



Application of fuzzy logic for adaptability and stability studies in conilon coffee clones in an agroecological system in the Zona da Mata of Minas Gerais State, Brazil

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ABSTRACT. The purpose of this study was to evaluate the efficiency of using fuzzy controllers as auxiliary tools for different adaptability and stability methods aiming at the selection of conilon coffee clones. Thirty-six conilon coffee clones were evaluated for grain yield (bag ha⁻¹), within seven harvests (2018 to 2024). Adaptability and stability were evaluated using the hybrid fuzzy controller (Eberhart & Russell, 1966; Cruz et al., 1989; Annicchiarico, 1992). There was significance for the effects of crops, clones, and clone by crop interaction. The Eberhart & Russell method classified clones 3, 16, 24, and 33 as having general adaptability, and 32 and 36 as having adaptability to unfavorable environments. In the Annicchiarico method (1992), clones 4, 10, 24, and 26 were classified as general behavior. Clones 2 and 8 show high adaptability to adverse environments, while clones 10, 23, and 29 excel in favorable conditions. By Cruz et al. (1989), clones 28 and 31 did not correspond to any classification through this controller. In this methodology, clone 29 presented the highest stability index. The use of these methodologies is a viable alternative for the classification of clones. The differentiated behavior of clones is influenced by environmental conditions, which justifies the use of different adaptability and stability methodologies. The use of fuzzy controllers in the recommendation of conilon coffee clones is a useful and promising tool in plant breeding programs. Clones 2 and 8 showed high adaptability to adverse environments, while clones 10, 23, and 29 excelled in favorable conditions.

Keywords: *Coffea canephora*; artificial intelligence; classification; plant breeding.

Received on July 7, 2025.

Accepted on November 6, 2025.

Introduction

Global coffee production in 2025/2026 is estimated at approximately 178.7 million bags, of which 56.7% will be *Coffea arabica* (Arabica coffee) and 43.3% will be *Coffea canephora* (Robusta/Conilon coffee) (United States Department of Agriculture [USDA], 2024). In Brazil, total coffee production for the 2025/26 harvest is estimated at 65.0 million bags, of which 24.1 million bags will be *Coffea canephora*.

This coffee species is recommended for low-altitude regions (<600 m), with an average annual temperature between 22 and 27°C, a water deficit of up to 200 mm, and an average rainfall of 1,200 mm year⁻¹ (Ferrão et al., 2017). The state of Minas Gerais ranks fourth in conilon coffee production in the country, with an estimated production of 443.7 thousand bags for the 2025 harvest, concentrated in the Zona da Mata, Rio Doce, and Central regions (65.7%) and the North, Jequitinhonha, and Mucuri regions (34.4%) (Companhia Nacional de Abastecimento [CONAB], 2025). Although this production is still incipient, the state has great potential for expanding conilon coffee cultivation, due to its favorable soil and climate conditions.

Conilon coffee, being an allogamous species, reproduces by cross-pollination, which confers high genetic variability among genotypes (Ferrão et al., 2017) and consequently significant interactions with the environment, posing a challenge for breeders (Partelli et al., 2022). Therefore, to maintain desirable traits, conilon coffee is commonly propagated vegetatively (clones), which provides uniform crop development and better fruit quality.

Phenotypic expression is the clone's action result under the influence of the environment. However, when considering a series of environmental effects, in addition to the effects of clones and environments, an

additional effect provided by the interaction between them is detected (van Eeuwijk et al., 2016; Silva Junior et al., 2021), entitled clone vs. environment interaction (C x E) (Bustos-Korts et al., 2016; Mannion, 2023). Thus, clones' relative behavior fundamentally depends on the environmental conditions to which they are subjected.

Estimating the C x E interaction is crucial to the coffee plant breeding, as it assesses how different clones respond to environmental variations, allowing the selection of clones that present high adaptability and phenotypic stability (Partelli et al., 2022). This interaction can make it difficult to recommend new clones, as they may have different behaviors in different environments (Eeuwijk et al., 2016). However, understanding this interaction allows us to take advantage of its beneficial effects and seek alternatives to investigate undesirable effects.

Adaptability and stability studies aim to identify genetic materials that consistently perform well in different environments. Traditional regression-based methods, such as those proposed by Eberhart and Russell (1966), Annicchiarico (1992), and Cruz et al. (1989), can be challenging to interpret, especially when presenting a large number of clones, due to the minimal variation between them. Furthermore, the classification complexity for adaptability and stability complicates the selection process. However, the high number of parameters can increase the risk of errors in clone recommendations. Thus, the application of new paradigms, such as computational intelligence, in plant breeding has provided new analysis alternatives to assist in the recommendation of cultivars.

Artificial intelligence is the area of computer science that aims to simulate in machines the ability to solve problems and perform tasks that are skills of natural human intelligence (Russell & Norvig, 2013). Among the various techniques of this nature, fuzzy logic is a tool with potential recognition for solving classification and prediction problems (Carneiro et al., 2018; Carneiro et al., 2019; Silva Junior et al., 2021). This methodology has a multivalent trait, that allows converting human experience into a form that is understood by computers, since machines are only capable of processing data according to Boolean logic, which is bivalent (Adeli & Jiang, 2003). Thus, the technology made possible by the fuzzy approach has immense practical value, in which it becomes possible to include the experience of human operators in systems called fuzzy controllers (Simões & Shaw, 2011).

Among artificial intelligence tools, fuzzy logic has great potential to assist in the cultivar recommendation stage, since this is a technique that aims to use the knowledge present in the literature and in the experience of the breeding programs themselves. Therefore, the purpose of this study was to evaluate the efficiency of using fuzzy controllers as auxiliary tools for different adaptability and stability methods, aiming at the selection of conilon coffee clones in the Zona da Mata of Minas Gerais State, Brazil.

Material and methods

Experiment description

The experiment was installed at the Experimental Field of the Minas Gerais State Agricultural Research Corporation (EPAMIG), in the municipality of Leopoldina, Minas Gerais State, Brazil (21°31'55" S, 42°38'35" W, 212 m). Thirty-six conilon coffee clones from the Capixaba Institute for Research, Technical Assistance and Rural Extension (Incaper) were evaluated. A randomized block design was used, with three replicates, nine coffee plants per plot, and 1.0 x 2.5 m spacing between plants and rows, respectively.

During the experiment, fertilization and cultural treatments were carried out annually, according to the recommendations for conilon coffee cultivation (Ferrão et al., 2017). Based on the soil analysis results, liming to correct soil acidity, foliar fertilization with a micronutrient solution, and top-dressing fertilization were carried out, in which priority was given to the use of chicken litter as a source of macronutrients and supplementation with chemical fertilizers when necessary. All fertilization was divided into three applications during the rainy season at intervals of 30 to 60 days. Weed management involved mowing between the rows, with the residues used as mulch. Yield was evaluated in 60 kg bags of processed coffee per hectare (bag ha⁻¹) (GY) over the period of seven consecutive harvests (2018 to 2024), which corresponded to the cultivation environments.

