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Fuzzy Modeling for a More Sustainable Nitrogen Management in Oat Crops

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HIGHLIGHTS (MANDATORY)

- Nitrogen adjustment at sowing and coverage increase oat productivity.
- Topdressing nitrogen application is dependent on oat environment and phenology.
- Fuzzy modeling is dependent on an adequate rule base structure.

Abstract Meteorological conditions affect the dynamics of nitrogen (N) by oat crops. Fuzzy logic allows the development of simulation models involving N management and the non-linearity of meteorological conditions. The objective of this study was to identify the most sustainable N management for oat crops considering N rates applied at sowing and as top-dressing with different timing. Potential variables were selected for the development of a rule base for fuzzy modeling and simulate grain yield for N managements considering the non-linearity of meteorological conditions. The experiment was carried out in Augusto Pestana, RS, Brazil, from 2015 to 2017. A randomized block design with four replications was used, in a 4×3 factorial arrangement, consisted of four N rates applied at sowing (0, 10, 30 and 60 kg/ha), using total N top-dressing rates of 70 kg/ha for the soybean-oat and 100 kg/ha for the maize-oat, applied at three timings (10, 30, and 60 days after emergence). The most sustainable N managements for oat crops were under absence of N and application 10 kg/ha of N at sowing, with the remainder applied as top-dressing at 10 and 30 days after emergence. The N application timing, mean air temperature, and rainfall depth are potential variables for the development of a rule base for fuzzy modeling, and efficient in simulating oat grain yield.

Keywords: Avena sativa L; stepwise; rotation systems; sustainable agriculture.

INTRODUCTION

Cereals are indispensable in the human diet and the main source of energy [1, 2]. White oat (Avena sativa L.) is among crop cereals of high agricultural value in the world. In Brazil, it is grown during the winter and, in recent years, has shown a considerable increase in cultivated area [3, 4]. Oats have stood out as an alternative grain for human consumption due to their high nutritional value, and recognized as a nutraceutical food due to their health benefits [5, 6].

Oat grain yield is connected to nitrogen (N) application, as N acts on metabolic processes and thousands of enzymatic reactions for plant development [7, 8]. The most used N source for soil fertilization is urea, due to its cost, effectiveness, and higher N concentration [9, 10]. The N fertilization efficiency when using urea is strongly dependent on the management in the cropping systems and meteorological conditions during the crop cycle [11, 12]. The N rate is defined based on the expected yield, soil organic matter contents, and rotation system; however, the rate applied does not always ensure the expected yield, since the expected yield by manual fertilization does not consider meteorological conditions that affect the dynamics of N use by plants [13, 14]. High temperatures and low soil moisture cause N losses by volatilization, drastically reducing the use efficiency to reach the expected grain yield [15, 16]. In addition, technical recommendations for oat crops include top-dressing between 30 and 45 days after plant emergence; however, adequate air temperature and soil moisture conditions are not always favorable within this interval, causing N losses and increasing production costs and environmental contamination [14, 17]. These losses have increasing public health concerns, regarding contamination of groundwater and surface waters by nitrate and even destruction of the ozone layer by emission of nitrous oxide, which result in emergence of skin cancers [18].

The expected grain yield is based on models that connect the total N rate applied to the percentage of soil organic matter in rotation systems [9, 13]. However, differences between expected and actual results of agricultural crops have been different [19, 20]. It highlights the need for expected yield models involving effects of meteorological conditions on N absorption dynamics in plants [21, 22]. In this sense, studies on modeling of agricultural processes by fuzzy logic have been found in the literature for oats [16], wheat [23], radish [24], and soybean [25]. Fuzzy logic is an artificial intelligence technique developed from elaborated rules, with an inference system of type “If <condition> Then <result>”, and enables to include controlled and uncontrolled variables in the proposition of simulation models [22, 26]. The efficiency of simulation models is connected to the choice of potential independent variables that assist in explaining changes on a dependent variable of interest [7, 27]. The selection of potential variables can be obtained by using the Stepwise technique, which iteratively selects variables that most affect the output set, excluding possible redundancies [13, 28].

The anticipation of N fertilizer applications under favorable conditions can be an alternative to reduce N losses and ensure satisfactory yield; it can extend the time for N application as top-dressing. Increasing the N rate at sowing and decrease the top-dressing rate from the total N to be applied could protect it from exposure to sunlight and higher air temperatures, reducing losses by volatilization, and promote greater contact of N with the roots. The selection of potential variables by the Stepwise technique and the development of a rule base for fuzzy modeling can qualify the oat expected yield involving N management along with the non-linearity of meteorological conditions during the crop cycle.

The objective of this study was to identify the most sustainable N management for oat crops considering N rates applied at sowing and as top-dressing at different timings, by selecting potential variables for the development of a rule base for fuzzy modeling and simulate grain yield by N management, considering the non-linearity of meteorological conditions in the main cropping systems.

MATERIAL AND METHODS

Study area and experimental design

The experiment was conducted under field conditions, in the 2015, 2016, and 2017 agricultural years, in Augusto Pestana, RS, Brazil (28°26'30"S; 54°00'58"W). The soil of the experimental area was classified as a Typic Hapludox (Latossolo Vermelho Distroferrico tipico [29]). The climate of the region is Cfa, with hot summers without a dry season, according to the Köppen classification. Soil analysis was carried out at 20 days before sowing to determine chemical characteristics (Table 1).

Table 1. Soil chemical characteristics of the experimental area.

