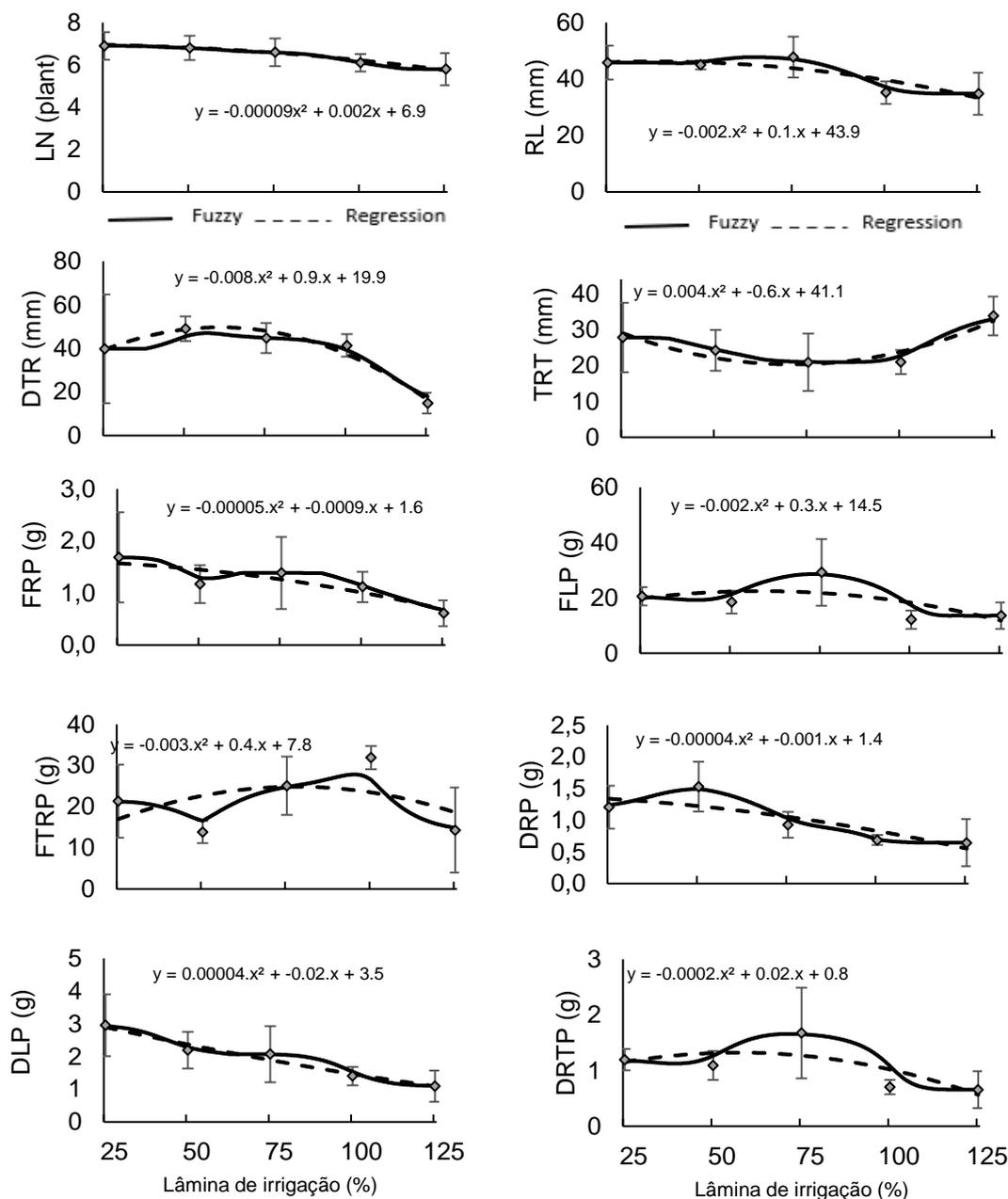


FIGURE 4. Comparison among the fuzzy and linear regression models of the biometric variables of the radish culture according to the irrigation depths. Variables: LN (leaf number); RL (root length); TRD (tuberous root diameter); TRL (tuberous root length); FRP (fresh root phytomass); FLP (fresh leaf phytomass); FTRP (fresh tuberous root phytomass); DRP (dry root phytomass); DLP (dry leaf phytomass); DTRP (dry tuberous root phytomass). In each variable, the quadratic regression equation is shown along the curve.

The response function for the number of leaves (LN) showed a difference between the proposed fuzzy model and the statistical model. However, when analyzing model validation, the fuzzy model presented an R^2 of 0.37 for LN, and 0.56 for RMSE, in contrast to the regression model that presented R^2 of 0.36 for LN, and 0.56 for RMSE.