Individual variance analyses were performed and, after verifying that the relationship between the largest and smallest mean square of the environment residues did not exceed the 7:1 relationship (Pimentel-Gomes, 2009), joint ANOVA was performed according to the statistical model described below:

$$Y_{ijk} = \mu + B/S_{jk} + C_i + S_j + CS_{ij} + e_{ijk}$$

where: Y_{ijk} is the observation in the k^{th} block, evaluated in the i^{th} clone and j^{th} harvest; μ is the overall average of the experiments; B/S_{jk} is the effect of block k within harvest j ; C_i is the effect of the i^{th} clone considered

as fixed; S_j is the effect of the j^{th} harvest considered as random; CS_{ij} is the random effect of the interaction between clone i and crop j ; e_{ijk} is the random error associated with the observation Y_{ijk} .

The analyses from the computational intelligence perspective were carried out with the aid of Matlab software (Matlab, 2016) in integration with Genes software (Cruz, 2016).

Adaptability and stability methods

Adaptability and stability assessments were based on the methods by Eberhart and Russell (1966), Annicchiarico (1992), and Cruz et al. (1989), as described below:

The method proposed by Eberhart and Russell (1966) is based on simple linear regression analysis, in which the regression coefficient of each clone ($\hat{\beta}_{1i}$), in relation to the environmental index, as a measure of adaptability parameters, while deviations from this regression ($\hat{\sigma}_{\delta_i}^2$) and coefficient of determination (R^2) provide stability estimates. Clones were classified by general or broad adaptability ($\beta_1 = 1$), specific adaptability to unfavorable environments ($\beta_1 < 1$), or specific adaptability to favorable environments ($\beta_1 > 1$). This classification is based on the t-test result over the parameter in question, in which the hypothesis is that $\beta_1 = 1$. Clones can be classified according to the variance component attributed to regression deviations ($\hat{\sigma}_{\delta_i}^2$) with high predictability ($\hat{\sigma}^2 = 0$) or with low predictability ($\hat{\sigma}^2 > 0$). In this case, the hypothesis of $d_i = 0$ is assessed using F-test. R^2 is considered a parameter that reflects the clones' behavior predictability, and predictability increases with R^2 .

The method proposed by Annicchiarico (1992) is based on the recommendation index $\omega_{i(g)}$, which informs about the evaluated clone group stability. The stability parameter is measured by the clone superiority in relation to the average of each environment (harvests). However, stability is described by $\omega_{i(g)} = \hat{\mu}_{i(g)} - z_{(1-\alpha)}\hat{\sigma}_{zi(g)}$, in which, $\omega_{i(g)}$ corresponds to the recommendation index, $\hat{\mu}_{i(g)}$ refers to the clone average, $\hat{\sigma}_{zi(g)}$ is the standard deviation of the Z_{ij} values, of the i^{th} clone, considering its behavior in all environments.

The Cruz et al. (1989) methodology is based on bi-segmented regression analysis and has as its adaptability parameters the average ($\hat{\beta}_{oi}$) and the linear response to unfavorable environments ($\hat{\beta}_{1i}$) and favorable environments ($\hat{\beta}_{1i} + \hat{\beta}_{2i}$). Clones' stability is assessed by the regression deviation ($\hat{\sigma}_{\delta_i}^2$) of each clone, depending on environmental variations.

Fuzzy logic and hybrid fuzzy controllers

The fuzzy inference system was implemented on the results of these methodologies as a tool for interpretation and decision-making regarding clone recommendations. Implementing the fuzzy inference system for clone recommendation involves several important steps. Initially, input parameters are defined, ensuring that all relevant factors are considered. These parameters may need to be standardized to maintain consistency across the dataset. Once standardized, the parameters are allocated into sets using fuzzy functions, which classify them into high or low categories, based on the specific problem to be modeled, as described by Zadeh (2015).

Then, fuzzy controllers are developed for each stability method. These controllers use Takagi-Sugeno inference systems (Takagi & Sugeno, 1985), which combine fuzzy sets into "if-then" linguistic rules. These rules are based on the interpretation of parameters and help making decisions about clone recommendation. The parameter values for each clone are submitted to these controllers, which determine their behavior through pertinence estimates. Furthermore, hybrid fuzzy controllers can be developed based on the association of different parameters from several stability methods, providing a comprehensive approach for clone recommendation. This methodology improves the interpretation and decision-making process, ensuring that the recommended clones are appropriate for the modeled problem.

The fuzzy inference system implementation for clone recommendation involves the definition of input parameters: identification of parameters; standardization of parameters: consistency in data; allocation in fuzzy sets: use of fuzzy function to categorize parameters; development of fuzzy controllers: creation of controllers using Takagi-Sugeno inference systems; application to clones: determination of clone behavior through pertinence values; development of hybrid fuzzy controllers: association of different parameters.

Thus, the hybrid fuzzy controller for each method – Eberhart and Russell (1966), Cruz et al. (1989), and Annicchiarico (1992) – was obtained, based on the association of each methodology parameters.

Hybrid fuzzy controller - Eberhart and Russell (1966)

The hybrid fuzzy controller was developed based on the association of parameters β and R^2 of the Eberhart and Russell (1966) method-ER. The overall clone averages were standardized on a 0 to 100 scale.

Standardization was based on the normal distribution of data, overall average value (μ) and standard deviation (σ). The values associated with $\mu - 3\sigma$ were given the 0 value, and those associated with $\mu + 3\sigma$ were given the 100 value. The clone averages were subdivided into two fuzzy sets, "Low" and "High," according to the spline-based pertinence functions in the forms of Z (zmf) and S (smf) (Figure 1A) (Adeli & Jiang, 2003). The regression coefficient (β_1) values were allocated into sets of "Less than 1", "Equal to 1," and "Greater than 1", using the pertinence functions "Z-form" (zmf), " π -form" (pimf), and "S-form" (smf), respectively (Figure 1B). The R^2 values were not standardized. Each normalized function value ranges from 0 to 1. These were allocated to the fuzzy sets "Low" and "High" using the membership functions "Z-form" (fmz) and "S-form" (fms), respectively (Figure 1C).

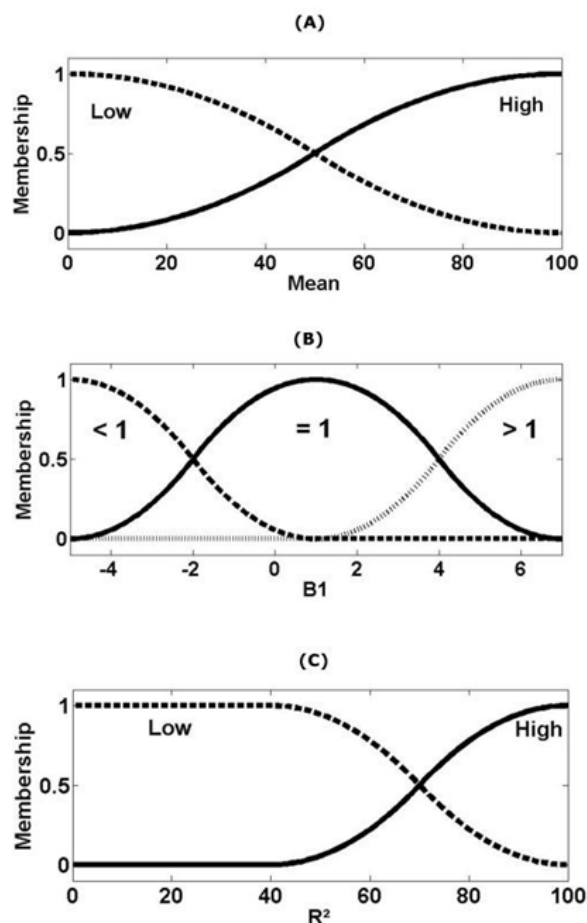


Figure 1. Fuzzy input variables used in hybrid fuzzy controllers - Eberhart & Russell (1966). Overall average for each clone evaluated (A), regression coefficient β_1 (B), and coefficient of determination R^2 (W).

