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Fuzzy logic in automation for interpretation of adaptability and stability in plant breeding studies

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ABSTRACT: The methods of Annicchiarico (1992) and Cruz et al. (1989) are widely used in phenotypic adaptability and stability analyses in plant breeding. In spite of the importance of these methodologies, their parameters are difficult to interpret. The aim of this research was to develop *fuzzy* controllers to automate the decision-making process employed by adaptability and stability studies following the methods adopted by Annicchiarico (1992) and Cruz et al. (1989) and check their efficiency using experimental data from common bean cultivars. *Fuzzy* controllers have been developed based on the Mamdani inference system proposed by these two methods of adaptability and stability studies. For the first *fuzzy* controller parameters were considered favorable environments and the recommendation index for unfavorable environments obtained by Annicchiarico's method (1992). For the second controller the parameters considered were the general mean (β_0), coefficient of regression of unfavorable environments (β_1) and coefficient of favorable environments ($\beta_{1i} + \beta_{2i}$) and the coefficient of determination of the method of Cruz et al. (1989). To check the performance of these drivers yield data from field trials on 18 common bean cultivars grown in 11 environments were used. The controllers were developed from established routines in the R software and, using the inference system based on the methods proposed by Annicchiarico (1992) and Cruz et al. (1989), classified the 18 genotypes appropriately in accordance with the criteria for each method. Thus, the methods used are effective, and are prescribed for decision-making automation in yield adaptability and stability studies pertaining to recommendation of cultivars.

Keywords: common bean, genotype by environment interaction, crop breeding, computational intelligence

Introduction

Phenotypic adaptability and stability analyses are tools which provide detailed information on cultivar behavior which help in the selection of genotypes that are less influenced by the interaction between genotypes and environments (G × E) (Almeida Filho et al., 2014). Two methods have been widely used to study adaptability and stability, namely, those advanced by Annicchiarico (1992) and Cruz et al. (1989).

In spite of the importance of these methodologies, their parameters are difficult to interpret, especially when a considerable number of genotypes are involved, which makes selection work slow and decisions by breeders difficult to make. Therefore, the use of tools and strategies that can help make assertive decisions are indispensable to the success of breeding programs (Carneiro et al, 2018). In this context *fuzzy* logic invites consideration.

Fuzzy logic translates vague and confusing verbal expressions common in human communication into numerical values, as well as allowing for the conversion of human experience into a computer decodable language (Simões and Shaw, 2011). Because of these properties and the ability to perform inferences, it has found significant applications in automation in several areas of knowledge, such as the risk of weed infestation in crops (Bressan et al., 2008), the determination of soil yield as a function of its physical and chemical characteristics (Duru et al., 2010), the support of nitrogen fertilization (Papadopoulos et al., 2011), the management of wheat crops (Islam et al., 2012), for Solum depth spatial prediction (Menezes et al., 2014), and irrigation and conservation in agriculture (Giusti and Marsili-Libelli, 2015) among others.

In the genetic improvement of plants, the *fuzzy* logic was applied by Carneiro et. al (2018) to the classification of cultivars regarding the adaptability and stability following the methods of Eberhart and Russell (1966). This author demonstrated that *fuzzy* logic had the capacity to interpret the parameters of these methods and, consequently, to automate the decisions that would be made by optimists.

Thus, the aim was to develop *fuzzy* controllers to automate decision-making in adaptability and stability studies in accordance with the methods of Annicchiarico (1992) and Cruz et al. (1989) and to verify their efficiency using, as an example, yield data from grains obtained from trials on common bean cultivars.

Materials and Methods

Methods of adaptability and stability

The methods of Annicchiarico (1992) and Cruz et al. (1989) were adopted to study the phenotypic adaptability and stability of common bean cultivars. The Annicchiarico method (1992) is based on the recommendation index ($\omega_{i(g)}$), in which stability and, also, genotypic adaptability is given by: $\omega_{i(g)} = \mu_{i(g)} - Z_{(1-\alpha)} \sigma_{zi}$ in which $\omega_{i(g)}$ is the recommendation index; $\mu_{i(g)}$ the average percentage of genotypes i; $Z_{(1-\alpha)}$ the percentage of the standard normal distribution function, and σ_{zi} the standard deviation of the values Z_{ij}, associated with the ith genotype.

