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Estimating sugarcane productivity: an approach using fuzzy logic[1]

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ABSTRACT - Brazil is a benchmark in sugarcane production, with the state of São Paulo standing out as the largest Brazilian producer. However, for sugarcane suppliers and mills to sustain this activity, there is a need to improve productivity per hectare and reduce production costs. In this regard, this study aimed to propose fuzzy systems to estimate sugarcane productivity based on planted area (Area) and total cost of soil tillage (TCST) for raw material suppliers and mills. To this end, two fuzzy inference systems were constructed for the output variable (productivity) from two input variables (Area and TCST), considering five membership functions (very low, low, medium, high, and very high). Additionally, a survey on 42 sugarcane suppliers and 31 mills in the state of São Paulo was used for model construction. The results showed that the relationship between Area and TCST reflects on the productivity of sugarcane suppliers and mills in distinct ways. For suppliers, an increase in productivity is observed when there is an almost negative relationship between both input variables. For mills, productivity rises when these variables fluctuate in the same direction. Therefore, the proposed method is viable and provides relevant information for conjecturing survival strategies for agents in the sugarcane energy sector.

Key words: Soil tillage cost. Sugarcane suppliers. Mills. Sugarcane energy sector. Fuzzy inference systems.

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INTRODUCTION

Brazil is the leading producer of sugarcane worldwide. Factors contributing to this position include extensive research, investments, and the expansion of the country's production area (AMORIM *et al*., 2019; BARBOSA *et al*., 2020). The domestic and international demand for sugarcane primarily stems from its by-products (sugar, ethanol, and electric power cogeneration) (GILIO; MORAES, 2016). The complexity of the sugar-energy sector makes it a captivating field for the development of computational systems, or more specifically, artificial intelligence systems (AIS), aimed at supporting decision-making within the sugarcane production system (JUNQUEIRA; MORABITO, 2017).

Among the existing AIS, fuzzy logic has been utilized and refined as a decision-making tool in agricultural production (DE; SINGH, 2021; RAMOS *et al*., 2021), among others. Specifically, in the sugarcane production system, noteworthy research includes cultivar selection (REA *et al*., 2016), estimation of cultivation areas (SILVA *et al*., 2015), productivity classification (NATARAJAN; SUBRAMANIAN; PAPAGEORGIOU, 2016), nutrient replenishment (MOLIN; CASTRO, 2008), weed detection (SUJARITHA *et al*., 2017), and feasibility studies for mill implantation (RODRÍGUEZ; GAUTHIER-MARADEI; ESCALANTE, 2017). Goldschmidt (2010) reported that fuzzy logic allows modeling and mathematical manipulation of vague and natural human language information, which in this case can be supplied by experts in the sugar-energy sector, making fuzzy logic a relevant tool to assess agricultural performance.

Soil tillage (ST) strategies are crucial for sugarcane crop development. In Brazil, there are four types of ST: conventional tillage, minimum tillage, localized tillage, and non-tillage systems. These systems can be distinguished based on the types of machines and equipment used to till the soil (AMORIM *et al*., 2020, 2021; BARBOSA *et al*., 2020). Conventional soil tillage (CST) is performed by tractors and the following equipment: harrows (tilling, intermediate, and leveling), subsoilers, or plows; minimal soil tillage (MST) is conducted by tractors, subsoilers, and harrows (intermediate or tilling); localized soil tillage (LST) is carried out by tractors, subsoilers, and rotary hoes; and non-tillage (NT) is performed by tractors and subsoilers (AMORIM *et al*., 2020, 2021).

For each ST system, there are two options for pH and soil acidity correction: the first is the fixed rate (FR), where corrective substances are applied uniformly across the area based on the average derived from soil analysis. The second is the variable rate (VR), where corrective substances are applied according to each point analyzed by grid, or management zone.

Knowing the relationship between such variables to maintain and/or improve sugarcane performance is indispensable to stakeholders in the sugar-energy sector. Overall, attempts are often made to correlate the planted sugarcane area and total soil tillage cost with sugarcane productivity, using mathematical and statistical models. In this regard, various models employing econometrics have been used, consisting of statistical techniques primarily based on linear regression models and non-linear models. Notable in the sugar-alcohol sector are econometric studies on adoption of precision agriculture and technical efficiency (CARRER *et al*., 2022), the growth of this sector in Brazil (MORAES; BACCHI; CALDARELLI, 2016), and analyses of sugarcane production (NARAYAN, 2004).

However, mathematical modeling applications has shown that intelligent system-based models can be highly suitable for a vast range of studies in various areas, as they are not confined to pre-structured equations in a linear, quadratic, or any other format. Such models allow much superior adaptability to response data compared to regression models.

In the sugar-alcohol sector, artificial intelligence systems have been used in energy production and environmental impacts of sugarcane production (KAAB *et al*., 2019), biofuel production from biomass (MEENA *et al*., 2021), and sugarcane production in IoT-based smart farming (WANG; HAFSHEJANI; WANG, 2021).

These systems have been widely employed in Agricultural Sciences, including poultry companies and production (CREMASCO; GABRIEL FILHO; CATANEO, 2010; PEREIRA *et al*., 2008), cattle farming (GABRIEL FILHO *et al*., 2011, 2016; MAZIERO *et al*., 2022), irrigation engineering (BOSO *et al*., 2021a, b; CASTRO; SAAD; GABRIEL FILHO, 2022; GABRIEL FILHO *et al*., 2022a, b; MATULOVIC *et al*., 2021; PUTTI *et al*., 2017, 2021; VIAIS NETO *et al*., 2019a, b), optimization of agricultural implements (GÓES *et al*., 2022), enhancement of plant vitality (PUTTI *et al*., 2014, 2017), the agricultural product market (GABRIEL FILHO; PIGATTO; LOURENZANI, 2015; MARTÍNEZ *et al*., 2020; OLIVEIRA *et al*., 2021), among others. Specifically in the sugar-alcohol sector, applications of fuzzy systems in the classification of sugarcane productivity (NATARAJAN; SUBRAMANIAN; PAPAGEORGIOU, 2016), combustion control in bagasse boilers (MELLO; CRUZ; SOUSA JÚNIOR, 2019), and weed detection in sugarcane fields (SUJARITHA *et al*., 2017) stand out.

This study aimed to use an artificial intelligence system to estimate sugarcane productivity. Since such an estimate is specifically based on the planted area and total cost of soil tillage, a fuzzy logic-based intelligent system was adopted. Therefore, two fuzzy models were proposed, one for sugarcane suppliers and another for mills, aiming to estimate crop productivity based on planted area and total cost of soil tillage.

MATERIAL AND METHODS

Data Collection

The research was conducted with a sample of 42 sugarcane suppliers and 31 mills, located in the state of São Paulo, Brazil. The location choice was intentional, given the state's representativeness for the sugarcane energy sector.