For this inference, we assumed that for a clone to be recommended, it should have an average higher than the general average of all environments and R^2 greater than 70%. If a clone does not meet at least one of these conditions, it is classified as "poorly adapted". Subsequently, specific recommendation was made according to the following classes β_1 : $\beta_1 = 1$, "high adaptability"; $\beta_1 > 1$, "adaptability to favorable environments"; and $\beta_1 < 1$, "adaptability to unfavorable environments" (Table 1).

Table 1. Classification of clones obtained using the Eberhart and Russel (1966) method and respective parametric values.

Classification	Parametric values	
AGPB	$\beta_{1i} = 1 \text{ e } \sigma^2_{di} > 0$	$M_i M_i > M, R_i^2 > 70\%$
AFPB	$\beta_{1i} > 1 \text{ e } \sigma^2_{di} > 0$	$M_i M_i > M, R_i^2 > 70\%$
ADPB	$\beta_{1i} < 1 \text{ e } \sigma^2_{di} > 0$	$M_i M_i > M, R_i^2 > 70\%$
AGPA	$\beta_{1i} = 1 \text{ e } \sigma^2_{di} = 0$	$M_i M_i > M, R_i^2 > 70\%$
AFPA	$\beta_{1i} > 1 \text{ e } \sigma^2_{di} = 0$	$M_i M_i > M, R_i^2 < 70\%$
ADPA	$\beta_{1i} < 1 \text{ e } \sigma^2_{di} = 0$	$M_i M_i < M, R_i^2 < 70\%$

M_i : average production of clone i; M: overall average; R_i^2 : clone i coefficient of determination; AGPB: General adaptability and low predictability; AFPB: Specific adaptability to favorable environments and low predictability; ADPB: Specific adaptability to unfavorable environments and low predictability; AGPA: General adaptability and high predictability; AFPA: Specific adaptability to favorable environments and high predictability; ADPA: Specific adaptability to unfavorable environments and high predictability.

The estimated parameters (β_0, β_1 , and R^2) for the thirty-six clones were subjected to the hybrid fuzzy controller to determine the behavior of these clones through the aggregated values obtained (pertinence). The fuzzy rules implemented in the hybrid fuzzy controller (Eberhart & Russell, 1966) are available in Table 1.

Hybrid fuzzy controller - Cruz et al. (1989)

The fuzzy hybrid controller using the Cruz et al. (1989), method was developed based on Mamdani's fuzzy inference system (Mamdani & Assilian, 1975). The input fuzzy linguistic traits included the overall average parameters (β_0), the regression coefficient of unfavorable environments (β_1), the coefficient of favorable environments ($\beta_{1i} + \beta_{2i}$), and the coefficient of determination (R^2). The fuzzy set was created for the trait using pertinence functions that allowed the classification of each cultivar evaluated based on adaptability and stability criteria, through the "fuzzification" process.

The cultivars general averages (β_0) were standardized on a 0 to 100 scale, based on the normal distribution of the data, the overall average value (μ), and the standard deviation (σ). Values associated with $\mu - 3\sigma$ received the zero value, while values associated with $\mu + 3\sigma$ received the 100 value (Figure 3A). The regression coefficients of unfavorable environments (β_1) and favorable environments ($\beta_{1i} + \beta_{2i}$) were allocated to the sets "Less than one", "Equal to one", and "Greater than one", using pertinence functions in the form of Z ("zmf"), π ("pimf"), and S ("smf"), respectively. Clones with relevance above 50% in the "Equal to one" set presented values of β_1 and $\beta_{1i} + \beta_{2i}$ statistically equal to one, according to Student's t-test. The original values of β_1 and $\beta_{1i} + \beta_{2i}$ of each clone were standardized based on a 95% probability confidence interval and a t-distribution, considering the null hypothesis that β_1 and $\beta_{1i} + \beta_{2i}$ are equal to one. At the lower limit of the confidence interval, the value -2 was assigned, and at the upper limit, the value four was assigned (Figure 2B and C). The coefficients of determination (R^2) were allocated to the "Low" and "High" fuzzy sets, using Z- and S-shaped pertinence functions, respectively (Figure 2D).

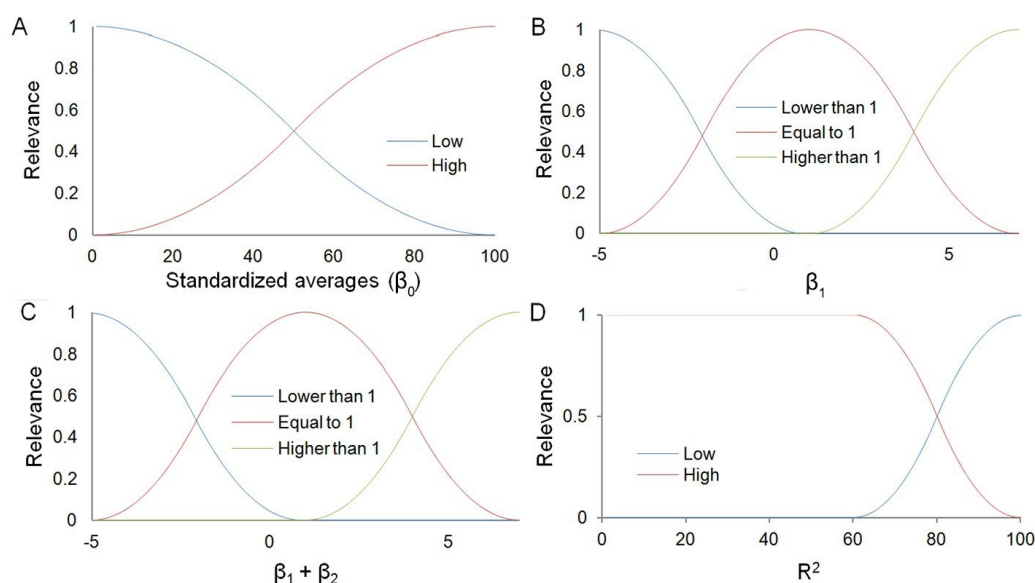


Figure 2. A) Pertinence functions assigned to the "standardized mean" (β_0). B) Linguistic variables (β_1). C) Standardized coefficient for favorable environments ($\beta_1 + \beta_2$). D) Coefficient of determination (R^2).