Cropping systems	Clay (%)	Organic matter (%)	pH (H_2O)	P (mg/dm^3)	K (mg/dm^3)	AL ($cmol_c/dm^3$)	Ca ($cmol_c/dm^3$)	Mg ($cmol_c/dm^3$)
				(2015+2016+2017)*				
Maize-oat	52	2.9	6.2	40.8	239.7	0	6.5	2.5
Soybean-oat	54	3.2	6.5	26.9	179.5	0	6.3	2.7

OM= organic matter; P= phosphor; K= potassium; Al= aluminum; Ca= calcium; Mg= magnesium; *= the values presented represent the average of the 3 years of cultivation, in the different succession systems.

A randomized block design with four replications was used, in a 4×3 factorial arrangement, consisted of four N rates applied at sowing (0, 10, 30 and 60 kg/ha), using total N top-dressing rates of 70 kg/ha for the soybean-oat and 100 kg/ha for the maize-oat rotation system, applied at three timings (10, 30, and 60 days after emergence). The expected oat grain yield was 4000 kg/ha. The N rates were applied at sowing and as top-dressing using urea as source, as shown in Table 2.

Table 2. Nitrogen application at sowing and as top-dressing for oat crops in rotation systems.

N Rate at sowing (kg/ha)	N rate as top-dressing (kg/ha)	Total N Rate (kg/ha)	Expected oat grain yield (kg/ha)	N top-dressing Timing (DAE)
		Soybean-oat system		
0	70	70	4000	10; 30; 60
10	60			
30	40			
60	10			
		Maize-oat system		
0	100	100	4000	10; 30; 60
10	90			
30	70			
60	40			

DAE = days after emergence.

Oat seeds were sown in the third week of June using a seeder-fertilizer. The plots consisted of 5 5-meter rows spaced 0.20 m apart, forming experimental units of 5 m^2. The population density used was 400 viable seeds/m^2. The Brisasul oat cultivar was used in all agricultural years; it is characterized by an early cycle, low height, and high yield potential. P and K fertilizers were applied at sowing, using 45 kg/ha of P2O5 and 60 kg/ha of K_2O, combined with the different N rates, according to the treatments (except in the control experimental unit – N rate = 0). The control of diseases and weeds was carried out by applying the fungicide tebuconazole (FOLICUR® CE at a rate of 0.75 l/ha), the herbicide metsulfuron-methyl (ALLY® at a rate of 4g/ha), and manual weeding whenever necessary.

Grain yield was evaluated by cutting plants in the three central rows of each plot when the grains were mature, presenting moisture close to 22%. The plants were threshed using a stationary harvester and sent to the laboratory for grain moisture correction to 13% and estimation of grain yield (kg/ha). The N management and the following meteorological variables were considered to test potential variables for the grain yield simulation model by fuzzy logic: rainfall depth (R; mm), minimum temperature (Tmin; °C), mean temperature (Tmean; °C), maximum temperature (Tmax; °C) and thermal sum (TS; TS degrees/day). The meteorological variables were obtained by the Total Automatic Station, installed 500 meters from the experiment.

The thermal sum was determined by Equation (1):

$$TS = \sum_{i=1}^{n} \left(\frac{T_{max_i} + T_{min_i}}{2} \right) - BT \tag{1}$$

where: n is the number of days from emergence to harvest and BT is the basal temperature. The base temperature used for the oats was 4 °C [30].

Statistical analysis

The data met the assumptions of homogeneity and normality by the Bartlet's test; thus, they were subjected to analysis of variance to detect main and interaction effects. The Stepwise technique was used for selecting potential variables for the fuzzy logic model. This technique consists in a sequence of regression models iteratively constructed, in which variables are added and removed, selecting the regression that presents the greatest correlation with the main variable. The addition and removal of variables was performed using partial F statistics, according to the model:

$$F_j = \frac{QS_R(\beta_j \mid \beta_1, \beta_0)}{QM_E(X_j, X_1)} \tag{2}$$

where: QS_R is the sum of squares of the regression and $QM_E(X_j, X_1)$ is the mean square of the error containing the variables X_j and X_1.

A system based on fuzzy rules was implemented, using the Fuzzy Logic Toolbox of the MATLAB® software and the Mamdani inference method, with the use of the connective "and (^)", for evaluation of the rules by the triangular membership function and defuzzification by the method of the smallest value of the maximum association function of the aggregate. The simulation was carried out using means of meteorological parameters of the three years of study for each N rate and rotation system. The fuzzification process was carried out in 4 successive modules. In module 1 (fuzzification), the information of input variables was mathematically modeled using fuzzy sets. Classes and class intervals were determined for each input and output variable of the model with the assistance of an agronomist with experience in oat crops, as well as the rule base that includes the fuzzy uncertainty logic.