Root length (RL) had higher estimates for irrigation depth of 75% *ETc* using the fuzzy model. For Wan & Kang (2006), more developed root systems may be related to low water availability in the soil, as roots tend to grow more to meet their water needs. The same behavior could be seen for fresh root phytomass (FRP) and dry root phytomass (DRP).

Results of tuberous root diameter (TRD) for irrigation depths of 50 and 75% *ETc* were similar for both

models analyzed. Likewise, Klar et al. (2015) analyzed TRD of radish and observed higher values for irrigation depths of 72 and 85% *ETc*. However, it reduced irrigation for irrigation depths of 25 and 125% *ETc*. This was also reported by Bregonci et al., (2008), who found TRD reductions when radish plants were submitted to water stress. Water deficit increases soil tension, increasing soil water retention and withdrawal by plants. On the other side, water excess decreases plant absorption of the oxygen in the soil, reducing development (Lacerda et al., 2017).

These radish development behaviors are physiological and biochemical consequences that affect biometric parameters. When subjected to stress, the first defense mechanism of plants is stomatal closure to prevent

water loss (Hosseinzadeh et al., 2016). As a result, internal CO₂ concentration increases, inhibiting Rubisco activity and hence photosynthesis (Rahbarian et al., 2011). Accordingly, it leads to biometric changes including increases in hypocotyls, internodes, petioles, sheaths, and leaf inclination angle; reductions in leaf area, branch length, and tillering; as well as early flowering (Zhang et al., 2019).

This can be seen also in the dry tuberous root phytomass (DTRP) and fresh tuberous root phytomass (FTRP), where they had low results with the irrigation depths of 25% and 125%, and (1.2 and 21.3) and (0.7 and 14.3) respectively. The tuberous root length variable (TRL) achieved productivity in the depth of 125% (34 mm), with approximation of its value in the depth of 25%, (28 mm), when observed by the fuzzy modeling.

Analyzing the efficiency of the irrigation depths, by the fuzzy modeling in the biometric variables, it is verified that the depth corresponding to 75% of ET_c presented

significant production and development, in the radish crop, over the other irrigation depths used. The same can be seen by the polynomial regression model, where the irrigation depth in 75% of the ET_c also demonstrates efficiency in the development of most of the biometric variables analyzed. This can be an option in the reduction of resources destined for irrigation for the radish crop, in the climate and local conditions of the experiment.

Regarding the neural network model, Figure 5 shows, from an agronomic point of view, the disadvantage of applying the model in data analysis. It is observed that among the irrigation depths of 100% and 125%, the values obtained from the productivity of the dry phytomass variable of the tuberous root reached negative points, as well as peaks in the data representation curve, which is not consistent with phenomena related to the plant growth and with the opposite representation of fuzzy modeling, which demonstrated with efficiency and smoothness the curves in the data estimation.

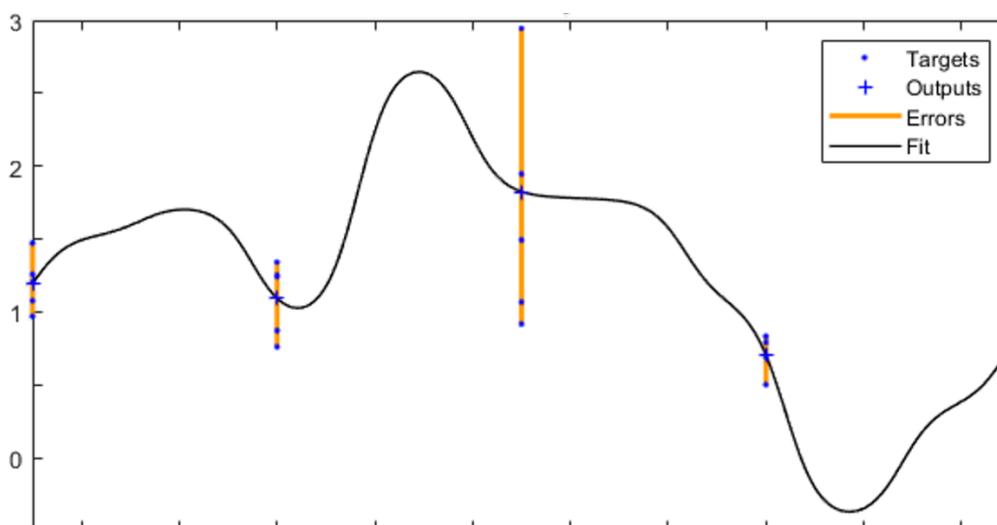


FIGURE 5. Graphical validation of the neural network model for the biometric variable Dry Tuberose Root Phytomass.