A linguistic fuzzy output variable called "Mamdani Behavior" was created, with values allocated to eight fuzzy sets based on the clones' performance in terms of adaptability and stability: Average Adaptability to Favorable Environment (AFE); Maximum Adaptability to Favorable Environment (MFE); Not Adapted (NA); Average General Adaptability (AGA); Maximum General Adaptability (MGA); Maximum Adaptability to Unfavorable Environments (MUE); Low Stability (LS) and Low Yield (LY). Table 3 presents the rules used in the developed fuzzy controllers, based on the parameter interpretation of the Cruz et al. (1989) method.

Hybrid fuzzy controller - Annicchiarico (1992)

The fuzzy hybrid controller by the Annicchiarico (1992) method was developed based on Mamdani's fuzzy inference system (Mamdani & Assilian, 1975). The fuzzy input linguistic traits included the recommendation index parameters for favorable (ω_f) and unfavorable (ω_d) environments. Fuzzy sets were generated for each

trait through pertinence functions, allowing the classification of each evaluated cultivar, based on these parameters, through the "fuzzification" process. The (ω_f) and (ω_d) values were assigned to the "Low" and "High" fuzzy sets using Z-shaped and S-shaped adjustment functions, respectively (Figure 3).

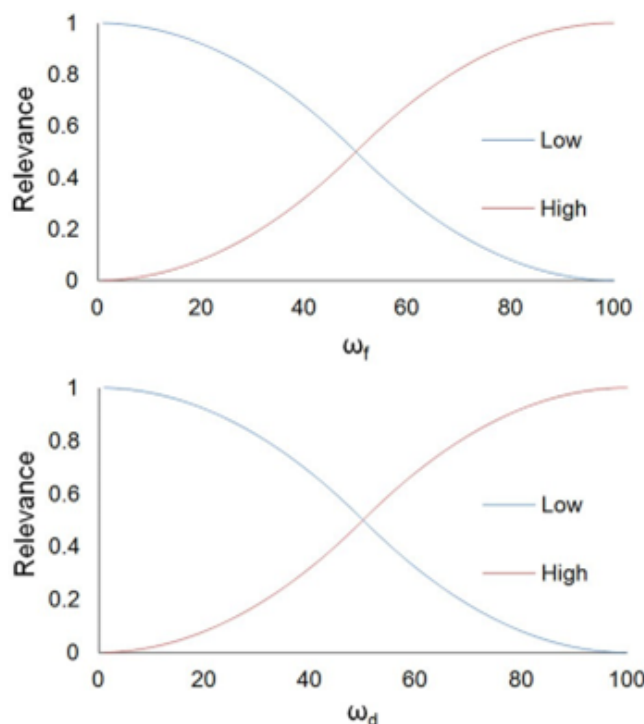


Figure 3. Pertinence functions assigned to linguistic variables for the recommendation index for favorable and unfavorable environments, ω_f and ω_d , respectively.

The values of the output fuzzy linguistic trait, called "Mamdani Behavior", were distributed into four fuzzy sets, based on their performance in terms of adaptability and stability of the evaluated clones: 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 Annicchiarico (1992) method parameters. Table 2 presents the rules applied to controllers developed based on this method.

Table 2. Genotype classes obtained using the Annicchiarico (1992) method.

Classification	Environment	
	ω_f	ω_d
General Environment (GE)	$M_{\max}$	$M_{\max}$
Favorable Environment (FE)	$M_{\max}$	$M_{\min}$
Unfavorable Environment (UE)	$M_{\min}$	$M_{\max}$
Not Indicated (NI)	$M_{\min}$	$M_{\min}$

$M_{\max}$: maximum yield in bag ha⁻¹ and $M_{\min}$: minimum yield in bag ha⁻¹; ω_f and ω_d recommendation index for favorable and unfavorable environments, respectively.

Table 3. Classification of clones obtained through the parameters of the Cruz et al. (1989) method and respective parametric values.

Classification	R^2	$\beta_1 + \beta_2$	β_1	β_0
AFE	$R_i^2 > 70\%$	$\beta_1 + \beta_2 = 1$	$\beta_1 = 1$	$\beta_0 = 1$
MFE	$R_i^2 > 70\%$	$\beta_1 + \beta_2 > 1$	$\beta_1 = 1$	$\beta_0 = 1$
NA	$R_i^2 > 70\%$	$\beta_1 + \beta_2 < 1$	$\beta_1 = 1$	$\beta_0 = 1$
AFE	$R_i^2 > 70\%$	$\beta_1 + \beta_2 = 1$	$\beta_1 = 1$	$\beta_0 = 1$
MFE	$R_i^2 > 70\%$	$\beta_1 + \beta_2 > 1$	$\beta_1 = 1$	$\beta_0 = 1$
NA	$R_i^2 > 70\%$	$\beta_1 + \beta_2 < 1$	$\beta_1 = 1$	$\beta_0 = 1$
AGA	$R_i^2 > 70\%$	$\beta_1 + \beta_2 = 1$	$\beta_1 = 1$	$\beta_0 = 1$
MGA	$R_i^2 > 70\%$	$\beta_1 + \beta_2 > 1$	$\beta_1 = 1$	$\beta_0 = 1$
MUA	$R_i^2 > 70\%$	$\beta_1 + \beta_2 < 1$	$\beta_1 = 1$	$\beta_0 = 1$
LY	$R_i^2 < 70\%$	$\beta_1 + \beta_2 < 1$	$\beta_1 < 1$	$\beta_0 < 1$

M_i : average production of genotype i; M : general average; R_i^2 : clone i coefficient of determination. AFE = Average adaptability to favorable environments; MFE = Maximum adaptability to favorable environments; NA = Not adapted; AGA = Average general adaptability; MGA = Maximum general adaptability; MUA = Maximum adaptability to unfavorable environments; LY = Low stability and yield.

Results and discussion

There was significance ($p < 0.01$) for the environment, clones, and clone by environment interaction effects for grain yield, indicating that the clones' behavior was influenced by environmental conditions (harvests) (Table 4), such as temperature, precipitation, solar radiation and relative humidity. This reinforces that it is possible to use methodologies that can classify clones according to their adaptability and stability.

The relationship between the largest and smallest residual mean square of the environments (QMr^+/QMr^-) was 6.78, an estimate that is close to 7.0, which, according to Gomes (1990) and Cruz and Regazzi (1997), can be considered as homogeneous residual variances. This low estimate enables performing joint variance analysis.

Table 4. Summary of joint analysis of variance regarding grain yield (bag ha^{-1}) for the thirty-six conilon coffee clones, in seven consecutive harvests in Leopoldina, Minas Gerais State, Brazil.

FV	DF	SSQ	MSQ	F value	Pr(>F)
C	35	278993	7971	15.042	2e-16***
R	2	2747	1373	2.591	0.0759
S	6	543484	90581	170.933	2e-16***
R:S	12	12870	1073	2.024	0.0207*
C:S	210	331722	1580	2.981	2e-16***
Residuals	490	259660	530		

***and*: significant at 0% and 1% probability by the F test, respectively. C: clone; R: repetition; S: harvest; DF: degree of freedom; SSQ: sum of squares; MSQ: mean sum of squares.