In module 2 (rule base), the variables were adjusted to their linguistic classifications, where each rule base satisfied the following structure:

If A is in A_i, then B is in B_i

where A_i and B_i being the fuzzy sets. The expression A is in A_i means that $\mu_{A_i}(a) \in [0,1]$. Both the A_i and B_i sets are Cartesian product of fuzzy sets, i.e., $A_i = A_{i1} \times A_{i2} \times \ldots \times A_{im}$ and $B_i = B_{i1} \times B_{i2} \times \ldots \times B_{in}$. In this case, each fuzzy set A_{ij} and B_{ik} represented a linguistic term for the j-th input variable and k-th output variable, and expression A is in A_i which means:

$$\mu_{A_i}(a) = \min\left\{\mu_{A_{i1(a)}}, \mu_{A_{i2(a)}}, \ldots, \mu_{A_{im(a)}}\right\} \in [0,1] \tag{3}$$

In module 3 (inference), the logical connectives used to establish the fuzzy relation for modeling the rule base were defined. The relationship between linguistic variables was characterized by the operator (MIN) of the fuzzy system. In each rule, a fuzzy relation R_i with degree of pertinence was considered for each pair (a,b):

$$\mu_{R_i}(a,b) = \min\{\mu_{A_i}(a), \mu_{B_i}(b)\} \tag{4}$$

The relation between each rule is characterized by the operator (MAX) of the fuzzy relation R that represents the model determined by a rule base obtained by the MAX union of each individual rule, so that for each pair (a,b) is obtained:

$$\mu_R(a,b) = \max_{1 \le i \le n}\{\mu_{A_i}(a) \wedge \mu_{B_i}(b)\} \tag{5}$$

where ^ represents the MIN operator.

Considering the Mamdani's method, the membership function of B is given by:

$$\mu_B(b) = \max_{1 \le i \le n}\left\{\max_a\{\mu_A(a) \wedge \mu_{A_i}(a)\} \wedge \mu_{B_i}(b)\right\} \tag{6}$$

If the input is a unitary classical set, then μ_A (a)= 1 and μ_Ai (a)≤1. So, the above expression results in:

$$\mu_B(b) = \max_{1 \le i \le n}\{\mu_{A_i}(a) \wedge \mu_{B_i}(b)\} \tag{7}$$

Therefore, the fuzzy set B represents the action for each input A.
In module 4 (defuzzification), the state of the fuzzy output variable provides the numerical value. One of the main defuzzification methods is the center of mass for continuous variables, given by the expression:

$$m(B) = \frac{\int b_{\mu B}(b)db}{\int \mu_B(b)db} \quad (8)$$

and of discrete variables, given by the expression:

$$m(B) = \frac{\sum_b b_{\mu B}(b)db}{\sum_b b_{\mu B}(b)b} \quad (9)$$

The fuzzy controller is described as a function f: R^(n)→ R^m, once given an input value, there is only one corresponding output value.

The rule bases and fuzzy models obtained were validated based on the calculation of the absolute error, given by the difference between simulated and observed grain yields. The validation in each cropping system considered the dynamics and parameters of the linear regression of the observed and simulated grain yield data as a function of N rates at sowing, in each N top-dressing application rate. The linear regression is given by the equation:

$$Y = b_0 \pm b_1 x \quad (10)$$

where: b_0 is the linear coefficient; b_1 is the angular coefficient; Y is the dependent variable represented by the grain yield; and x is the independent variable corresponding to the different N rates. The free software GENES [31] was used for the application of statistical tests.

RESULTS

The minimum, mean, and maximum grain yield according to the nitrogen (N) applyications at sowing and top-dressing in the soybean-oat system, and information on meteorological variables for the three agricultural years are shown in Table 3. The results of air temperature area shown as means and rainfall depth and thermal sum is shown as cumulative means from the crop emergence to the N application in each fertilization rate at sowing. The data showed significant variations in minimum and maximum grain yield and rainfall depth. N application at 10 and 30 days after emergence showed the highest means under absence of N fertilization at sowing. Top-dressing at 10 and 30 days after emergence showed the most expressive yields when using fertilization at sowing with 10 kg/ha of N.

Table 3. Minimum, mean, and maximum values of grain yield and meteorological variables for nitrogen applications at sowing and as top-dressing in the soybean-oat system.

N Rate (kg ha^{-1}) (Sowing – Top-dressing)	NAT (DAE)	Value	GY (kg/ha)	R (mm)	T_{mean} (°C)	T_{max} (°C)	T_{min} (°C)	TS (degrees/day)
		(2015+2016+2017)						
(0 – 70)*	10	Mean	3149	51	15.6	22.0	9.1	116
	30		3195	112	15.0	21.3	8.7	343
	60		2355	233	16.5	22.7	10.3	755
(0 – 70)	General	Minimum	1697	10	13.9	18.9	7.8	96
		Mean	2900	142	15.7	22.0	9.3	404
		Maximum	4324	336	17.2	24.0	12.3	796
(10 – 60)	10	Mean	2954	51	15.6	22.0	9.1	116
	30		3062	112	15.0	21.3	8.7	343
	60		2424	233	16.5	22.7	10.3	755
(10 – 60)	General	Minimum	1718	10	13.9	18.9	7.8	96
		Mean	2813	142	15.7	22.0	9.3	404
		Maximum	3995	336	17.2	24.0	12.3	796
(30 – 40)	10	Mean	2800	51	15.6	22.0	9.1	116
	30		2981	112	15.0	21.3	8.7	343
	60		2531	233	16.5	22.7	10.3	755

Cont. Table 3

(30 – 40)	General	Minimum	1610	10	13.9	18.9	7.8	96
		Mean	2771	142	15.7	22.0	9.3	404
		Maximum	3824	336	17.2	24.0	12.3	796
(60 – 10)	10	Mean	2603	51	15.6	22.0	9.1	116
	30		2798	112	15.0	21.3	8.7	343
	60		2491	233	16.5	22.7	10.3	755
(60 – 10)	General	Minimum	1339	10	13.9	18.9	7.8	96
		Mean	2631	142	15.7	22.0	9.3	404
		Maximum	3721	336	17.2	24.0	12.3	796

NAT = nitrogen application timing; GY = grain yield; R = rainfall depth; T_{mean} = mean temperature; T_{max} = maximum temperature; T_{min} = minimum temperature; TS = thermal sum; DAE = days after emergence; * = the first and second values inside parentheses correspond to the nitrogen rates at sowing and top-dressing, respectively.