The Cruz et al. (1989) method is based on bisegmented regression analysis, using the following statistical model: $Y_{ij} = \beta_{0i} + \beta_{1i} I_j + \beta_{2i} T(I_j) + \delta_{ij} + \varepsilon_{ij}$ in which Y_{ij} is the average of the i-th genotype in the jth environment; β_{0i} the average of the i-th genotype; β_{1i} the linear regression coefficient; I_j the encoded environmental index $\left(\sum_j^i I_j = 0\right)$ and where: $I_j \leq 0$, then $T(I_j) = 0$; however, if $I_j > 0$, then $T(I_j) = I_j - I_+$, where: I_+ is the average of the indexes (I_j) positives.

In order to bring automation to the decision making process, two *fuzzy* controllers were developed, one for the Annicchiarico (1992) and a second for the Cruz et al. (1989) method. The controllers were developed based on routines established in the R software (R Development Core Team, 2010), and all the algorithms used in this study have been presented by Carneiro et al. (2018).

Development of the *fuzzy* methodology for the Annicchiarico method

For the Annicchiarico method (1992), the *fuzzy* controller based on the *fuzzy* inference system proposed by Mamdani (Mamdani and Assilian, 1975) was developed. The input *fuzzy* linguistic variables used were the recommendation index parameters for favorable environments (ω_f) and the recommendation index parameters for unfavorable environments (ω_d). *Fuzzy* sets were generated for each variable by means of pertinence functions that allowed, through the "fuzzification" process, for the classification of each cultivar evaluated for these parameters. The values of (ω_f) and ω_d were allocated to the *fuzzy* sets "Low" and "High", by means of the form-fitting functions of Z and S-shape, respectively (Figure 1).

An output linguistic *fuzzy* variable, called "Mamdani Behavior", was generated. The values of this variable were allocated in four *fuzzy* sets based on performance regarding the adaptability and stability of the genotypes evaluated: General (GE); Favorable environment (FE); Unfavorable Environment (UE) and Not Indicated (NI). The rules used in the developed *fuzzy* controllers were based on the interpretation of the parameters of the method of Annicchiarico (1992). Table 1 presents the rules applied to the controllers developed based on the Annicchiarico method (1992).

Development of the *fuzzy* methodology for the Cruz et al. method

For the Cruz et al. (1989) method, the *fuzzy* controller was also developed based on the *fuzzy* inference system proposed by Mamdani (Mamdani and Assilian, 1975). The *fuzzy* linguistic input variables used were the general mean parameters (β_0), the coefficient of regression of unfavorable environments (β_1), the coefficient of favorable environments ($\beta_{1i} + \beta_{2i}$) and the coefficient of determination (R^2). *Fuzzy* sets were generated for each variable by means of pertinence functions that allowed, by means of the "fuzzification" process, for the classification of each cultivar evaluated based on the criteria of adaptability and stability.

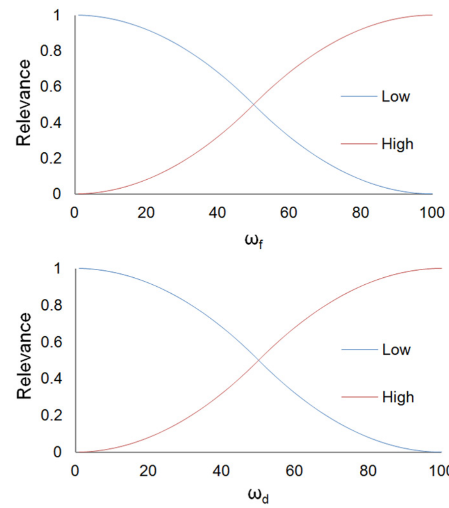

Figure 1 – Assigned membership functions for linguistic variables ω_f and ω_d.