As a way to analyze the development relationship among the biometric variables, the Pearson correlation coefficient was calculated (Table 4). The Pearson ratio verifies the association degree between two variables, through the correlation coefficient and of the p-value.

TABLE 4. Correlations among the biometric output variables of the fuzzy model, for the radish culture, referring to the DAS 35. Variables with the symbol “ * ” demonstrated correlation at a 5% significance level of the F test. Variables: RL (root length); LN (Leaves Number); DTR (Diameter of the tuberous root); TRL (tuberous root length); FRP (fresh root phytomass); FLP (fresh leaf phytomass); FTRP (fresh tuberous root phytomass); DRP (dry root phytomass); DLP (dry leaf phytomass); DTRP (dry tuberous root phytomass).

	LN	RL	TRD	TRL	FRP	FLP	FTRP	DRP	DLP
RL	0,52*								
TRD	0,47*	-							
TRL	-	-	-0,411*						
FRP	0,61*	0,58*	-	-					
FLP	0,44*	0,81*	-	-	0,51*				
FTRP	-	-	-	-	0,42*	-			
DRP	0,49*	0,53*	0,53*	-	-	-	-		
DLP	0,73*	0,69*	-	-	0,89*	0,55*	-	0,49*	
DTRP	0,46*	0,84*	0,40*	-	0,58*	0,97*	-	-	0,62*

It was verified that the variables, dry leaf phytomass (DLP) and fresh root phytomass (FRP) presented r (correlation coefficient index) high and positive, with the leaf number variable (LN), with values 0.726 and 0.614 respectively. According to Putti (2015), this phenomenon occurs due to the high temperatures that are perceived in the site during the performance of an experiment, since high temperatures cause the plant to have greater growth in the initial phenological phases.

The root length variable (RL) presented high correlation with the dry tuberous root phytomass (DTRP) and fresh leaf phytomass (FLP) variables. According to El-Desuki et al. (2005), the root length productivity is related to the plant leaf number and the leaf area. This relation occurs due to a light interception, generating a greater production of photoassimilates.

Regarding the tuberous root diameter variable (TRD), a negative correlation was observed with the tuberous root length (TRL), that is, the variables are inverse. As the tuberous root diameter increases, the length decreases and vice versa. This is due to the high temperature in the cultivation period. According to Lima & Oliveira (2018), the tuberous root growth is impaired by the high environment temperatures and by the excess of irrigation before the tuberous root development period. This promotes a fast TRD growth and a decrease of its length. The tuberous root growth coefficient with the other variables did not demonstrate significance at the level of 5%.

The fresh leaf phytomass variable (FLP) reached a high correlation (0.970), with the dry tuberous root phytomass variable (DTRP). Hence, according to Lacerda et al. (2017), the relation between fresh leaf phytomass and the dry tuberous root phytomass is directed with the water availability. In his study, the author mentions that the crop productivity obtained better results when applied a depth of 100% and 125%.

The similarity among the biometric variables can be related to the environment conditions, which allows better photosynthetic performance and higher quantity of photoassimilates (Santos et al., 2019; Silva et al., 2016)

CONCLUSIONS

According to the validation of the developed models (fuzzy and linear regression), the fuzzy model showed to be superior over the statistical model for all biometric parameters, with higher R^2 values and lower error indexes (MRSP and MAE), thus demonstrating its efficiency in data estimation for the decision-making in setting irrigation timing. The quadratic polynomial regression model exhibited correlation coefficients (R^2) of $p > 0.05$, therefore, it is not a significant model for the analyzed data.

The same analysis also showed that the fuzzy modeling was also superior to the neural network and smoothing splines models, which had mean errors of RMSE for biometric parameters superior to the RMSE of the fuzzy modeling.

Neural network model cannot be used to represent yield data for radish crop since it showed curves with unsuitable behavior for agronomic representation.

The analyses showed that the fuzzy modeling was predominant in all developed models, with emphasis on its superiority over neural network modeling due to its more suitable R^2 and RMSE for data validation, as well as its

smooth graphical representation that is closer to the agronomic reality of crop development.

Based on the biometric parameters analyzed, radish crop can achieve high yields with an irrigation depth of 75% of the crop evapotranspiration, which can lead to great savings in relation to the final cost of production.

Correlation coefficients demonstrate that biometric parameters of radish have association with plant yield and photoassimilate productions.

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