Although the N application at 10 and 30 days after emergence resulted in higher means when using N rates of 30 and 60 kg/ha applied at sowing, the yield tended to decrease as the N rate was increased at sowing and decreased for top-dressing (Table 3).

Results of minimum, mean, and maximum grain yield according to the applying N at sowing and top-dressing together and meteorological variables in the maize-oat system are shown in Table 4. Significant variations were found for minimum, mean, and maximum grain yield and rainfall depth. In this system, the most expressive yield under absence of N fertilization at sowing was found for the total N application 10 days after emergence. When using 10 kg/ha of N at sowing, the N application at 10 and 30 days after emergence showed higher grain yield.

Table 4. Minimum, mean and maximum values of grain yield and meteorological variables according to nitrogen applications at sowing and as top-dressing in the maize-oat system.

N Rate (kg ha^{-1}) (Sowing – Top-dressing)	NAT (DAE)	Value	GY (kg/ha)	R (mm)	T_{mean} (°C)	T_{max} (°C)	T_{min} (°C)	TS (degrees/day)
			(2015+2016+2017)					
(0 – 100)*	10	Mean	3372	51	15.6	22.0	9.1	116
	30		3183	112	15.0	21.3	8.7	343
	60		2146	233	16.5	22.7	10.3	755
(0 – 100)	General	Minimum	1142	10	13.9	18.9	7.8	96
		Mean	2900	142	15.7	22.0	9.3	404
		Maximum	4386	336	17.2	24.0	12.3	796
(10 – 90)	10	Mean	3095	51	15.6	22.0	9.1	116
	30		3063	112	15.0	21.3	8.7	343
	60		2174	233	16.5	22.7	10.3	755
(10 – 90)	General	Minimum	1145	10	13.9	18.9	7.8	96
		Mean	2777	142	15.7	22.0	9.3	404
		Maximum	4001	336	17.2	24.0	12.3	796
(30 – 70)	10	Mean	2748	51	15.6	22.0	9.1	116
	30		2815	112	15.0	21.3	8.7	343
	60		2278	233	16.5	22.7	10.3	755
(30 – 70)	General	Minimum	1126	10	13.9	18.9	7.8	96
		Mean	2614	142	15.7	22.0	9.3	404
		Maximum	3807	336	17.2	24.0	12.3	796

Cont. table 4

(60 – 40)	10	Mean		2479	51	15.6	22.0	9.1	116
	30			2526	112	15.0	21.3	8.7	343
	60			2137	233	16.5	22.7	10.3	755
(60 – 40)	General		Minimum	921	10	13.9	18.9	7.8	96
			Mean	2381	142	15.7	22.0	9.3	404
			Maximum	3368	336	17.2	24.0	12.3	796

NAT = nitrogen application timing; GY = grain yield; R = rainfall depth; T_{mean} = mean temperature; T_{max} = maximum temperature; T_{min} = minimum temperature; TS = thermal sum; DAE = days after emergence; * = the first and second values inside parentheses correspond to the nitrogen rates at sowing and top-dressing, respectively.

The highest oat grain yields were found for the application of 30 and 60 kg/ha of N at sowing with the remainder applied 10 and 30 days after emergence. The general means in the maize-oat system showed that the yields decreased as the N rate at sowing was increased and the N rate as top-dressing was decreased, regardless of the application timing.

However, the results shown in Tables 3 and 4 represent actual crop conditions, allowing the validation of potential variables with fuzzy logic simulation, combining N management with yield and uncontrolled meteorological variables in agricultural systems. It also enables to evaluate scenarios of higher N use efficiency for the development of plants with lower environmental impacts. The results of the analysis for selection of potential variables by the Stepwise technique and determination of input variables for the fuzzification process is shown in Table 5. Variables related to air temperature, rainfall depth and application timing of different N rates at sowing and as top-dressing were analyzed, using grain yield as the dependent variable.

Table 5. Selection of variables by the Stepwise technique for different nitrogen rates at sowing and as top-dressing in different agricultural years and rotation systems.

Source of Variation	Mean Square - Nitrogen rates in kg ha^{-1} (Sowing – Top-dressing)			
	(0 – 70)**	**(10 – 60)**	**(30 – 40)**	**(60 – 10)**
	Soybean-oat system (2015+2016+2017)			
Regression	4877986*	4108023*	3403699*	2462444*
T_{mean} (°C)	4045086*	6807769*	6272526*	550115*
T_{min} (°C)	ns	Ns	ns	ns
T_{max} (°C)	ns	Ns	ns	456503*
TS (degrees/day)	ns	Ns	ns	ns
R (mm)	3066714*	417701*	966799*	410246*
NAT (DAE)	3840198*	504532*	804254*	420756*
Deviations	352386	277421	299349	309230
Source of Variation	**Mean Square - Nitrogen rates in kg ha^{-1} (Sowing – Top-dressing)**			
	(0 – 100)	**(10 – 90)**	**(30 – 70)**	**(60 – 40)**
	Maize-oat system (2015+2016+2017)			
Regression	6345546*	5391114*	5549487*	3674042*
T_{mean} (°C)	2070344*	2313058*	802114*	5540776*
T_{min} (°C)	1848364*	2178491*	ns	ns
T_{max} (°C)	ns	Ns	852803*	5869896*
TS (degrees/day)	11518659*	7211592*	ns	ns
R (mm)	5447636*	6648691*	761484*	4761436*
NAT (DAE)	5132062*	5970142*	709409*	5165772*
Deviations	399873	288359	310061	347668

* = significant at 5% probability of error; ns = not significant at 5% error probability. T_{mean} = mean temperature; T_{max} = maximum temperature; T_{min} = minimum temperature; TS = thermal sum; R = rainfall depth; NAT = nitrogen application timing; DAE = days after emergence; the values in parentheses correspond to the nitrogen rates applied at sowing and top-dressing. ** = the first and second values inside the parentheses correspond to nitrogen rates at sowing and top-dressing, respectively.