Fuzzy controller - Eberhart and Russell (1966)

Based on the fuzzy controller by the Eberhart and Russell (1966) method, the clones with general adaptability and low predictability were 3 and 16 (early maturing, originating from the clonal variety EMCAPA 8111), 24, and 33 (late maturing, originating from the clonal variety EMCAPA 8131), that is, they presented the highest pertinence values (AGPB) in the general group (Table 5). This means that they met the method's parameters to indicate an ideal clone, which include a high average for β_0 , β_1 equal to 1 and R^2 (Cruz et al., 2013). According to Cruz (2013), with R^2 above 80% it is indicative of greater stability. Therefore, these clones are capable of delivering good results in both favorable and unfavorable environments. In this group, clone 24 can be considered promising, as it obtained the highest pertinence estimate.

Most clones were classified as having specific adaptability to unfavorable environments and high predictability (ADPA) due to their lower β_0 , β_1 or R^2 . However, clones 4, 25, and 31, that present resistance to drought and intermediate maturation, originating from the clonal variety, EMCAPA 8141- Robsutão Capixaba, showed specific adaptability to favorable environments and high predictability, fitting into this group, due to the β_0 and $\beta_1 > 1$ high average. Furthermore, these clones presented R^2 above 80%, which is indicative of high predictability (stability) and, therefore, they are recommended when the goal is to increase yield through environmental improvement, especially for crops that employ a high level of technology, as is the case with coffee growing.

Although the controller, based on the method of Eberhart and Russell (1966), did not identify clones with adaptability to unfavorable environments, clones 32 and 36 of late maturation cycle and originating from the clonal variety EMCAPA 8131. These clones presented the highest pertinence estimate in the group, which was classified as having behavior with specific adaptability to unfavorable environments and low predictability. This classification is explained by the β_1 low estimate. Therefore, these clones are best suited for unfavorable environments. This is important information, as it shows that the fuzzy methodology not only allows classification, but also identification of better clones by the pertinence magnitude, as reported by Carneiro et al. (2018).

Table 5. Input variables and behavior classification for the thirty-six conilon coffee clones, in seven different harvests subjected to the fuzzy controller based on the Eberhart and Russell (1966) method.

Clone	Input			Relevance of behavior (%)					
	$\hat{\beta}_0$ (bag ha^{-1})	$\hat{\beta}_1$	R^2	AGPB	AGPA	ADPA	AFPA	AFPB	ADPB
1	44.33	0.9677	0.8920	36	0	64	0	0	0
2	50.22	0.8044	0.6869	9	0	55	0	0	9
3	58.98	1.0859	0.9409	60	0	40	3	0	0
4	108.28	2.2738	0.8367	0	0	33	67	0	0
5	37.94	0.6225	0.6368	2	0	53	0	0	2
6	47.87	0.6277	0.6704	6	0	51	0	0	6

7	38.38	0.7022	0.5695	0	0	67	0	0	0
8	49.07	0.6979	0.6502	3	0	57	0	0	3
9	47.23	0.7837	0.6474	3	0	59	0	0	3
10	78.69	1.3751	0.6832	9	0	52	9	0	0
11	40.94	0.9916	0.9191	69	0	0	0	0	0
12	30.27	0.5813	0.7888	19	0	55	0	0	19
13	53.25	0.9205	0.6077	0	0	50	0	0	0
14	37.91	0.7778	0.6165	0	0	73	0	0	0
15	37.70	0.8603	0.7652	27	0	66	0	0	7
16	53.57	0.7743	0.8618	51	0	49	0	0	19
17	41.77	0.8439	0.8725	33	0	67	0	0	9
18	59.32	1.2218	0.7153	17	0	60	17	0	0
19	50.28	1.0046	0.6736	7	0	55	0	0	0
20	30.51	0.6323	0.6242	1	0	50	0	0	1
21	30.39	0.5612	0.6041	0	0	67	0	0	0
22	46.91	1.0257	0.8899	40	0	60	0	0	0
23	86.10	1.2771	0.3208	0	0	72	0	0	0
24	73.87	1.2447	0.8502	72	0	28	22	0	0
25	61.27	1.4320	0.9412	34	0	37	63	0	0
26	81.00	1.0566	0.5845	0	0	86	0	0	0
27	29.11	0.5206	0.5397	0	0	76	0	0	0
28	83.97	1.9061	0.7264	0	0	80	20	0	0
29	91.81	1.7781	0.6758	0	0	93	7	0	0
30	58.45	0.9687	0.6392	2	0	59	0	0	0
31	59.28	1.4480	0.8300	31	0	40	60	0	0
32	33.84	0.5312	0.7841	23	0	58	0	0	23
33	59.02	1.2017	0.8880	60	0	40	15	0	0
34	32.27	0.8183	0.8581	21	0	75	0	0	12
35	47.79	0.9938	0.7632	33	0	59	0	0	0
36	37.69	0.6868	0.9336	27	0	64	0	0	27

AGPB: General adaptability and low predictability; AGPA: General adaptability and high predictability; AFPB: Specific adaptability to favorable environments and low predictability; AFPA: Specific adaptability to favorable environments and high predictability; ADPB: Specific adaptability to unfavorable environments and low predictability; ADPA: Specific adaptability to unfavorable environments and high predictability.

Fuzzy controller - Cruz et al. (1989)

Table 6 represents the pertinence estimates by the fuzzy controller based on the Cruz et al. (1989) method. In this Table, the estimates were allocated into eight fuzzy sets based on their performance regarding adaptability and stability of the clones. However, only three classification sets were observed, such as maximum general adaptability, maximum adaptability to favorable environment and maximum adaptability to unfavorable environments. For this methodology none of the clones showed behavior indicated for favorable and unfavorable environments (MFE and MUE). This agrees with the estimated parameters, since no clone that presented high yield (β_0); low sensitivity to adverse conditions in unfavorable environments ($\beta_1 < 1$); responsiveness to environmental improvement ($\beta_1 + \beta_2 > 1$), and high coefficient of determination ($R^2 > 0.80$) was obtained. The clones with maximum overall adaptability were 1, 2, 5, 8, 12, 14, 15, 16, 17, 20, 21, 27, 32, 34, and 36 which demonstrated the highest pertinence estimates for this group (Table 6). On the other hand, clones 3, 4, 10, 13, 19, 22, 23, 24, 25, 26, 29, 30, and 33 were classified as poorly adapted. Clones 28 and 31 did not match any classification through this controller. All these clones present different maturation cycles and genetic origin, as shown in the Supplementary material.

Clone 4 presented an overall average of 108.28 bag ha⁻¹ and clone 23 of 86.10 bag ha⁻¹ stand out for their high yield, suggesting potential for regions with favorable conditions. On the other hand, clones 27 and 21 demonstrated lower grain yields, 29.10 bag ha⁻¹ and 30.39 bag ha⁻¹, respectively, indicating that they may not be the most suitable for all conditions. In the stability index estimate, clones 28 (1.40) and 29 (2.14) obtained the highest index. These clones are more consistent across different harvests, which is desirable to ensure stable production. The lowest stability index estimates were for clones 27 (0.40) and 20 (0.45), which may be more sensitive to environmental variations.