Data collection was carried out through a structured questionnaire with ten questions involving the following agricultural specifics: planted area in hectares (ha), average productivity in ton/ha (t/ha), type of soil tillage performed, and its respective total cost (in dollars) for the 2017/18 harvest.

First, data were analyzed using descriptive statistics (descriptive measures and scatter plots). Then, two fuzzy models (one for sugarcane suppliers and another for mills) were constructed to estimate sugarcane productivity as a function of the planted area and total cost of soil tillage.

Fuzzy systems modeling

According to Costa Branco and Dente (2001), fuzzy systems modeling involves several structures, the first is the information in the training set, obtained in the following ways: (i) knowledge about the system phenomenon (usually expressed in a mathematical model); (ii) experimental data; and (iii) linguistic knowledge of fuzzy if-then rules. This structure also includes the system's previously selected variables (considered the most representative of its behavior) and the fuzzy partition assigned to each of them.

Still, according to the same authors, the second structure is about the learning algorithm, which interprets the acquired learning examples and combines them into a rule set or knowledge base. Finally, the defined third structure is performing a reasoning process considering the extracted rules.

In this third step, the system can perform an "action" in the environment, such as triggering some mechanical device to modify one of the input variables described in the first structure. In the present work, this action comprised the calculation of crop productivity, and such input variables are the planted area and total cost of soil tillage.

Thus, the model used was elaborated with an input processor (fuzzifier), a set of linguistic rules, a fuzzy inference method, and an output processor (defuzzifier) that generates a real output number.

Among the existing inference methods and of greater computational simplicity, there is the method employed by Mamdani, whose responses are calculated based on the input variables, according to the rule set in the knowledge base (MAMDANI; ASSILIAN, 1975). The most commonly used mechanism to transform qualitative information into quantitative (defuzzification) is the center of gravity or centroid, which is based on a weighted average.

In this work, two systems based on fuzzy logic were defined, equivalent to AIS, which are illustrated in Figures 1 and 2. Once five fuzzy sets were defined for each input variable, 25 (5 × 5) rules were obtained.

As previously mentioned, the input variables for both systems were planted area (Area) and total cost of soil tillage (TCST), which are parameters that can be evaluated qualitatively and categorized by linguistic variables for the construction of fuzzy systems to obtain estimates of the output variable, i.e., productivity (Prod) of a given supplier or mill.

The use of qualitative variables with fuzzy sets is essential because systems are structured based on fuzzy rules. In this study's model, the qualitative input variables grouped data closely, and the chosen methodology helped develop the model's rules.

Therefore, a cause-effect relationship could be established through the function $f_i : R^2 \rightarrow R,\ f(x, y) = z, i = 1{,}2$, where χ represents the planted area and y is the total cost of soil tillage, with f_1 being the function for the suppliers' model, while f_2 represents the function for the sugarcane mills.

Table 1 and Figure 3 show the five membership functions for each input variable (Area and TCST) associated with sugarcane suppliers, namely, Very Low (VL), Low (L), Medium (M), High (H), and Very High (VH). The functions were defined based on the range between the minimum and maximum values of the input variables, ensuring a symmetric behavior of these functions. It is important to note that these functions represent the membership degree of each point within a fuzzy set.

Additionally, it is highlighted that the membership functions corresponding to the minimum and maximum values of the range for each input variable were defined as trapezoidal, while the functions within the range were defined as triangular. This approach ensured that values near the minimum and maximum points of the range had membership degrees of one.

On the other hand, the output variable (Productivity or Prod) generates a fuzzy response for the analyzed variables due to the level of TCST and Area. Initially, 25 rules were defined which, by the present methodology, would result in the generation of 25 fuzzy sets.

Figure 1 - Fuzzy logic-based system for sugarcane suppliers with two inputs and one output

