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# Using fuzzy logic to select coloured-fibre cotton genotypes based on adaptability and yield stability

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**ABSTRACT.** Cotton (*Gossypium hirsutum* L.) is the world's leading natural textile fibre and is grown in over 60 countries, including Brazil, where it is an important agricultural commodity. The cultivation area currently covers approximately one million hectares in Brazil and has expanded into every region of the country, especially the Cerrado biome. Because of this expansion, it is necessary to analyse the influence of the environment on the genotype behaviour to optimize yields. Thus, the objective of this study was to compare fuzzy logic to traditional methods for selecting coloured-fibre cotton genotypes with high adaptability and yield stability. The experiment was conducted on the 2013/2014, 2014/2015, 2015/2016, and 2016/2017 crops of the Capim Branco farm at the Federal University of Uberlândia, Uberlândia, Minas Gerais, Brazil. The following methods were used to select genotypes for adaptability and stability: the Lin and Binns model, additive main effects and multiplicative interaction (AMMI) analysis and the Sugeno fuzzy logic controller. An interaction of the genotype with the environment that affected yield was detected. Environment 4 (the 2016/2017 crop) showed to the lowest genotype to environment interaction. The fuzzy logic approach showed agreement with AMMI and the nonparametric Lin and Binns method. The linguistic fuzzy logic used in the Sugeno fuzzy logic controller demonstrated the potential for selecting cotton genotypes in plant breeding programmes. The UFUPJ-16 and UFUPJ-17 genotypes were adaptable, stable and showed promising yields within the tested environments. The fuzzy logic method was effective for estimating adaptability and stability.

**Keywords:** computational intelligence; *Gossypium hirsutum*; plant breeding.

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## Introduction

Cotton (*Gossypium hirsutum* L.) is the most prominent natural fibre in the world and is grown in more than 60 countries. This crop is an important agricultural commodity in Brazil and is cultivated on more than one million hectares (Companhia Nacional de Abastecimento [CONAB], 2019).

Due to its socio-economic importance, cotton cultivation has expanded into all regions of the country and especially into the Cerrado biome. Naturally coloured cotton fibres are gaining prominence, as they do not need to be dyed; many dyes cause pollution, and using naturally coloured cotton fibres can reduce the use of water and is thus more environmentally friendly. Given this expansion, it is necessary to optimize the yield by determining the influence of the environment on genotype response (CONAB, 2019; Cruz, Regazzi, & Carneiro, 2014a).

Genotype response can be determined by identifying the genotype to environment interactions. If interactions exist, then the adaptability and stability should be examined to predict the genotype response and responsiveness to environmental stimuli (Queiroz, Costa, Neves, Seabra Junior, & Barelli, 2014).

Several methodologies can be used to determine adaptability and stability. These methodologies vary by the statistics used, which in turn are determined by the degree of precision needed, the number of environments under consideration and the information involved.

The most common methods are based on analysis of variance (e.g., Plaisted & Peterson, 1959), simple linear regression (e.g., Eberhart & Russell, 1966), nonparametric methods (e.g., the Centroid method,

Nascimento et al., 2009), and the associated modifications (Nascimento et al., 2009) and multivariate methods such as the additive main effects and multiplicative interaction (AMMI) model (Duarte & Vencovsky, 1999).

The Eberhart and Russell (1966) method is the simplest to interpret and is therefore widely used in breeding. However, this method is affected by bias when examining fewer than 10 environments, which reduces the accuracy of genotype classification and leads to the non-rejection of false null hypotheses (Nascimento et al., 2013).

To circumvent this limitation, fuzzy logic mathematical modelling can be used to simulate the approximations and uncertainties of human logic (Carneiro et al., 2017; Carneiro et al., 2019) and assign degrees of pertinence to the elements. Fuzzy logic has been used to select common bean cultivars (Carneiro et al., 2017) and to select common bean cultivars for adaptability and stability (Carneiro et al., 2017).