The stability index trend estimate found that clones 14 and 31 demonstrate positive estimates, 1.36 and 1.64, respectively. This indicates that it provides a trend of improving stability over time. Clones 4 (-1.91) and 23 (-1.70) had a negative trend. The negative estimate indicates that the clones have a tendency towards reduced stability. Regarding the coefficient of regression estimate ($\beta_1 + \beta_2$), clones 28 (4.20) and 31 (2.80) indicate a strong response to environmental variations, being potentially more adaptable in favorable

conditions. On the other hand, clones 19 (-0.13) and 26 (-0.29) may have a lower response to environmental variations, which limits their adaptability. The clones that obtained the highest coefficient of determination estimates were 31 (0.98) and 28 (0.95), indicating that the regression model explains well the variation in production, suggesting that the data is reliable.

Table 6. Input variables and behavior classification for thirty-six conilon coffee clones, in seven different harvests subjected to the fuzzy controller, based on the method of Cruz et al. (1989).

Clone	$\hat{\beta}_o$ (bag ha ⁻¹)	Input				Relevance of behavior (%)		
		IJ	TIJ	$\beta_1 + \beta_2$	R^2	MGA	MFE	MEU
1	44.33	0.86	0.58	1.44	0.93	6	0	0
2	50.21	0.61	1.07	1.69	0.86	46	0	0
3	58.97	1.07	0.07	1.14	0.94	0	2	0
4	108.28	2.61	-1.91	0.69	0.92	0	7	0
5	37.94	0.73	-0.63	0.09	0.73	21	0	0
6	47.87	0.62	0.029	0.65	0.67	6	0	0
7	38.37	0.76	-0.37	0.39	0.59	0	0	0
8	49.06	0.53	0.91	1.45	0.81	57	0	0
9	47.22	0.94	-0.90	0.04	0.77	1	0	0
10	78.69	1.22	0.82	2.05	0.71	0	16	0
11	40.94	0.94	0.23	1.18	0.92	1	0	0
12	30.27	0.53	0.27	0.80	0.81	57	0	0
13	53.25	1.12	-1.11	0.002	0.73	0	4	0
14	37.91	0.53	1.36	1.90	0.89	46	0	0
15	37.70	0.92	-0.36	0.56	0.78	2	0	0
16	53.57	0.82	-0.28	0.53	0.87	9	0	0
17	41.76	0.87	-0.16	0.70	0.87	5	0	0
18	59.32	1.03	1.02	2.06	0.78	0	0	0
19	50.28	1.25	-1.39	-0.13	0.86	0	19	0
20	30.51	0.45	0.96	1.42	0.83	68	0	0
21	30.39	0.61	-0.29	0.31	0.62	1	0	0
22	46.91	1.06	-0.22	0.83	0.89	0	1	0
23	86.10	1.59	-1.7	-0.16	0.40	0	22	0
24	73.86	1.13	0.63	1.76	0.88	0	5	0
25	61.26	1.44	-0.08	1.36	0.949	0	4	0
26	81.00	1.35	-1.64	-0.29	0.79	0	13	0
27	29.10	0.40	0.65	1.06	0.66	5	0	0
28	83.96	1.40	2.80	4.20	0.95	0	0	0
29	91.80	2.14	-2.03	0.10	0.80	0	47	0
30	58.45	1.17	-1.13	0.03	0.76	0	9	0
31	59.28	1.15	1.64	2.80	0.98	0	0	0
32	33.83	0.46	0.36	0.83	0.83	68	0	0
33	59.01	1.32	-0.66	0.65	0.92	0	6	0
34	32.27	0.71	0.58	1.30	0.92	25	0	0
35	47.79	0.830	0.91	1.74	0.85	9	0	0
36	37.68	0.68	0.005	0.69	0.93	30	0	0

MGA: Maximum general adaptability; MFE: Maximum adaptability to favorable environment; MEU: Maximum adaptability to unfavorable environments.

Fuzzy controller - Annicchiarico (1992)

Table 7 presents the pertinence estimates through the fuzzy controller based on the Annicchiarico (1992) method, indicating in which of the four groups each clone should be classified by the fuzzy controller. Clones 4, 10, 24, and 26 were classified as general behavior, since they presented a high recommendation index for both favorable (ω_f) and highly unfavorable (ω_d) environments. These clones are versatile and can be recommended for cultivation in a wide variety of environmental conditions. Furthermore, their high adaptability is a positive aspect, since even in adverse conditions they present stability in production. Clones 23, 25, 29, and 33 were classified as suitable for favorable environments. This is because the recommendation rate for favorable environments is high (ω_f) (average yield above the general average, which is 82.73 bag ha⁻¹ in favorable environments), which demonstrates superior performance in ideal growing conditions, being recommended for regions where environmental conditions are more favorable.

Clones 2, 8, 16, and 28 showed high clone behavior pertinence (AD) values in unfavorable environments. Clones 1, 3, 5, 6, 7, 9, 11, 12, 13, 14, 15, 17, 18, 19, 20, 21, 22, 27, 30, 31, 32, 34, 35, and 36 were classified as not recommended (NI), which can be attributed to the low recommendation rate, both for favorable

environments (ω_f) as well as for unfavorable environments (ω_d), which justifies their inferior performance, making them less recommended for cultivation.

The classification of coffee clones based on the Annicchiarico (1992) method and the fuzzy controller allows identifying which clones are most suitable for different environmental conditions. Thus, clones with general behavior are versatile and can be grown in a variety of conditions. Meanwhile, specific clones for favorable or unfavorable environments are recommended for regions with specific environmental conditions. Clones not listed should be avoided due to their inferior performance.

Table 7. Recommendation index estimates by the fuzzy controller for the behavior of thirty-six coffee clones, in seven environments, based on the Annicchiarico (1992) method.

Clone	Input			Relevance of behavior (%)			
	ω_g	ω_f	ω_d	FAV	AD	GD	NI
1	70.59	70.88	68.65	25	24	24	75
2	77.54	54.73	103.18	15	53	15	47
3	94.64	97.80	91.26	48	42	42	52
4	137.91	202.30	104.26	46	0	54	0
5	52.62	61.17	44.52	19	10	10	81
6	78.29	62.27	94.83	19	45	19	55
7	56.13	53.87	54.40	15	15	15	85
8	75.81	58.48	101.69	17	52	17	48
9	70.08	70.88	65.07	25	21	21	75
10	108.11	104.64	112.59	38	45	55	38
11	60.35	78.20	49.10	31	12	12	69
12	40.94	38.63	40.74	7	8	7	92
13	73.86	75.96	72.70	29	26	26	71
14	50.96	32.38	65.71	5	22	5	78
15	48.71	63.31	41.52	20	9	9	80
16	93.36	83.27	103.72	35	54	35	46
17	59.45	78.67	48.95	31	12	12	69
18	82.37	81.22	80.54	33	32	32	67
19	61.83	88.04	48.55	39	12	12	61
20	39.27	29.48	45.97	4	11	4	89
21	41.61	47.26	35.87	11	6	6	89
22	71.08	96.30	58.05	46	17	17	54
23	82.73	118.81	54.72	67	15	15	33
24	107.67	110.70	110.50	40	40	60	40
25	90.67	120.26	77.01	68	30	30	32
26	118.76	106.31	122.28	30	44	56	30
27	34.17	28.11	38.32	4	7	4	93
28	100.26	75.71	112.75	29	62	29	38
29	111.96	164.59	77.36	70	6	30	6
30	87.26	87.79	82.64	39	34	34	61
31	75.25	66.91	77.49	22	30	22	70
32	40.95	54.00	43.09	15	9	9	85
33	86.53	106.65	75.52	56	29	29	44
34	45.46	48.48	41.27	12	9	9	88
35	66.98	65.72	66.39	22	22	22	78
36	61.85	68.38	59.44	23	18	18	77