The variables selected were those that showed significance in the sources of variation in all N fertilization managements, sowing and top-dressing (Table 5). Therefore, mean temperature, rainfall depth, and N application timing were classified for the fuzzy logic simulation, regardless of the cropping system.

The rule base for fuzzy modeling was developed with the assistance of an expert in the area, using grain yield as the output variable (Tables 6 and 7). In the soybean-oat system, the N application timing was defined within the interval domain of [0, 60], classifying 10 days after emergence as early application (E), 30 days after emergence as medium application (M), and 60 days after emergence as late application (L) (Table 6). The interval domain for mean temperature (Tmean) was [13, 17], classifying temperatures ≤15 °C as low (LW), 14 to 16 °C as suitable (S), and ≥15 °C as high (H). The interval domain for rainfall depth (mm) was [10, 336], classifying rainfall depths ≤125 mm as low (LW), 100 to 250 mm as suitable (S), and ≥225 mm as high (H).

Table 6. Fuzzy rule base with grain yield as the output variable in the soybean-oat rotation system.

n	NAT (days)	T_{mean} (°C)	R (mm)	Grain Yield - Nitrogen rates in kg ha^{-1} (Sowing – Top-dressing)			
				(0 – 70)*	(10 – 60)	(30 – 40)	(60 – 10)
1	E	LW	LW	G	G	G	G
2	E	LW	S	LW	LW	LW	LW
3	E	LW	H	LW	LW	LW	LW
4	E	S	LW	LW	LW	LW	LW
5	E	S	S	LW	LW	LW	LW
6	E	S	H	LW	LW	LW	LW
7	E	H	LW	LW	LW	LW	LW
8	E	H	S	R	R	R	R
9	E	H	H	LW	LW	LW	LW
10	M	LW	LW	LW	LW	LW	LW
11	M	LW	S	VG	VG	VG	VG
12	M	LW	H	R	R	R	R
13	M	S	LW	R	R	R	R
14	M	S	S	G	G	G	G
15	M	S	H	LW	LW	LW	LW
16	M	H	LW	LW	LW	LW	LW
17	M	H	S	R	R	R	R
18	M	H	H	LW	LW	LW	LW
19	L	LW	LW	LW	LW	LW	LW
20	L	LW	S	R	R	R	R
21	L	LW	H	LW	LW	LW	LW
22	L	S	LW	LW	LW	LW	LW
23	L	S	S	R	R	R	R
24	L	S	H	R	R	R	R
25	L	H	LW	LW	LW	LW	LW
26	L	H	S	LW	LW	LW	LW
27	L	H	H	LW	LW	LW	LW

NAT = nitrogen application timing; T_{mean} = mean temperature; E = early application; G = good; LW = low; M = medium; S = suitable; L = late; R = regular; H = high; VG = very good; * = the first and second values inside parentheses correspond to the nitrogen rates at sowing and top-dressing, respectively.

Table 7. Fuzzy rule base with grain yield as the output variable in maize-oat rotation system.

n	NAT (days)	T_{mean} (°C)	R (mm)	Grain Yield - Nitrogen rates in kg ha^{-1} (Sowing – Top-dressing)			
				(0 – 100)	(10 – 90)	(30 – 70)	(60 – 40)
1	E	LW	LW	G	G	G	G
2	E	LW	S	LW	LW	LW	LW
3	E	LW	H	LW	LW	LW	LW
4	E	S	LW	LW	LW	LW	LW
5	E	S	S	LW	LW	LW	LW
6	E	S	H	LW	LW	LW	LW
7	E	H	LW	LW	LW	LW	LW
8	E	H	S	R	R	R	R
9	E	H	H	LW	LW	LW	LW
10	M	LW	LW	LW	LW	LW	LW
11	M	LW	S	VG	VG	VG	VG
12	M	LW	H	R	R	R	R
13	M	S	LW	R	R	R	R
14	M	S	S	G	G	G	G
15	M	S	H	LW	LW	LW	LW
16	M	H	LW	LW	LW	LW	LW
17	M	H	S	R	R	R	R
18	M	H	H	LW	LW	LW	LW
19	L	LW	LW	LW	LW	LW	LW
20	L	LW	S	R	R	R	R
21	L	LW	H	LW	LW	LW	LW
22	L	S	LW	LW	LW	LW	LW
23	L	S	S	R	R	R	R
24	L	S	H	R	R	R	R
25	L	H	LW	LW	LW	LW	LW
26	L	H	S	LW	LW	LW	LW
27	L	H	H	LW	LW	LW	LW

NAT = nitrogen application timing; T_{mean} = mean temperature; E = early application; G = good; LW = low; M = medium; S = suitable; L = late; R = regular; H = high; VG = very good; * = the first and second values inside parentheses correspond to the nitrogen rates at sowing and top-dressing, respectively.