Table 1 – Linguistic *fuzzy* rules implemented in behavioral *fuzzy* controllers regarding the adaptability and stability of the Annicchiarico method (1992).

Inputs		Output
ω_d	ω_f	Mamdani behavior
High	High	General
Low	High	Favorable environment
High	Low	Unfavorable environment
Low	Low	Not indicated

ω_f = recommendation index for favorable environments; ω_d = recommendation index for unfavorable environments.

The general averages of cultivars (β_0) were standardized on a scale of zero to 100. Standardization was based on the normal distribution of the data, the overall mean value (μ) and the standard deviation (σ) of these data. The values associated with $\mu - 3\sigma$ were assigned the value zero and the values associated with $\mu + 3\sigma$ the value of 100 (Figure 2A).

The values of the regression coefficients of unfavorable environments (β_1) and of the coefficient of favorable environments ($\beta_1 + \beta_2$) were allocated to the sets "Less than one", "Same as one" and "Greater than one", by means of the form membership functions of Z ("*zmf*"), form of "π" ("*pimf*") and form of S ("*smf*"), respectively. In this classification, the cultivars that were considered had relevance above 50 %, in the set "Equal to one", and presented values of β_1 and $\beta_{1i} + \beta_{2i}$ statistically equal to one according to Student's *t* test. The values of the β_1 and $\beta_{1i} + \beta_{2i}$ originals of each genotype, when submitted to the controller, were standardized. This standardization was based on a confidence interval with 95 % probability, and a t-distribution, considering the null hypothesis whereby β_1 and $\beta_{1t} + \beta_{2i}$ are equal to one. At the lower limit of the confidence interval, -2 was assigned and the upper limit was assigned the value four (Figure 2B and C). The values of the coefficients of determination (R^2) were allocated to the *fuzzy* sets "Low" and "High", by means of the form membership functions of Z and the form of S, respectively (Figure 2D).

An output linguistic *fuzzy* variable called "Mamdani Behavior" was generated. The values of this variable were allocated to eight *fuzzy* sets based on performance in terms of adaptability and stability of genotypes: Average adaptability to favorable environment (AFE), Maximum adaptability to favorable environment (MaxFE), Not adapted (NA), Average general adaptability (AGA), Maximum general adaptability (MaxGA), Maximum adaptability to unfavorable environments (MaxUE), Low stability (LS) and Low yield (LY). Table 2 presents the rules used in *fuzzy* controllers developed based on the interpretation of the parameters of the method proposed by Cruz et al. (1989).

Field trials with common bean cultivars

In order to test the efficiency of developed *fuzzy* controllers, real grain yield data were obtained from field evaluation trials on 18 cultivars from the commercial group "Carioca" (Alba, BRS Cometa, BRS Estilo, BRS Horizonte, BRSMG Majestoso, BRSMG Pioneiro, BRSMG Talismã, BRS Pontal, BRS Requinte, Campeão 2, Guará, IAC Tybatã, IPR Colibri, IPR Juriti, IPR Saracura, Magnífico, Pérola and Rubi).

The trials were conducted at 11 locations and in the following years: Ponta Grossa, in the state of Parana, longitude 50°09′43″ O, latitude 25°05′42″ S, and elevation 956 m, in the 2006, 2008 and 2010 growing seasons and in the 2007 and 2010 off seasons; in Santo Antônio of Goiás, in the state of Goiás, longitude 49°18′32″ O, latitude 16°29′8″ S, and elevation 823 m, in the 2006, 2008, and 2010 winter seasons and in Uberlândia, in the state of Minas Gerais, longitude 48°16′38″ O latitude 18°55′07″ S, and elevation 780 m, in the 2007 and 2008 winter seasons and in the 2008 off season. The experimental design was a randomized block design, with three replications. The experimental plots consisted of four lines, 4.0 m in length, spaced 0.5 m apart. The yield data were col-

Table 2 – Language *fuzzy* rules implemented in the Mamdani *fuzzy* controller based on the adaptability and stability of the Cruz et al. method (1989).