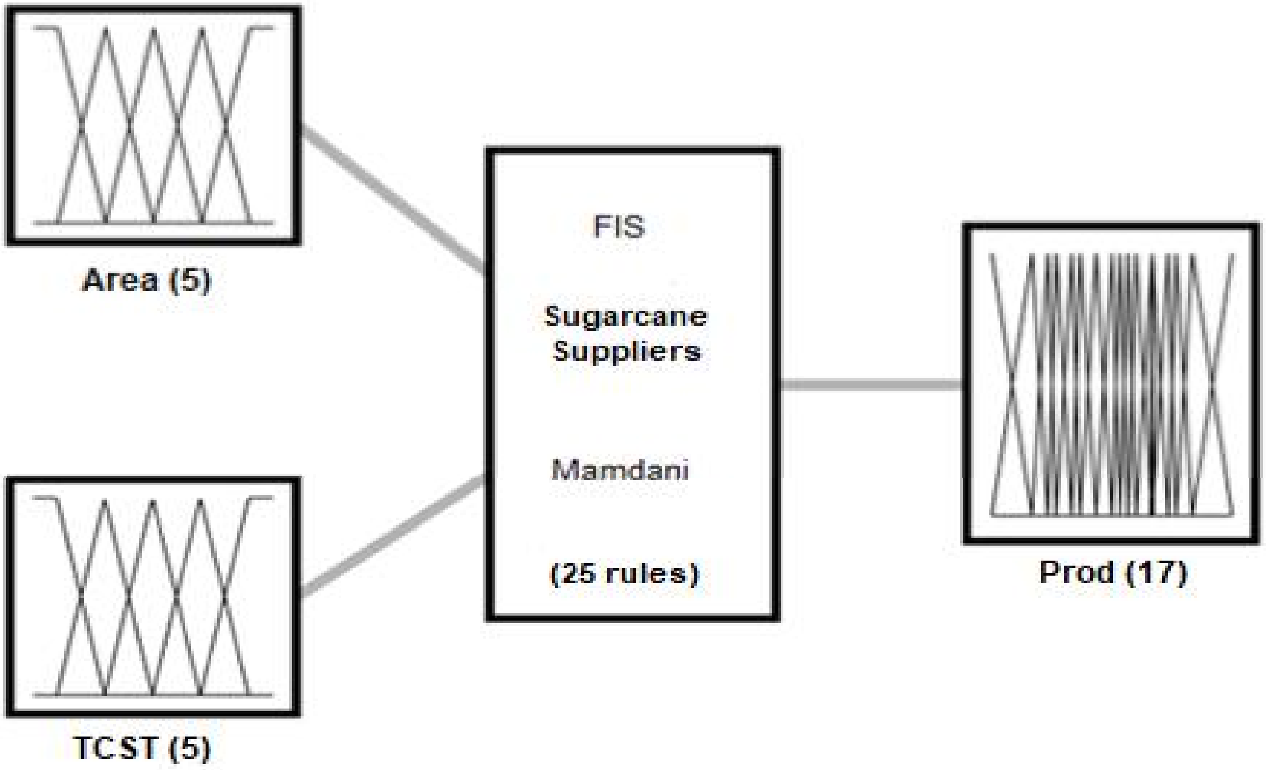
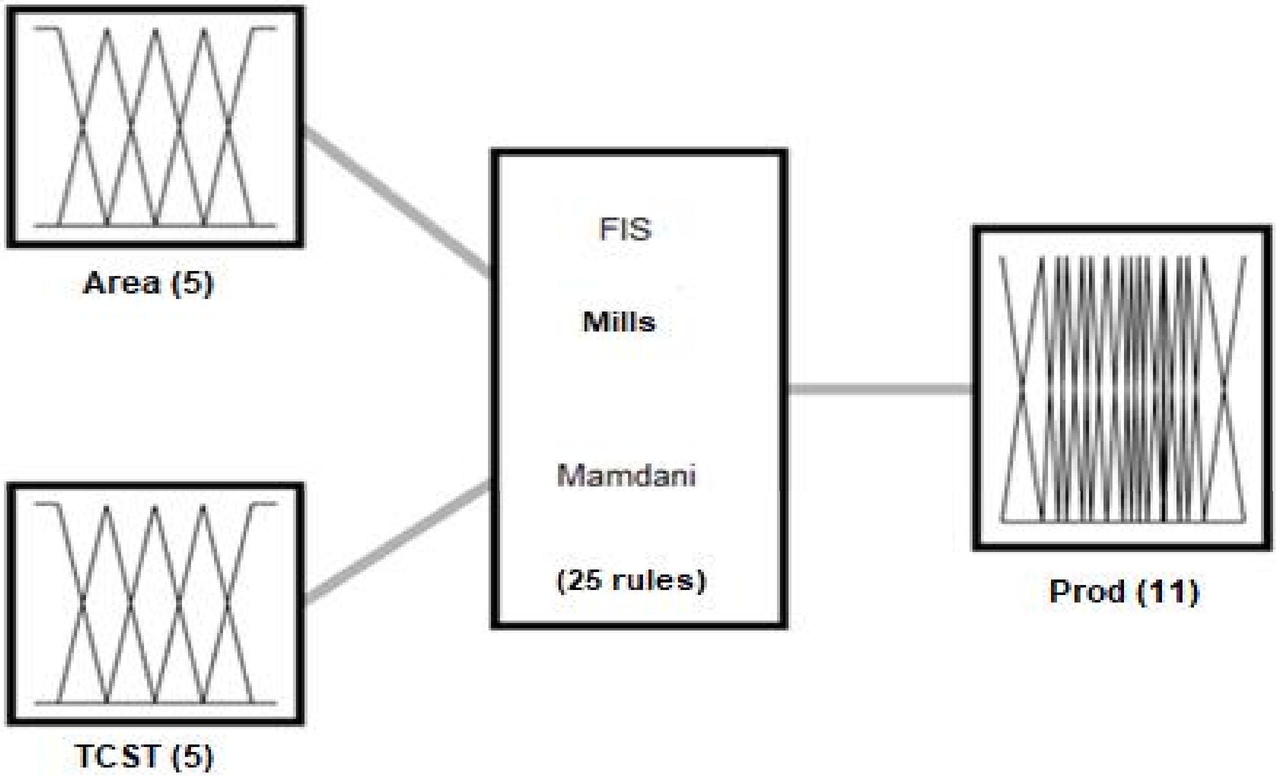


Figure 2 - Fuzzy logic-based system for mills with two inputs and one output



For every pairing of the five fuzzy sets from the input variable Area and the five sets from the TCST input variable, an average value for the output variable, productivity (Prod), was derived from the database. This process produced 25 average values. However, eight out of these 25 values were identical, resulting in only 17 unique average values. Consequently, there were 17 distinct fuzzy sets for the output variable, labeled as C1, C2, ... up to C17, for the sugarcane suppliers. It is important to note that the triangular functions created are not symmetric because their boundaries are defined by these specific average values.

Therefore, 25 rules (5 × 5) or combinations between the fuzzy sets of the two input variables considered for the construction of the rule base of the fuzzy system for sugarcane suppliers were obtained. Thus, 17 pairs of TCST × Area were established, as per Table 1 and Figure 3. It is emphasized that the degrees of membership explicated in Figure 3 indicate the membership of each point of the variable to a respective fuzzy set.

Similarly, Table 2 and Figure 4 show the five membership functions for each input variable (Area and TCST) associated with the mills, being them, Very Low (VL), Low (L), Medium (M), High (H), and Very High (VH). The output variable of the system, productivity (Prod), generates a fuzzy response for the analyzed variables due to the level of TCST and Area. Thus, 11 fuzzy sets of the output variable (C1, C2, ..., C11) were defined for the mills.

Table 1 - Parameters of the triangular membership functions for the input and output variables of the fuzzy system for sugarcane suppliers

Variable		Fuzzy set	Function type	Delimiters
Input	Area	VL	trapezoidal	[-260 0 130 390]
		L	triangular	[130 390 650]
		M	triangular	[390 650 910]
		H	triangular	[650 910 1170]
		VH	trapezoidal	[910 1170 1300 1560]
	TCST	VL	trapezoidal	[152 168 176 192]
		L	triangular	[176 192 208]
		M	triangular	[192 208 224]
		H	triangular	[208 224 240]
		VH	trapezoidal	[224 240 248 263]
Output	Productivity (Prod)	C1	triangular	[70 75 80]
		C2	triangular	[75 80 82]
		C3	triangular	[80 82 83]
		C4	triangular	[82 83 85]
		C5	triangular	[83 85 86]
		C6	triangular	[85 86 88]
		C7	triangular	[86 88 90]
		C8	triangular	[88 90 91]
		C9	triangular	[90 91 92]
		C10	triangular	[91 92 93]
		C11	triangular	[92 93 95]
		C12	triangular	[93 95 95]
		C13	triangular	[95 95 97]
		C14	triangular	[95 97 98]
		C15	triangular	[97 98 100]
		C16	triangular	[98 100 105]
		C17	triangular	[100 105 110]

Figure 3 - Membership functions of fuzzy sets for the input and output variables of the fuzzy system for sugarcane suppliers