GD: general behavior; FAV: favorable environments; DES: unfavorable environments; NI: not indicated; ω_g : general environment; ω_f : favorable environment; ω_d : unfavorable environment (ω_d).

Table 8 shows the results of adaptability and stability according to the fuzzy logic of methods by Annicchiarico (1992), Eberhart and Russell (1966), and Cruz et al. (1989). Clone 2, using the ER method, was classified as having specific adaptability to unfavorable environments and high predictability. However, by using the CRV method, this same clone received the maximum general adaptability rating and may be of interest to a wide range of environmental conditions. And by the AM method it was considered AD, suggesting that it may have acceptable performance in some specific conditions. Clone 2 presented a hybrid profile adaptable to unfavorable environments using the ER method and, at the same time, with high general adaptability using the CRV method. This can make it an interesting option for locations where conditions are unpredictable. Clone 8 obtained the same classification by all methods, and like clone 2, had high adaptability to adverse conditions, being an option for less favorable scenarios. The MGA classification by the CRV method suggests the potential to be used in different environments. However, both clones share the characteristic of

good adaptation to unfavorable environments and high predictability, but have maximum overall adaptability, making them promising materials for more versatile management. Therefore, these clones can be valuable options to ensure productive stability in variable environmental conditions.

Table 8. Summary of adaptability and stability according to fuzzy logic of methods by Eberhart and Russell (1966) (ER), Annicchiarico (1992) (AM), and Cruz et al. (1989) (CRV).

Clone	ER	CRV	AM	Clone	ER	CRV	AM
1	ADPA	MGA	NI	19	ADPA	MFE	NI
2	ADPA	MGA	AD	20	ADPA	MGA	NI
3	AGPB	MFE	NI	21	ADPA	MGA	NI
4	AFPA	MFE	GD	22	ADPA	MFE	NI
5	ADPA	MGA	NI	23	ADPA	MFE	FAV
6	ADPA	MGA	NI	24	AGPB	MFE	GD
7	ADPA	-	NI	25	AFPA	MFE	FAV
8	ADPA	MGA	AD	26	ADPA	MFE	GD
9	ADPA	MGA	NI	27	ADPA	MGA	NI
10	ADPA	MFE	GD	28	ADPA	-	AD
11	AGPB	MGA	NI	29	ADPA	MFE	FAV
12	ADPA	MGA	NI	30	ADPA	MFE	NI
13	ADPA	MFE	NI	31	AFPA	-	NI
14	ADPA	MGA	NI	32	ADPA	MGA	NI
15	ADPA	MGA	NI	33	AGPB	MFE	FAV
16	AGPB	MGA	AD	34	ADPA	MGA	NI
17	ADPA	MGA	NI	35	ADPA	MGA	NI
18	ADPA	-	NI	36	ADPA	MGA	NI

AGPB: General adaptability and low predictability; AGPA: General adaptability and high predictability; AFPA: Specific adaptability to favorable environments and low predictability; AFPA: Specific adaptability to favorable environments and high predictability; ADPB: Specific adaptability to unfavorable environments and low predictability; ADPA: Specific adaptability to unfavorable environments and high predictability; GD: general behavior; FAV: favorable environments; DES: unfavorable environments; NI: not indicated; MGA: Maximum general adaptability; MFE: Maximum adaptability to favorable environment.

Clones 10 and 23 were classified by the ER method as ADPA and by the CRV method as MFE, suggesting that their best performance occurs in favorable environments. On the other hand, both obtained different classifications using the AM method. Using this method, clone 10 was classified as GD, indicating general behavior in different environmental conditions, and clone 23 was classified as FAV, reinforcing its preference for favorable environments. This clone has a clear profile of superior performance in more favorable environmental conditions, being a strategic choice for locations with good growing conditions. Clone 29 was classified by the ER method as ADPA, indicating a good response in unfavorable environments, and by the CRV method as MFE, indicating maximum adaptability in favorable environments, and by the AM method as FAV, confirming the preference for favorable environments. Thus, like clone 23, clone 29 is highly recommended for favorable environments, being a great option for growing conditions that offer stability. Therefore, clones 23 and 29 are strongly indicated for favorable environments, showing that their stability and yield are better in suitable conditions.

Hybrid fuzzy controllers were developed to automate the decision-making process in adaptability and stability studies by integrating the parameters of methodologies proposed by Eberhart and Russell (1966), Annicchiarico (1992), and Cruz et al. (1989) (Carneiro et al., 2019).

In addition to classifying clones into groups, fuzzy controllers establish relevant parameters for the composition of these clone groups. According to Kuo et al. (2009), this systematization of imprecise knowledge is essential. In plant breeding, this is crucial, as it allows the selection of clones that are most suited to the desired group in the absence of clones with the interest classification. This facilitates the choice of parents in breeding programs and the recommendation of cultivars most appropriate for certain growing conditions. Therefore, fuzzy controllers based on the methods of Eberhart and Russell (1966), Annicchiarico (1992), and Cruz et al. (1989) have proven useful and efficient in automating decision-making for clone recommendation, using established fuzzy rules. This technique becomes a valuable ally for plant breeding programs due to its simplicity and automation capacity, especially when a large number of clones is evaluated.

In addition to classifying clones, fuzzy logic produces pertinence parameters, that is, the probability of a clone belonging to a certain class (Silva Junior et al., 2021). For plant breeding, this information is important because if recommended clones are not found for a class of environments of interest, more relevant clones for the desired environmental class can be used. Automation of genotype classification by fuzzy logic is a

viable option in the case of multiple clones as well as multiple parameters. Fuzzy inference, as used in this study, aggregated available experiences in the literature and the rules necessary for classification into a single system that can report the clone affiliation strength with each adaptability and stability class.

The efficiency of these controllers is due to their powerful ability to model complex human reasoning (Uncu & Türksen, 2007). Carneiro et al. (2019) suggested that this technique could become an important tool in breeding programs due to its simplicity and automation capability. The current study demonstrates the usefulness of automated decision making in assessing adaptability and stability based on a fuzzy hybrid model for conilon coffee. Although only a few clones were recommended for general adaptability, the hybrid model analyzed a greater number of parameters and allowed a better classification of the genotypic response to environmental variations.