Inputs				Output
Average	β_1	$\beta_1+\beta_2$	R^2	Mamdani behavior
High	Equal to 1	Equal to 1	High	AFE
High	Equal to 1	Higher than 1	High	MaxFE
High	Equal to 1	Lower than 1	High	NA
High	Higher than 1	Equal to 1	High	AFE
High	Higher than 1	Higher than 1	High	MaxFE
High	Higher than 1	Lower than 1	High	NA
High	Lower than 1	Equal to 1	High	AGA
High	Lower than 1	Higher than 1	High	MaxGA
High	Lower than 1	Lower than 1	High	MaxUE
Other combinations			Low	LY
Low	Other combinations			LY

AFE = Average adaptability to favorable environments; MaxFE = Maximum adaptability to favorable environments; NA = Not adapted; AGA = Average general adaptability; MaxGA = Maximum overall adaptability; MaxUE = Maximum adaptability to unfavorable environments; LS = Low stability; and LY = Low yield.

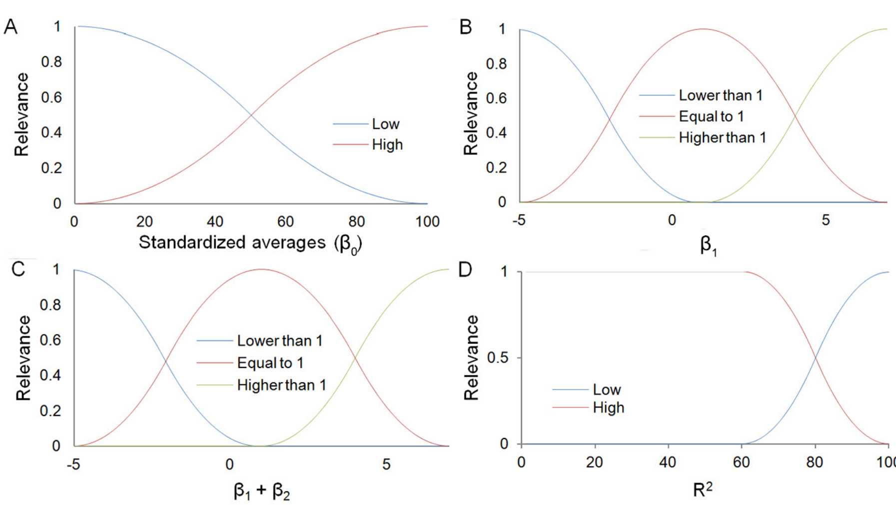

Figure 2 – A) Assigned membership functions for the "standardized average" (β_0). B) linguistic variables (β_1). C) standardized coefficient for favorable environments ($\beta_1 + \beta_2$). D) coefficient of determination (R^2).

lected from the two central lines of each plot, whose yield was measured and converted into kg ha^{-1}, with 13 % of grain moisture.

The experimental data were submitted to analysis of individual variance, the residues being found to be homogeneous, which ensured the viability of the joint analysis. After analyzing the significance of the interaction of genotypes by environments using the F test at 5 %, analyses of adaptability and stability were performed in accordance with the methods of Annicchiarico (1992) and Cruz et al. (1989). Subsequently, the parameters obtained by these methods were submitted to the *fuzzy* controllers created in order to determine behavior and establish the recommendation of these cultivars.

Results

Table 3 presents the estimates of pertinence through the *fuzzy* controller based on the Annicchiarico method (1992), which indicate in which of the four groups each of the genotypes was to be classified by the *fuzzy* controller. Thus, the BRS Pontal cultivar was classified as general behavior (GB). This classification is correct, since this genotype presented high index of recommendation readings both for favorable environments (ω_f) and highly unfavorable (ω_d).The cultivars BRS Estilo, Campeão 2 and IPR Juriti were classified as indicated for favorable environments (FE). This is due to the recommendation index for favorable environments being (ω_f) High (average yield above the general average, which is 1,952 kg ha^{-1} in favorable environments).