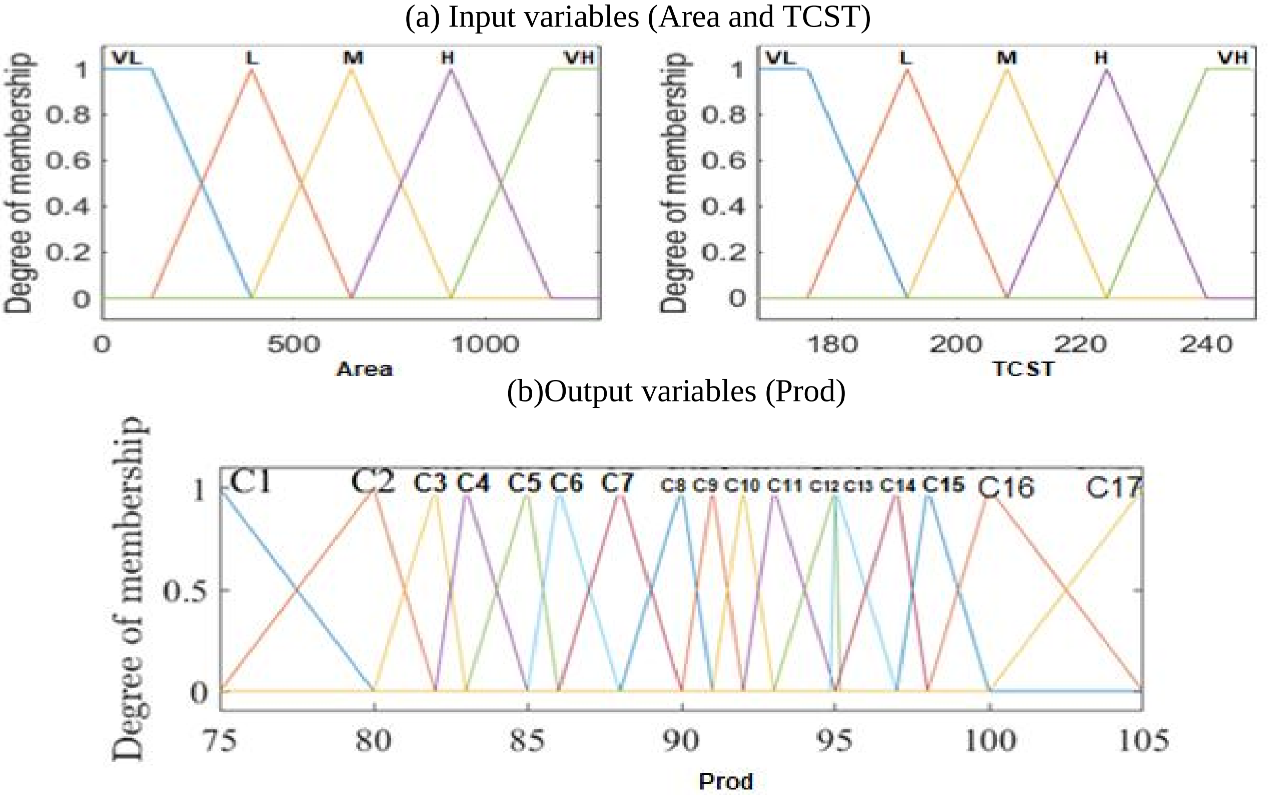
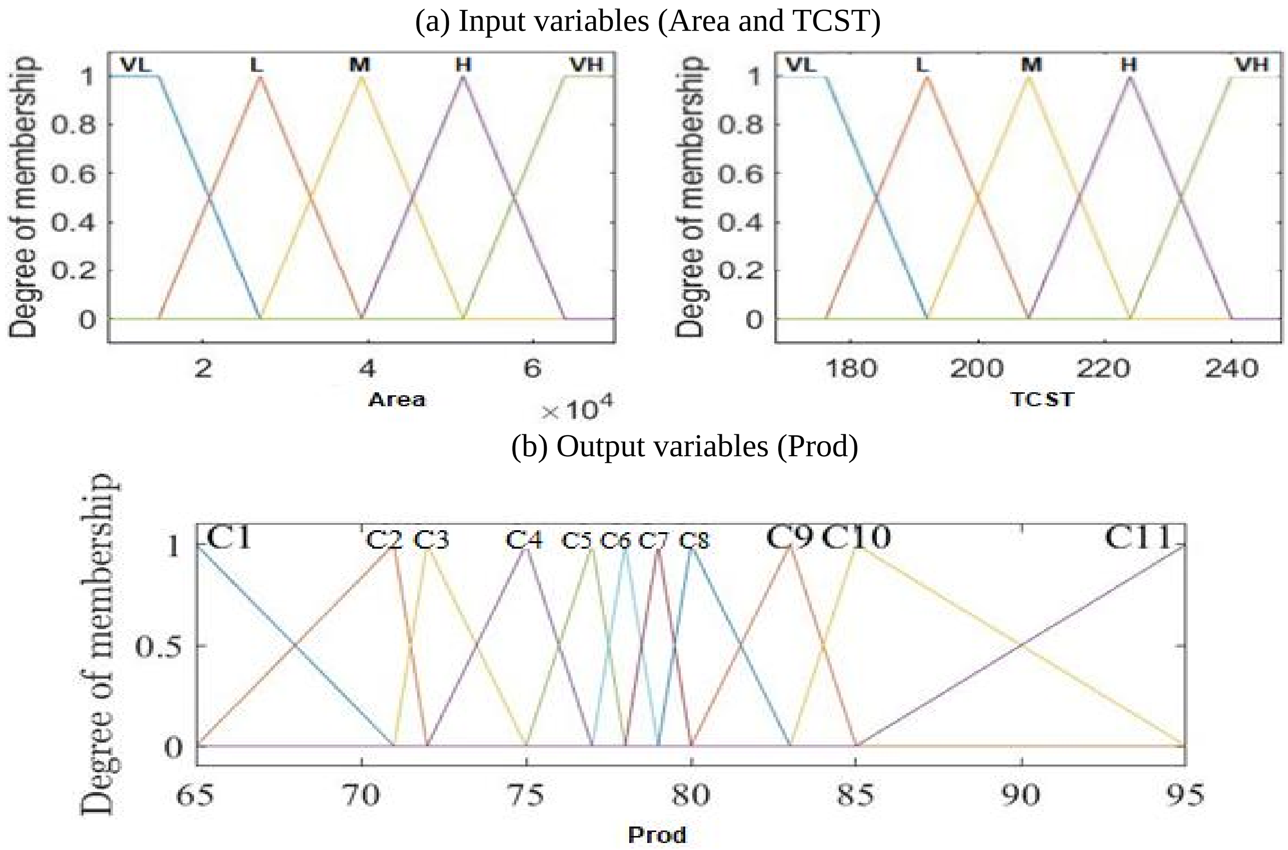


Table 2 - Parameters of the triangular membership functions for the input and output variables of the fuzzy system for mills