The results show that different evaluation methods can provide varying insights into clone adaptability and stability. This highlights the importance of using multiple criteria when selecting clones to ensure that choices are well-informed and suited to specific growing conditions.

Conclusion

The differentiated behavior of clones is influenced by environmental conditions, which justifies the use of different adaptability and stability methodologies. The use of fuzzy controllers in the recommendation of conilon coffee clones is a useful and promising tool in plant breeding programs. Clones 2 and 8 showed high adaptability to adverse environments, while clones 10, 23, and 29 excelled in favorable conditions in the Zona da Mata of Minas Gerais State, Brazil.

Data availability

The data are available from the corresponding author upon request.

Acknowledgements

We thank the Minas Gerais State Research Support Foundation (FAPEMIG), and the National Council for Scientific and Technological Development (CNPq) for the financial support for this research and grants granted to the authors.

References

- Adeli, H., Asce, F., & Jiang, X. (2003). Neuro-fuzzy logic model for freeway work zone capacity estimation. *Journal of Transportation Engineering*, 129(5), 484-493. [https://doi.org/10.1061/\(ASCE\)0733-947X\(2003\)129:5\(484\)](https://doi.org/10.1061/(ASCE)0733-947X(2003)129:5(484))
- Annicchiarico, P. (1992). Cultivar adaptation and recommendation from alfalfa trials in Northern Italy. *Journal of Genetics and Breeding*, 46, 269-278.
- Bustos-Korts, D., Malosetti, M., Chapman, S., & van Eeuwijk, F. (2016). Modelling of genotype by environment interaction and prediction of complex traits across multiple environments as a synthesis of crop growth modelling, genetics and statistics. In X. Yin, & P. Struik (Eds.), *Crop systems biology: Narrowing the gaps between crop modelling and genetics* (pp. 55-82). Springer. https://doi.org/10.1007/978-3-319-20562-5_3
- Carneiro, A. R. T., Sanglard, D. A., Azevedo, A. M., Souza, T. L. P. O., Pereira, H. S., & Melo, L. C. (2019). Fuzzy logic in automation for interpretation of adaptability and stability in plant breeding studies. *Scientia Agricola*, 76(2), 123-129. <https://doi.org/10.1590/1678-992x-2017-0207>
- Carneiro, V. Q., Prado, A. L., Cruz, C. D., Carneiro, P. C. S., Nascimento, M., & Carneiro, J. E. S. (2018). Fuzzy control systems for decision-making in cultivars recommendation. *Acta Scientiarum. Agronomy*, 40(1), 1-8. <https://doi.org/10.4025/actasciagron.v40i1.39314>
- Companhia Nacional de Abastecimento. (2025). *Brazilian coffee production statistics*. CONAB.
- Cruz, C. (2016). Genes software-extended and integrated with the R, Matlab and Selegen. *Acta Scientiarum. Agronomy*, 38(4), 547-552. <https://doi.org/10.4025/actasciagron.v38i4.32629>
- Cruz, C. D. (2013). Genes: a software package for analysis in experimental statistics and quantitative genetics. *Acta Scientiarum. Agronomy*, 35, 271-276. <https://doi.org/10.4025/actasciagron.v35i3.21251>

- Cruz, C. D., & Regazzi, A. J. (1997). *Modelos biométricos aplicados ao melhoramento genético* (2. ed.). UFV.
- Cruz, C. D., Torres, R. A. A., & Vencovsky, R. (1989). An alternative approach to the stability analysis proposed by Silva and Barreto. *Revista Brasileira de Genética*, 12(3), 567-580.
- Eberhart, S. A., & Russell, W. A. (1966). Stability parameters for comparing varieties. *Crop Science*, 6(1), 36-40. <https://doi.org/10.2135/cropsci1966.0011183X000600010011x>
- Ferrão, R. G., Fonseca, A. F. A., Ferrão, M. A. G., & De Muner, L. H. (2017). *Café Conilon* (2. ed.). Incaper.
- Gomes, F. P. (1990). *Curso de estatística experimental* (13. ed.). Nobel.
- Kuo, T. C., Wu, H. H., & Shieh, J. I. (2009). Integration of environmental considerations in quality function deployment by using fuzzy logic. *Expert Systems with Applications*, 36, 1748-1756. <https://doi.org/10.1016/j.eswa.2008.08.029>
- Mamdani, E. H., & Assilian, S. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. *International Journal of Man-Machine Studies*, 7, 1-13. [https://doi.org/10.1016/S0020-7373\(75\)80002-2](https://doi.org/10.1016/S0020-7373(75)80002-2)
- Mannion, A. M. (2023). Encyclopedia of quality of life and well-being research. In F. Maggino (Ed.), *Gene-environment interaction* (pp. 2729-2730). Springer. https://doi.org/10.1007/978-3-031-17299-1_1143
- Matlab. (2016). *Matlab (R2016b)*. The MathWorks Inc.
- Partelli, F. L., Silva, F. A., Covre, A. M., Oliosi, G., Correa, C. C. G., & Viana, A. P. (2022). Adaptability and stability of *Coffea canephora* to dynamic environments using the Bayesian approach. *Scientific Reports*, 12(11608), 1-10. <https://doi.org/10.1038/s41598-022-15190-x>
- Pimentel-Gomes, F. (2009). *Curso de estatística experimental* (15. ed.). FEALQ.
- Russell, S., & Norvig, P. (2013). *Artificial intelligence: A modern approach* (3rd ed.). Pearson.
- Silva Júnior, A. C., Silva, M. J., Costa, W. G., Sousa, I. C., Cruz, C. D., Nascimento, M., & Soares, P. C. (2021). Application of fuzzy logic for adaptability and stability studies in flood-irrigated rice (*Oryza sativa*). *Plant Breeding*, 140(6), 1002-1010. <https://doi.org/10.1111/pbr.12973>
- Simões, M. G., & Shaw, I. S. (2011). *Control and modeling: Control and modelagem fuzzy*. Blucher.
- Takagi, T., & Sugeno, M. (1985). Fuzzy identification of systems and its application to modeling and control. *IEEE Transactions on Systems, Man, and Cybernetics*, 15(1), 116-132. <https://doi.org/10.1109/TSMC.1985.6313399>
- Uncu, O., & Turksen, I. B. (2007). Discrete interval type 2 fuzzy system models using uncertainty in learning parameters. *IEEE Transactions on Fuzzy Systems*, 15(1), 90-106. <https://doi.org/10.1109/TFUZZ.2006.889765>
- United States Department of Agriculture. (2024). *Coffee: World markets and trade*. USDA.
- van Eeuwijk, F. A., Bustos-Korts, D. V., & Malosetti, M. (2016). What should students in plant breeding know about the statistical aspects of genotype environment interactions. *Crop Science*, 56(5), 2119-2140. <https://doi.org/10.2135/cropsci2015.06.0375>
- Zadeh, L. A. (2015). Fuzzy logic-A personal perspective. *Fuzzy Sets and Systems*, 281, 4-20. <https://doi.org/10.1016/j.fss.2015.05.009>

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