Alba cultivars BRS Cometa, BRS Horizonte, BRSMG Majestoso, BRSMG Pioneiro, BRSMG Talismã, BRS Requinte, Guará, IAC Tybatã, IPR Colibri, IPR Saracura, Magnífico, Perola and Rubi had already been classified as non-indicated (NI). This can be justified by their low recommendation index, both for favorable environments (ω_f) and for unfavorable environments (ω_d). However, it should be noted that the Pearl was already the most widely cultivated bean cultivar in the country, showing good comparative performance in different growing regions and sowing times, considering real farming conditions.

The largest estimates of pertinence presented (Table 4) indicate in which of the eight groups each of the genotypes should be classified by the *fuzzy* controller. Based on the Cruz et al. (1989) method, none of the cultivars presented behavior indicated for favorable and unfavorable environments (MaxFE and MaxUE). This agrees with the estimated parameters, since no genotype showed high yield (β_0); low sensitivity to adverse conditions in unfavorable environments ($\beta_{1i} < 1$); responsiveness to environmental improvement ($\beta_{1i} + \beta_{2i} > 1$) and a high coefficient of determination ($R^2 > 0.80$). Although no cultivar was indicated for both favorable and unfavorable environments (MaxFE and MaxUE), genotypes BRS Horizonte, BRS Requinte, IPR Colibri and IPR Saracura came closest to this classification, due to the greater relevance to these groups.

Cultivars BRS Estilo, BRS Pontal, Campeão 2, IAC Tybatã and IPR Juriti were classified by the *fuzzy* controllers as having medium adaptability to favorable environments (AFE). This classification is correct, and can be justified by means of the high readings in the

Table 3 – Recommendation index estimates for favorable environments (ω_f), unfavorable (ω_d) and classification by the fuzzy controller of the behavior of 18 common bean cultivars, in 11 environments, based on the Annicchiarico method (1992).

Cultivars	Index of recommendation		Behavior in pertinences				Classification
	ω_f	ω_d	GB	FE	UE	NI	
Alba	81.77	74.63	28	33	28	67	NI
BRS Cometa	91.91	85.75	37	42	37	58	NI
BRS Estilo	107.40	97.69	48	52	43	43	FE
BRS Horizonte	82.98	75.08	28	34	28	66	NI
BRSMG Majestoso	89.72	84.73	36	40	36	60	NI
BRSMG Pioneiro	95.46	87.81	39	46	39	54	NI
BRSMG Talismã	97.34	86.54	37	47	37	53	NI
BRS Pontal	109.19	101.52	52	48	41	41	GB
BRS Requinte	75.78	97.26	29	29	47	53	NI
Campeão 2	101.33	99.63	49	50	49	49	FE
Guará	90.19	91.96	41	41	42	58	NI
IAC Tybatã	98.99	93.49	44	49	44	51	NI
IPR Colibri	75.78	82.56	29	29	34	66	NI
IPR Juriti	103.15	95.63	46	53	46	47	FE
IPR Saracura	90.56	92.29	41	41	43	57	NI
Magnífico	77.93	82.30	30	30	34	66	NI
Pérola	99.81	80.09	32	49	32	50	NI
Rubi	89.08	72.87	27	40	27	60	NI

Classifications: General behavior (GB), Favorable environment (FE), Unfavorable environment (UE) and Not indicated (NI).

Table 4 – Estimates of the general average (β_0), linear response to unfavorable environments (β_1), linear response to favorable environments (β_{1i} + β_{2i}), determination coefficient (R^2) and classification by the *fuzzy* controller of the behavior of 18 common bean cultivars, based on the Cruz et al. (1989) method.