Variable		Fuzzy set	Function type	Delimiters
Input	Area	VL	trapezoidal	[-3800 8500 14650 26950]
		L	triangular	[14650 26950 39250]
		M	triangular	[26950 39250 51550]
		H	triangular	[39250 51550 63850]
		VH	trapezoidal	[51550 63850 70000 82300]
	TCST	VL	trapezoidal	[152 168 176 192]
		L	triangular	[176 192 208]
		M	triangular	[192 208 224]
		H	triangular	[208 224 240]
		VH	trapezoidal	[224 240 248 263]
Output	Productivity (Prod)	C1	triangular	[60 65 70]
		C2	triangular	[65 70 75]
		C3	triangular	[70 75 78]
		C4	triangular	[75 78 79]
		C5	triangular	[78 79 82]
		C6	triangular	[79 82 83]
		C7	triangular	[82 83 84]
		C8	triangular	[83 84 85]
		C9	triangular	[84 85 88]
		C10	triangular	[85 88 90]
		C11	triangular	[88 90 92]

Figure 4 - Membership functions of fuzzy sets of input and output variables of the fuzzy system for mills



Again, as in the previous model, 25 averages were generated. However, 14 of them were equivalent (with non-significant differences), thus leaving 11 distinct averages, which led to the generation of 11 fuzzy sets.

Also, 25 rules (5 × 5) or combinations between the fuzzy sets of the two input variables of the fuzzy system for mills were obtained. In this case, 11 pairs of TCST × Area were established, as per Table 2 and Figure 4.

The systems were proposed based on fuzzy logic using the Fuzzy Logic Toolbox tool of the MATLAB® software version 7.0 (MATLAB: Copyright 1984-2015 The MathWorks, Inc.). It was coupled with determination of surfaces and contour maps of the systems.

RESULTS AND DISCUSSION

Descriptive Analysis of sugarcane suppliers and mills

Table 3 presents the main descriptive measures regarding the input variables (Area and TCST) and the output variable (productivity or Prod) for the researched sugar cane suppliers and mills.

Mills showed much larger planted areas than did sugarcane suppliers and, in both cases, there are large size variations. However, the average TCST of suppliers was lower than that of mills, albeit with greater range and relative dispersion (coefficient of variation). Regarding productivity, mills had lower average productivity, but with higher relative variation. The total range in productivity was equal for both, however, the minimum and maximum values were higher for suppliers.

It is deduced that this group of sugarcane suppliers, on average, has higher productivity (about 10% more) with lower TCST and Area compared to the mills. In this case, it can be suggested that the technological packages used by the larger areas do not correspond with an increase in productivity per hectare and cost reduction, contradicting the assertion by Torquato, Jesus, and Zorzo (2015) that smaller-scale sugarcane suppliers find it challenging to invest in new agricultural machinery and, consequently, have lower competitiveness. Therefore, Santos *et al*. (2021) mentioned that indebtedness of suppliers and mills is a factor that hinders the sugarcane energy sector.

Table 3 - Descriptive measures concerning the input and output variables of the fuzzy systems for sugarcane suppliers and mills

Descriptive measure	Sugarcane suppliers			Mills		
	Area (ha)	TCST (US$/ha)	Prod (ton/ha)	Area (ha)	TCST (US$/ha)	Prod (ton/ha)
Minimum	112.00	173.22	75.00	8,500.00	173.22	65.00
Maximum	1,244.00	248.02	105.00	70,000.00	242.90	95.00
Total range	1,132.00	74.80	30.00	61,500.00	69.68	30.00
Average	531.39	202.48	90.61	30,263.48	205.49	82.42
Standard deviation	362.61	21.27	8.67	14,385.45	18.31	9.65
Coefficient of variation[4]	68.24%	10.51%	9.57%	47.53%	8.91%	11.71%

Figure 5, shown below, presents a scatter plot using Cartesian coordinates to display related values from the data set of sugarcane suppliers, supporting the definition of the rule base for the respective fuzzy system. The data is displayed as a collection of points, each with the value of one variable determining the position on the horizontal axis (Area) and the value of the other variable determining the position on the vertical axis (TCST).

Based on Figure 5, about 67% of the sugarcane suppliers have planted areas below 600 ha, with a focus on the range of 200 to 400 ha, which accounts for nearly 54% of this percentage. Regarding the total production cost, about 78.5% of the suppliers have a TCST below 220.00 US$/ha, with a notable range of 180.00 to 190.00 US$/ha, which represents almost 30.5% of this total. However, it is observed that the relations between Area of 200 to 600 ha and TCST of 210.00 to 230.00 US$/ha and between Area of 800 to 1200 ha and TCST of 180.00 to 200.00 US$/ha equally represent the highest percentage among all (19.1%). Hence, a linear dispersion of data is not apparent, but generally, the planted areas with smaller sizes were slightly less cost-efficient, confirming the results obtained by other authors (MANOEL *et al*., 2018; TORQUATO; JESUS; ZORZO, 2015).

Figure 6, following, displays the scatter plot to exhibit related values from the data set of the mills. Similarly, here the data are displayed as a collection of points, each with the value of one variable determining the position on the horizontal axis (Area) and the value of the other variable determining the position on the vertical axis (TCST).

According to Figure 6, about 64.5% of the mills have planted areas between 20,000 and 40,000 ha, notably within the range of 30,000 to 40,000 ha, which accounts for almost 60% of this percentage. Regarding total production cost, approximately 74% of the mills had a TCST between 180.00 and 220.00 US$/ha, with the range of 180.00 to 190.00 US$/ha representing nearly 35% of this total. Additionally, the relationships between the Area of 20,000 to 40,000 ha and TCST of 180.00 to 200.00 US$/ha, and between the Area of 20,000 to 40,000 ha and TCST of 210.00 to 230.00 US$/ha, both represent the highest percentage among all (29%). In this case, a linear data dispersion is also not evident but occurs differently compared to the suppliers. Generally, half of the mills with planted areas smaller than 40,000 ha highlighted production costs below the average value. Therefore, the relationship between TCST and Area tends to be almost positive. In this scenario, the assertions of Manoel *et al*. (2018) that economies of scale prevail in this sector, are also confirmed.

Fuzzy system for estimating productivity of sugarcane suppliers

Using the created rule base and the Mamdani inference method, the values for the output variable (Prod) were computed. The creation of basic rules stemmed from identifying the highest degree of membership, pinpointing the operational range of the membership function, and hence structuring the fuzzy model. As a result, 17 pairs of the form (TCST × Area) were generated. This approach aligns with the method utilized by Mamann *et al*. (2020) e Putti *et al*. (2021).

The rule base, articulated linguistically using the "if-then" structure, was established for the sugarcane suppliers' fuzzy system (Table 4). The first fuzzy rule is described as: If (TCST is "VL") and (Area is "VL"), then (Prod is "C11") and the supplier's productivity will be 93 t/ha. A similar description applies to the other rules.

It is worth noting that from the developed fuzzy system, a cause-and-effect relationship is established, explained by the function generated by the model itself, which enables the generation of a surface and a contour map, and is mainly governed by a set of rules that define such a mathematical function.