The output variable, grain yield (kg/ha), under the N rate of 0 kg/ha at sowing and 70 kg/ha as top-dressing, the interval domain was [1650, 4350], classifying grain yields ≤ 2350 kg/ha as low (LW), 1650 to 3000 kg/ha as regular (R), 2650 to 4000 kg/ha as good (G), and ≥3650 kg/ha as very good (VG). The interval domain under the N rates of 10 kg/ha at sowing and 60 kg/ha as top-dressing was [1700, 4000], classifying grain yields ≤2275 kg/ha as low (LW), 1700 to 2850 kg/ha as regular (R), 2575 to 3700 kg/ha as good (G), and ≥3450 kg/ha as very good (VG). The interval domain under the N rates of 30 kg/ha at sowing and 40 kg/ha as top-dressing was [1600, 3850], classifying grain yields ≤2200 kg/ha as low (LW), 1600 to 2725 kg/ha as regular (R); 2450 to 3575 kg/ha as good (G), and ≥3300 kg/ha as very good (VG). The interval domain under the N rates of 60 kg/ha at sowing and 10 kg/ha as top-dressing was [1300, 3750], classifying grain yields ≤1900 kg/ha as low (LW), 1300 to 2525 kg/ha as regular (R), 2220 to 3450 kg/ha as good (G), and ≥3125 kg/ha as very good (VG).

The fuzzy rule base for the maize-oat rotation system and soybean-oat had the same classification for the explanatory variables when N was applied: mean temperature and rainfall depth (Table 7). However, when using grain yield as the output variable, the interval domain under the N rates of 0 kg/ha at sowing and 100 kg/ha as top-dressing was [1150, 4400], classifying grain yields ≤1975 kg/ha as low (LW), 1150 to 2775 kg/ha as regular (R), 2400 to 4000 kg/ha as good (G), and ≥3625 kg/ha as very good (VG). The interval domain under the N rates of 10 kg/ha at sowing and 90 kg/ha as top-dressing was [1150, 4000], classifying grain yields ≤1875 kg/ha as low (LW), 1150 to 2575 kg/ha as regular (R), 2225 to 3650 kg/ha as good (G), and ≥3275 kg/ha as very good (VG). The interval domain under the N rates of 30 kg/ha of N at sowing and 70 kg/ha as top-dressing was [1100, 3800], classifying grain yields ≤1775 kg/ha as low (LW), 1100 to 2450 kg/ha as regular (R), 2100 to 3450 kg/ha as good (G), and ≥3100 kg/ha as very good (VG). The interval domain under the N rates of 60 kg/ha of N at sowing and 40 kg/ha as top-dressing was [900, 3400], classifying grain yields ≤525 kg/ha as low (LW), 900 to 2150 kg/ha as regular (R), 1850 to 3100 kg/ha as good (G), and ≥2775 kg/ha as very good (VG).

The mean grain yields, observed and simulated by fuzzy logic, according to the N managements used in the soybean-oat system are shown in Table 8. The observed and simulated mean grain yields decreased as the N rate was increased at sowing and decreased as top-dressing. The highest mean grain yields were found for the N application timings of 10 and 30 days after emergence, regardless of the rate applied at sowing and as top-dressing. The simulations carried out by the fuzzy model showed grain yields close to those observed in the field in the different proposed scenarios. In some simulated scenarios, the difference between the simulated and observed grain yields was less than 30 kg/ha, denoting a very good representation of grain yield in the soybean-oat systems.

Table 8. Mean grain yields, observed and simulated by fuzzy logic, according to the nitrogen managements used in the soybean-oat rotation system.

N Rate (kg ha^{-1}) (Sowing – Top-dressing)	**NAT (Days)**	**GY$_O$ (kg/ha)**	**GYs (kg/ha)**	**Absolute Error (kg/ha)**
		(2015+2016+2017)		
	10	3149 a	3330	181
(0 – 70)*	30	3195 a	3330	135
	60	2355 b	2330	25
Mean		2900 A	2997	113
	10	2954 a	3140	186
(10 – 60)	30	3062 a	3140	78
	60	2424 b	2280	144
Mean		2813 A	2853	136
	10	2800 a	3010	210
(30 – 40)	30	2981 a	3010	29
	60	2531 b	2370	161
Mean		2771 B	2730	133
	10	2603 a	2830	227
(60 – 10)	30	2798 a	2830	32
	60	2491 b	2250	241
Mean		2631 B	2523	166

NAT = nitrogen application timing; GYo = observed grain yield; GYs = simulated grain yield; Means followed by the same letter in the column do not differ statistically at 5% probability of error using the Scott & Knott test; * = The first and second values inside parentheses correspond to the nitrogen rates at sowing and top-dressing, respectively.

The mean grain yields, observed and simulated by fuzzy logic, according to the N managements used in the maize-oat system are shown in Table 9. The observed and simulated results of grain yield decreased as the N rate was increased at sowing and decreased as top-dressing. The N application at 10 and 30 days after emergence increased the grain yield in all N fertilization managements. The fuzzy logic simulations in the maize-oat system showed low absolute error values between observed and simulated grain yields, which were similar results to those obtained for the soybean-oat system. In the fuzzy set, the bases for the development of 27 rules were satisfactory due to the quality of simulations obtained.

Table 9. Mean grain yields, observed and simulated by fuzzy logic, according to the nitrogen managements used in the maize-oat rotation system.