Cultivars	Parameters				Behavior in Pertinences								Group
	β_0	β_1	$\beta_{1i}+\beta_{2i}$	R^2	AFE	MaxFE	NA	AGA	MaxGA	MaxUE	LS	LY	
Alba	1.757	0.99^{ns}	1.20^{ns}	0.89	21	21	0	0	0	0	16	77	LY
BRS Cometa	1.811	1.02^{ns}	0.85^{ns}	0.96	31	0	12	0	0	0	2	69	LY
BRS Estilo	2.103	1.11^{ns}	1.28^{ns}	0.96	57	43	0	0	0	0	2	13	AFE
BRS Horizonte	1.752	0.81*	0.98^{ns}	0.83	21	0	0	21	0	0	21	64	LY
BRSMG Majestoso	1.881	1.00^{ns}	0.99^{ns}	0.89	45	0	0	0	0	0	15	55	LY
BRSMG Pioneiro	2.016	1.05^{ns}	0.55**	0.88	13	0	74	0	0	0	17	26	NA
BRSMG Talismã	1.851	1.07^{ns}	0.96^{ns}	0.97	39	0	1	0	0	0	1	61	LY
BRS Pontal	2.113	1.11^{ns}	1.12^{ns}	0.97	71	8	0	0	0	0	1	12	AFE
BRS Requinte	1.835	0.83*	1.14^{ns}	0.79	34	10	0	35	10	0	35	52	LY
Campeão 2	2.079	1.15^{ns}	1.28^{ns}	0.94	51	44	0	0	0	0	4	16	AFE
Guará	2.012	1.11^{ns}	0.43**	0.76	0	0	33	0	0	0	67	27	LS
IAC Tybatã	1.934	1.03^{ns}	1.20^{ns}	0.98	58	23	0	0	0	0	1	42	AFE
IPR Colibri	1.719	0.78**	111^{ns}	0.88	13	7	0	16	7	0	16	81	LY
IPR Juriti	2.017	1.07^{ns}	0.80^{ns}	0.98	74	0	23	0	0	0	0	26	AFE
IPR Saracura	1.875	0.83*	0.78^{ns}	0.94	34	0	26	44	0	26	4	56	LY
Magnífico	1.640	0.74**	0.91^{ns}	0.91	2	0	2	7	0	5	7	91	LY
Pérola	1.970	1.21**	1.47**	0.97	10	65	0	0	0	0	1	35	MaxFE
Rubi	1.859	1.09^{ns}	0.94^{ns}	0.89	40	0	2	0	0	0	16	60	LY

Coefficients followed by ns, * and ** are, respectively: not significant at the 5 % level, significant at the 5 % level and significant at the 1 % probability level by the t test when considering as a null hypothesis that $\beta_1 = 1$, and $\beta_{1i} + \beta_{2i} = 1$. AFE = Average adaptability to favorable environments; MaxFE = Maximum adaptability to favorable environments; NA = Not adapted; AGA = Average general adaptability; MaxGA = Maximum general adaptability; MaxUE = Maximum adaptability to unfavorable environments; LS = Low stability; and LY = Low yield.

genotypes (above the average overall by 1.952 kg ha^{-1}); $\beta_1 \geq 1$; $\beta_1 + \beta_2 = 1$ and high determination coefficient $R^2 > 80$ %. Cultivar Pérola had already been classified as having maximum adaptability to favorable environments (MaxFE), which is justified by a β_0 higher than the general average of 1.952 kg ha^{-1}; $\beta_1 \geq 1$; $\beta_1 + \beta_2 > 1$ and R^2 high (above 80 %).

Cultivar Guará was classified as low stability (LS). This is a consequence of β_1 being greater than one, indicating that this cultivar is highly sensitive to the adverse conditions of unfavorable environments and R^2 above 80 %. Cultivars Alba, BRS Cometa, BRS Horizonte, BRSMG Majestoso, BRSMG Talismã, BRS Requinte, IPR Colibri, IPR Saracura, Magnífico and Rubi were considered to be low yield, with estimates lower than 1.952 kg ha^{-1}. Finally, cultivar BRSMG Pioneiro was considered not appropriate (NA). This can be justified by the β_1 being slightly higher than one and $\beta_1 + \beta_2$ lower than one, indicating that this cultivar presents high sensitivity to adverse conditions in unfavorable environments (Table 3).

The *fuzzy* controllers based on the methods of Annicchiarico (1992) and Cruz et al. (1989) classified the 18 cultivars adequately and in accordance with the established *fuzzy* rules and parameters of each method.