The model operates by determining the fuzzy sets that each input point belongs to. In the present model, each point generally belongs to a single set or two.

Figure 5 - Scatter plot of data from sugarcane suppliers (X: Area and Y: TCST)

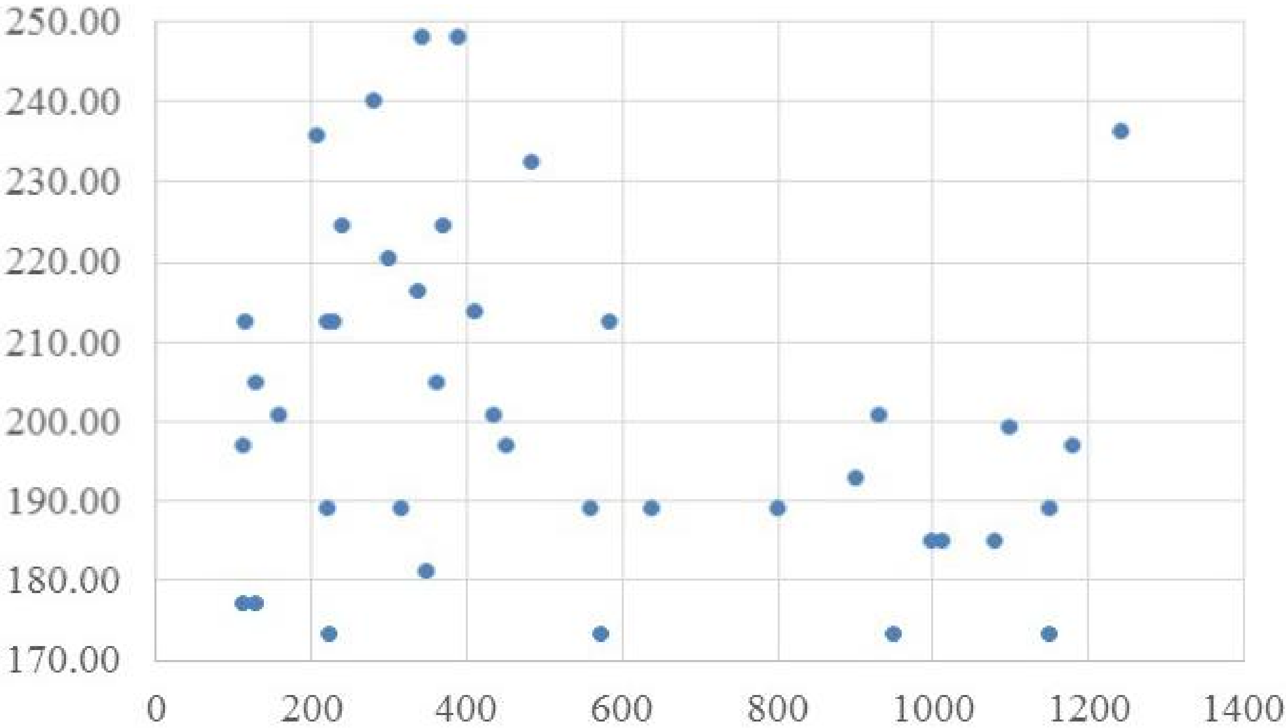
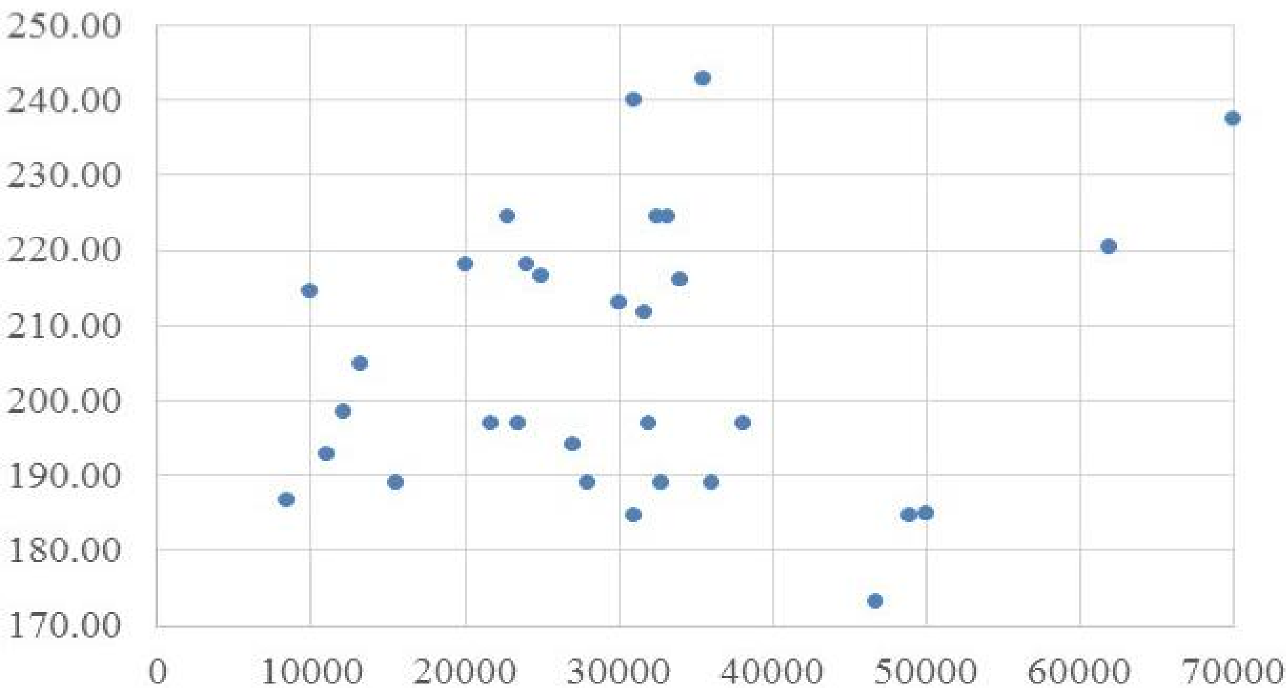


Figure 6 - Scatter plot of data from mills (X: Area and Y: TCST)



Thus, considering a simulation of a sugarcane supplier Area = 200 and TCST = 180, it is found that Area 200 simultaneously belongs to fuzzy sets VL and L (Figure 7). The other input variable value TCST = 180 also belongs to the fuzzy sets VL and L (according to Figure 3 and Table 1).

To obtain the productivity associated with such a point, the system combines four rules simultaneously (Rules 1, 2, 6, and 7 from Table 4), as these rules represent the four combinations of such fuzzy sets. After defuzzification and application of the center of gravity method, the Area over regions is calculated from the membership functions of the fuzzy sets of the output variable Prod, namely: C11, C7, C14, and C5. This process returns a real number representing productivity.