N Rate (kg ha^{-1}) (Sowing – Top-dressing)	NAT (Days)	GYo (kg/ha)	GYs (kg/ha)	Absolute Error (kg/ha)
		(2015+2016+2017)		
	10	3372 a	3200	172
(0 – 100)	30	3183 a	3200	17
	60	2146 b	1970	176
Mean		2900 A	2790	121
	10	3095 a	2940	155
(10 – 90)	30	3063 a	2930	133
	60	2174 b	2170	4
Mean		2777 A	2580	97
	10	2748 a	2770	22
(30 – 70)	30	2815 a	2780	35
	60	2278 b	2080	198
Mean		2614 B	2443	85
	10	2479 a	2480	1
(60 – 40)	30	2526 a	2480	46
	60	2037 b	1820	217
Mean		2381 C	2160	88

NAT = nitrogen application timing; GYo = observed grain yield; GYs = simulated grain yield; Means followed by the same letter in the column do not differ statistically at 5% probability of error using the Scott & Knott test; * = The first and second values inside parentheses correspond to the nitrogen rates at sowing and top-dressing, respectively.

The dynamics and parameters of the regression equation for the effect of N rate at sowing within each top-dressing management are shown in Figure 1.

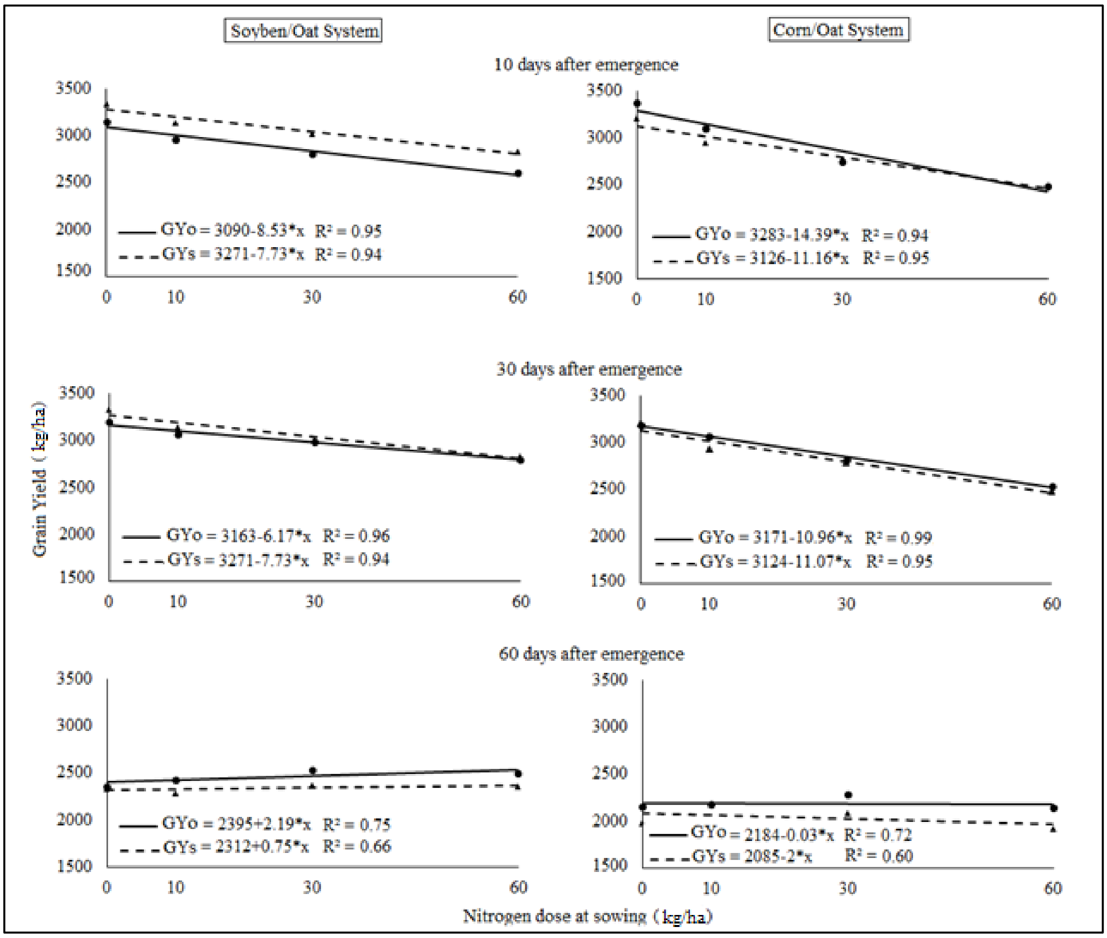

Figure 1. Dynamics and parameters of the linear regression for grain yield data, observed and simulated by fuzzy logic, as a function of nitrogen rates at sowing. GYo = observed grain yield (kg/ha); GYs = simulated grain yield (kg/ha); * = significant at 5% probability of error by t-test; R^2 = coefficient of determination.

The observed and simulated results showed decreased in the regression line for the scenarios indicated for top-dressing 10 and 30 days after emergence, denoting that increases in N rate at sowing with decreases in N top-dressing rates, compared to the total rate, decreases grain yield. In addition, the linear regression parameters showed similar results for all N application managements in the soybean-oat and maize-oat systems. For example, the results obtained with application 30 days after emergence (most suitable time for fertilization according to technical recommendation), showed linear coefficients for observed and simulated in soybean-oat system of 3163 and 3271 kg/ha, a small difference of only 108 kg. In addition, the negative linear coefficient of the observed data indicates a decrease of 6.17 kg/ha in grain yield for each kilogram of N added at sowing, similar to the angular coefficient obtained with the simulated data, which showed a decrease of 7.73 kg/ha in grain yield that for each kilogram of N added at sowing. These are similar results to those found for the maize-oat system with top-dressing 30 days after emergence, with observed and simulated linear coefficients of 3171 and 3123 kg/ha, respectively, and observed and simulated negative angular coefficients of 10, 96, and 11.07, confirming the similarity.