Discussion

The studies of phenotypic adaptability and stability are important to breeding programs. They allow for the identification of genotypes with the capacity to take advantage of the stimulus of the environment, with predictable behavior patterns which respond to the environmental variations, be they under specific or broad conditions (Gauch, 1992), or even those ampler and general genotypes with little sensitivity to environmental variation. However, when a substantial number of genotypes are evaluated, the interpretation of the parameters of adaptability and stability becomes laborious, requiring considerable time on the part of the breeder and can lead to misunderstandings. In this case, automation of genotype classification by *fuzzy* logic is a viable option (Carneiro et al., 2018).

Among the various methods of adaptability and stability are those of Annicchiarico (1992) and Cruz et al. (1989). The Annicchiarico method (1992) takes as a reference the average of each of the environments, being calculated from the index of confidence or recommendation, which represents the chance of cultivar *i* to present a phenotypic performance superior to the general average for favorable environments (ω_f) and unfavorable (ω_d) environments. On the other hand, the Cruz et al. method (1989), is based on estimates of parameters obtained in bissegmented regression (β_0, β_{1i} + β_{2i}, and R^2), and takes into consideration how genotypes behave differently in both favorable (with negative values of the environmental index) and unfavorable environments (with positive values of the environmental index).

For the *fuzzy* controller adapted for both the Annicchiarico (1992) and the Cruz Torres and Vencovsky approach (1989), it was found that the classification of genotype stability and adaptability had been made correctly, according to the traditional interpretation of estimated parameters. The same was verified by Carneiro et al. (2018), when using *fuzzy* controllers in genotype classification for adaptability and stability following the methods of Eberhart and Russell (1966) and Lin and Binns (1988) using grain yield data from experiments with bean genotypes evaluated in nine environments. The correct classification by the *fuzzy* controllers is due to the composition of the input and output linguistic variables, allowing for the operator's experience to be codified in rules, enabling the computer to interpret and provide accurate and useful information for decision making (Simões and Shaw, 2011). That is, its efficiency is due to its powerful ability to model complex human reasoning (Türksen, 2007). This ability makes *fuzzy* logic superior to other more classical statistical methodologies in decision making (Blanco-Fernandez et al., 2013, 2014; Piterbarg, 2011; Viertl, 2011), even though there are uncertainties arising from the lack of definition of limits in the interpretation of the components (parameters) studied (Qin et al., 2007).

An additional and important item of information in the use of the *fuzzy* controllers is that in addition to classifying the genotype in a group, it also establishes pertinent parameters for the composition of genotype groups. This additional information can be justified, according to Kuo et al. (2009), by the systematization of imprecise knowledge. For genetic improvement, this is very important as if there are no genotypes with a classification of interest, one can use genotypes that are more pertinent to the desired group, such as the selection of parents in breeding programs and the recommendation of cultivars more suited to a given growing condition.

Therefore, *fuzzy* controllers based on the Annicchiarico (1992) and Cruz et al. (1989) methods have been shown to be useful and efficient as aids to the decision-making automation process in the recommendation of cultivars, according to established *fuzzy* rules. Consequently, this technique becomes a major ally of breeding programs because of its simplicity and automation capacity, especially when a large number of genotypes are evaluated.

Conclusions

The *fuzzy* controllers developed allowed for the correct classification of common bean cultivars according to the traditional interpretation of the parameters of adaptability and stability for the Annicchiarico (1992) and Cruz et al. (1989) methods.

The methods used were efficient in the automation of decision making in the recommendation of cultivars for studies of phenotypic adaptability and stability.

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Authors' Contributions

Conceptualization: Carneiro, A.R.T., Azevedo, A.M. Data acquisition: Souza, T.L.P.O., Pereira, H.S., Melo, L.C. Data analysis: Azevedo, A.M. Design of Methodology: Azevedo, A.M. Writing and editing: Carneiro, A.R.T., Sanglard, D.A., Azevedo, A.M., Souza, T.L.P.O., Pereira, H.S., Melo, L.C.

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