This procedure is conducted for all combinations of Area values with the values of TCST, generating all possible productivities. The representation of such values was made, in this work, from the three-dimensional surfaces, and from the contour maps.

The surface and contour map of the fuzzy model for sugarcane suppliers are shown in Figure 8, providing relevant information for understanding and evaluating their productivity.

Figure 8 shows that the variation of the Area indicates a significant increase in the productivity of sugarcane suppliers unless it is under 200 ha or above 600 ha and is associated with high values of TCST (at least 210.00 US$/ha).

On the other hand, the same figure shows that suppliers with Area between 200 and 600 ha along with TCST between 195.00 and 225.00 US$/ha (which can be considered a median CPTS), or with Area above 1000 ha associated with TCST between 185.00 and 205.00 US$/ha, approximately, tend to have higher productivity.

Even though a well-defined pattern is not observed, there is an indication that an approximately negative relationship between the two input variables (Area and TCST) tends to yield higher productivity for sugarcane suppliers.

Table 4 - Rule base of the fuzzy model for sugarcane suppliers

Rule	TCST	Area	Prod	
1	VL	VL	C11	93
2	VL	L	C7	88
3	VL	M	C12	95
4	VL	H	C2	80
5	VL	VH	C5	85
6	L	VL	C14	97
7	L	L	C5	85
8	L	M	C17	105
9	L	H	C15	98
10	L	VH	C8	90
11	M	VL	C10	92
12	M	L	C5	85
13	M	M	C5	85
14	M	H	C6	86
15	M	VH	C7	88
16	H	VL	C9	91
17	H	L	C8	90
18	H	M	C4	83
19	H	H	C1	75
20	H	VH	C3	82
21	VH	VL	C12	95
22	VH	L	C16	100
23	VH	M	C10	92
24	VH	H	C4	83
25	VH	VH	C3	82

Figure 7 - Simulation for a sugarcane supplier with Area = 200 and TCST = 180

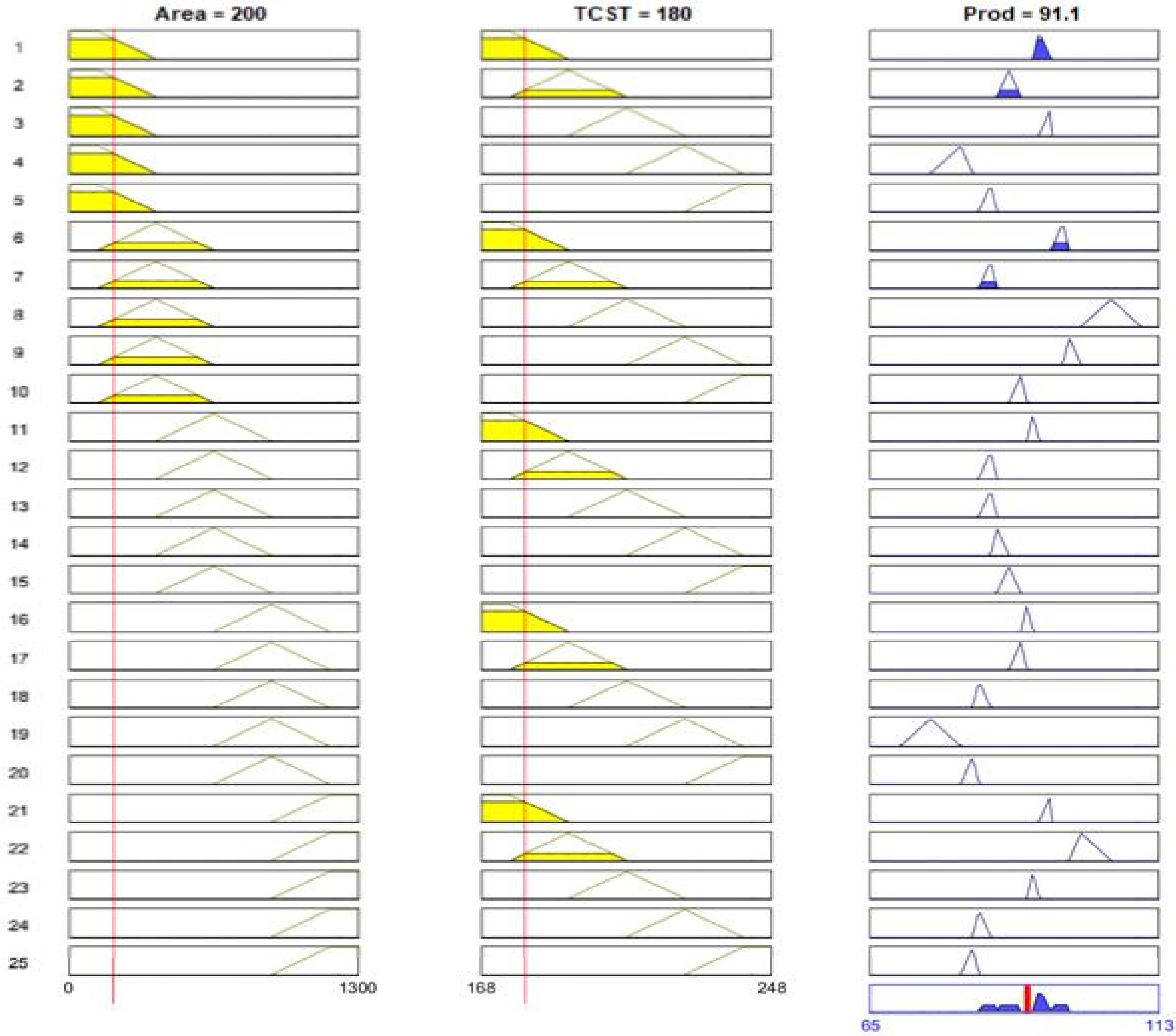
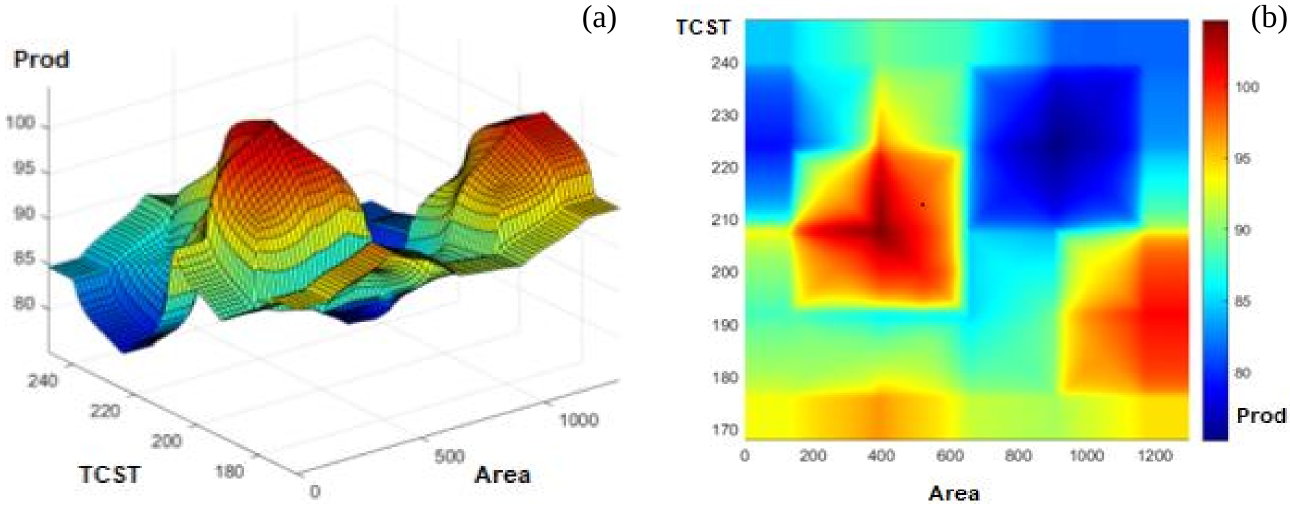