DISCUSSION

Agriculture is the economic activity most dependent on meteorological conditions; crop yield is strongly affected by air temperature and rainfall distribution and volume [13]. According to Marolli and coauthors [15], rainfall is the meteorological variable that affects the most the crop yields due to its interaction with temperature, insolation, and radiation. Thus, water stress has negative effects on plant survival and growth [32]. Moreover, the rainwater stored in the soil affects the dynamics of humidity in the environment, which is directly linked to the efficiency of nitrogen absorption by the plant [22]. Air temperature and photoperiod also interfere with the development of grasses [33]. Air temperature is decisive for plant development and productivity, acting as a catalyst for biological processes, which is why plants require a minimum and maximum temperature for normal physiological activities [7].

The efficiency of nitrogen uptake by urea is dependent on meteorological conditions and soil moisture during fertilizer application [34]. The high mobility dynamics of the nitrogen in the soil leads to easy losses by leaching due to rainfall after application, and volatilization by reduced soil moisture and high temperatures [35]. These conditions generate decreased efficiency, leading to lower productivity and environmental contamination [36].

These conditions reinforce the essential need to balance the productivity of the species, profitability, care for the environment, and human health by employing more sustainable management of nitrogen [37]. For this, studies focused on other forms of nutrient supply can help reduce losses and, consequently, the negative effects arising from the use of nitrogen in crops.

Oat productivity is associated with a great variability in growing conditions, with the agricultural year being the biggest contributing factor [38]. Favorable and unfavorable crop years and succession systems of high and low N-residual release alter the dynamics of availability and the efficiency of nutrient use by the plant, generating instability in productivity [17]. Therefore, strategies that minimize nitrogen losses at the time of application and ensure better use by plants in obtaining satisfactory productivity are essential [39]. In the literature, studies can be found that evaluate the effect of different forms of nitrogen supply in sowing and coverage and application times on crop productivity, such as wheat [40], corn [41], rice [42], oatmeal [43], and others.

Mathematical and computational models describing agricultural processes can assist in developing and validating technologies and managements that are more adequate from a technical, economic, and environmental point of view [23]. In this sense, artificial intelligence techniques have emerged as an alternative for simulating and optimizing agricultural systems [22]. Therefore, agricultural prediction models should involve biological and environmental variables [28].

The Stepwise technique is one of the most used methods for selection of variables, as it iteratively selects variables that have the most effect on the output set, excluding possible redundancies [13]. The use of the Stepwise technique is reported by Gouache and coauthors[44], who selected fundamental meteorological variables to determine wheat yield; Mantai and coauthors [13], who defined the most efficient components of oat inflorescence using the Stepwise technique to compose a grain yield simulation model; Marolli and coauthors [15], who evaluated the thermal sum, rainfall, solar radiation, and N rates as potential variables for the composition of a simulation model for oat biomass yield under use of growth regulator; Alessi and coauthors [28], who identified the most significant components of wheat for including in multiple regression simulation models for the simulation of grain yield; and Abbas and coauthors [45], who identified the agronomic characteristics that most contribute to increase wheat yield.

Considering the great technological evolution occurring in agricultural processes, fuzzy logic has become a highly satisfactory resource for decision-making [46, 47]. Moreira and coauthors [48]) used fuzzy logic for the diagnosis of fungal diseases (Septoria sp.) that affects tomato. De Mamann and coauthors [23] adapted a fuzzy logic model to simulate biomass and grain yield in wheat crops by N applications and the non-linearity of maximum air temperature, under use of a biopolymer hydrogel. Scremin and coauthors [16] adapted a fuzzy logic model to simulate biomass and grain yield of oat crops by N applications and the nonlinearity of the maximum air temperature and found high simulation quality. Peter and coauthors [49] used fuzzy logic simulation of grain yield as a function of N rates with the combined action of meteorological parameters, with satisfactory results for oat grain yield.

Gabriel Filho and coauthors [50] developed a system using fuzzy logic to model the effect of irrigation depths on beet cultivars and found that the proposed model allowed evaluating the effect of water deficit, with an adequate comparison between the adopted cultivars. However, the dynamics and values of linear coefficients of observed and simulated yields using N, together with effects of air temperature and rainfall, also show the efficiency of fuzzy modeling in representing grain yield in oats, enabling analysis of scenarios in the searching for more efficient and sustainable managements. The fuzzy models are techniques that allow the description of complex systems, produced from rules, that must be elaborated by specialists, providing their experience to the elaboration of an inference system [51]. In this perspective, fuzzy logic has been increasingly used in different areas of knowledge, allowing to assign linear and non-linear effects of the processes with the experience gained from the observer [52].

CONCLUSION

The most sustainable nitrogen management for oat crops is N absence or use of the N rate of 10 kg/ha at sowing, with the remainder applied as top-dressing at 10 and 30 days after emergence, in soybean-oat and maize-oat rotation systems.

The nitrogen application timing, mean air temperature, and rainfall depth are potential variables for the development of a rule base for fuzzy modeling of oat grain yield.

Fuzzy modeling is efficient in simulating oat grain yield involving nitrogen management and the non-linearity of meteorological conditions in cropping systems.

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Conflicts of Interest The authors declare no conflict of interest.

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