Figure 8 - Surface (a) and contour map (b) of the output variable Prod as a function of the input variables Area and TCST for sugarcane suppliers



Fuzzy system for estimating the productivity of sugar mills

Similarly, to the approach taken for sugarcane suppliers, the construction of basic rules for calculating the values of the output variable (Prod) also relied on identifying the highest degree of membership, pinpointing where the membership function is at play, and structuring the fuzzy model for the mills. In this case, 11 pairs of the form (TCST × Area) were created. Thus, the rule base (handled linguistically with the "if-then" structure) constructed for the fuzzy system of the mills can be found in Table 5, where the first fuzzy rule is described as: If (TCST is "VL") and (Area is "VL"), then, (Prod is "C10") and the productivity of the mill will be 88 t/ha. The description is analogous for the remaining rules.

The surface and contour map of the fuzzy model for mills are shown in Figure 9, providing relevant information for understanding and evaluating their productivity.

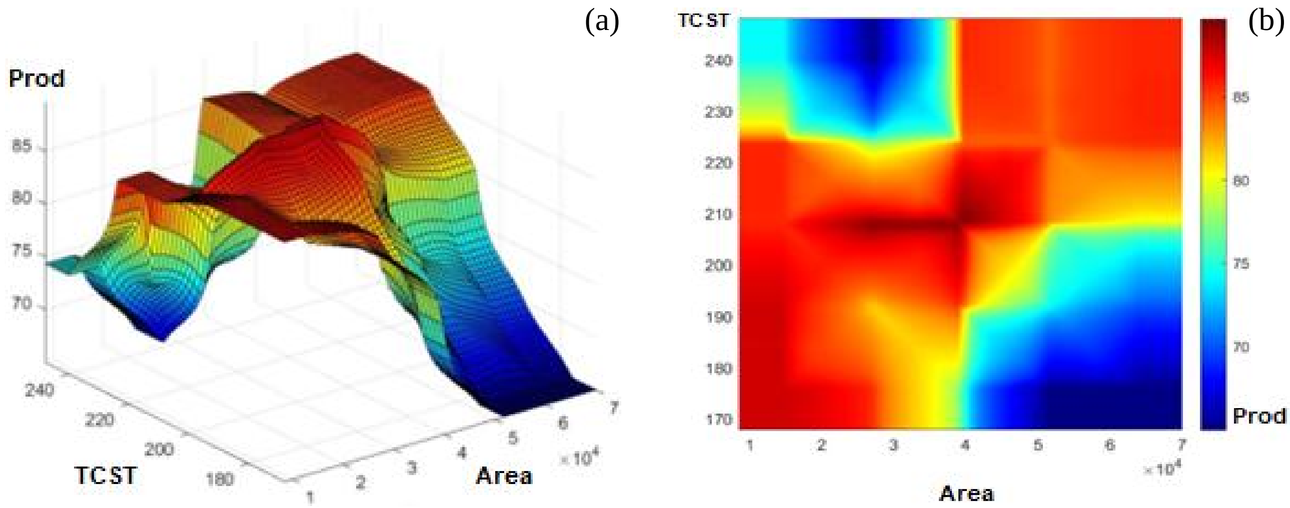
Figure 9 points out that the variation in Area indicates a significant increase in the productivity of the mills, except if it has a size larger than 40,000 ha and is associated with TCST values below 200.00 US$/ha, or if it has a size smaller than 40,000 ha and is associated with TCST values above 225.00 US$/ha, approximately.

In this case, it is evident that the existence of a positive relationship between the two input variables (Area and TCST) tends to provide higher productivity to the mills. As mentioned earlier, economies of scale are a relevant factor for this sector.

Table 5 - Rule base of the fuzzy model for mills

Rule	TCST	Area	Prod	
1	VL	VL	C10	88
2	VL	L	C10	88
3	VL	M	C9	85
4	VL	H	C9	85
5	VL	VH	C3	75
6	L	VL	C9	85
7	L	L	C6	82
8	L	M	C11	90
9	L	H	C4	78
10	L	VH	C1	65
11	M	VL	C4	78
12	M	L	C9	85
13	M	M	C11	90
14	M	H	C8	84
15	M	VH	C9	85
16	H	VL	C1	65
17	H	L	C3	75
18	H	M	C7	83
19	H	H	C8	84
20	H	VH	C8	84
21	VH	VL	C1	65
22	VH	L	C2	70
23	VH	M	C5	79
24	VH	H	C9	85
25	VH	VH	C9	85

Figure 9 - Surface (a) and contour map (b) of the output variable Prod as a function of the input variables Area and TCST for sugarcane mills



CONCLUSIONS

1. This study introduced two fuzzy systems to estimate the productivity of sugarcane suppliers and mills. These systems aid in evaluating competitiveness concerning soil tillage, offering vital information for devising survival strategies in the sugarcane alcohol sector;

2. The findings demonstrate the method's viability, emphasizing that the relationship between agricultural area size and soil tillage costs affects the productivity of sugarcane suppliers and mills differently. For suppliers, productivity increases when there is a nearly negative relationship between the two input variables (Area and TCST). On the other hand, for mills, productivity seems to rise when these variables move in the same direction;

3. The method can be easily adapted to assess competitiveness in other agribusiness sectors, with the necessary adjustments and specifications;

4. Future research could involve comparing productivity between mills and sugarcane suppliers in other productive states of Brazil, namely Goiás and Minas Gerais.

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