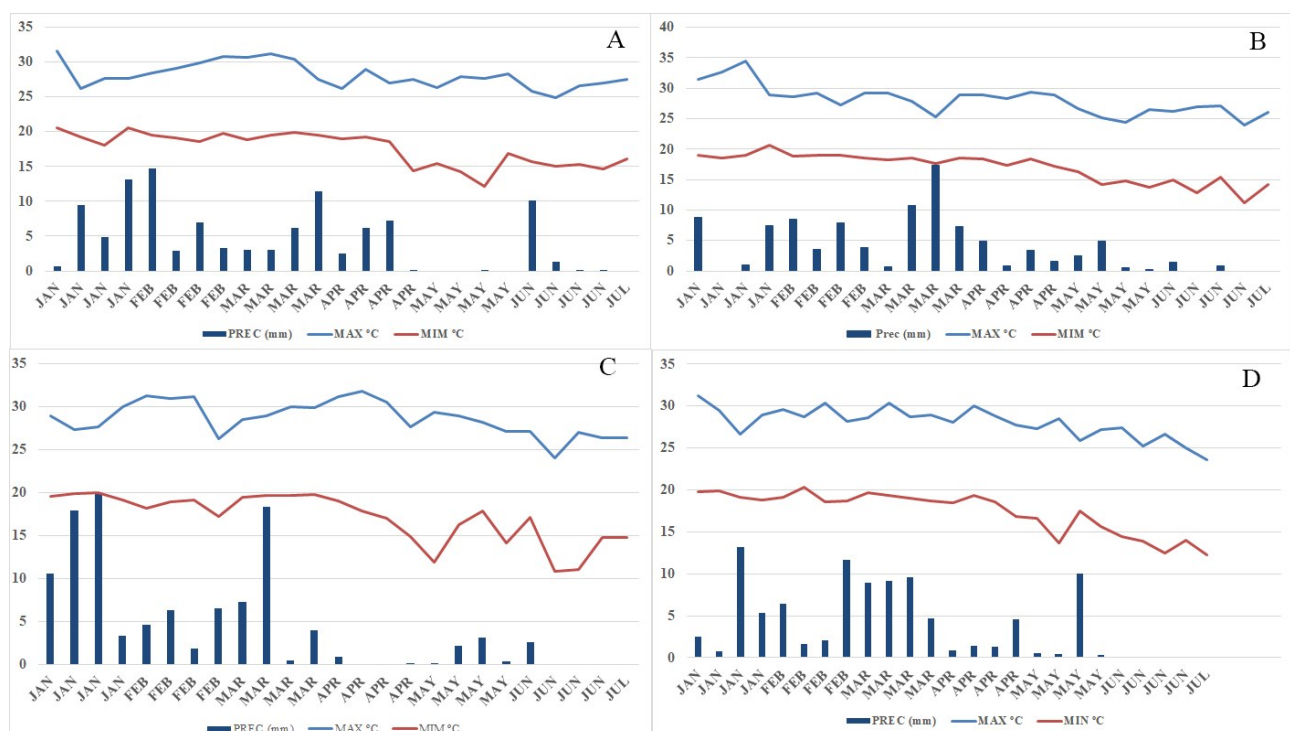
Thus, the objective of this study was to compare the use of fuzzy logic to traditional methods for selecting highly adaptable and stable cotton genotypes.

## Material and methods

The experiment was conducted on the 2013/2014 (environment 1), 2014/2015 (environment 2), 2015/2016 (environment 3), and 2016/2017 (environment 4) crops at the Capim Branco farm (18° 52' S; 48° 20' W, 805 m altitude) of the Federal University of Uberlândia, Uberlândia, Minas Gerais State, Brazil.

According to climate data from 1981 to 2008 (Institute of Geography, Federal University of Uberlândia), Uberlândia has an average air temperature of 22.4°C, an average relative humidity of 70% and an average annual rainfall of 1,584 mm per year.

The weather conditions during the experiment were monitored using a Davis Vantage Pro 2 automatic weather station with temperature and rainfall sensors (Figure 1A to D).



**Figures 1.** Weather data from 12/2013 to 06/2014 (A), 12/2014 to 06/2015 (B), 12/2015 to 06/2016 (C), and 12/2016 to 06/2017 (D). MAX (°C) – maximum temperature; MI (°C) – minimum temperature; and PREC (mm) – precipitation.

Twelve coloured-fibre cotton genotypes were evaluated. Ten of these were from the cotton breeding programme at the Federal University of Uberlândia (PROMALG-UFU): UFUJP-01, UFUJP-02, UFUJP-05, UFUJP-08, UFUJP-09, UFUJP-11, UFUJP-13, UFUJP-16, UFUJP-17, and two were commercial cultivars: BRS Rubi (RC), and BRS Topázio (TC).

A randomized complete block (RCB) design with three replications was used. The plots consisted of four 5-metre rows spaced one metre apart, of which the central 4 metres of the two centremost rows were examined.

The soil of the experimental area was classified as a dystrophic clayey Dark-Red Latosol. The tillage consisted of ploughing and harrowing. This was followed by liming and fertilization according to the crop recommendations.

Sixteen seeds per linear metre (2 cm depth) were sown during the last week of December. The seedlings were thinned to eight plants per linear metre 30 days after emergence.

The following evaluations were carried out at full maturity (Borém & Freire, 2014) on five plants from each plot.

Seed cotton productivity: All open bolls within the useful area of each plot were collected and weighed ( $\text{kg ha}^{-1}$ ).

The adaptability and stability were determined with the Eberhart and Russell (1966) method, which uses a simple linear regression of the genotypes.

The modified Lin and Binns method (Cruz, Carneiro, & Regazzi, 2014b) estimates the adaptability and stability by identifying the genotypes with the highest averages that are the most responsive in each environment regarding proximity to other genotypes and classifying them using the overall mean square ( $P_i$ ), and constituent means in favourable ( $P_{if}$ ) and unfavourable ( $P_{iu}$ ) environments. An ideal genotype is indicated by the lowest  $P_i$  value, which is linked to the lowest values in the favourable ( $P_{if}$ ) and unfavourable environments ( $P_{iu}$ ).

The Eberhart and Russell (1966) fuzzy controller method, which is based on the fuzzy inference system proposed by Sugeno (Takagi & Sugeno, 1985; Sugeno & Kang, 1988a and b; Sugeno & Tanaka, 1991; Sugeno & Yasukawa, 1993), uses the general mean ( $\beta_0$ ), regression coefficient ( $\beta_1$ ), and coefficient of determination ( $R^2$ ), which are components of the Eberhart and Russell (1966) method. Each variable that was allocated by the fuzzification process classified each genotype for the given variable. The overall mean was classified as "low" or "high" by the Z-shaped ("zmf") and S-shaped ("smf") pertinence functions, respectively. These ranged from 0 to 100, depending on the normal distributions of the inputs, for the overall mean ( $\mu$ ) and standard deviation ( $\sigma$ ). The values associated with  $\mu - 3\sigma$  were assigned a value of 0, while the values associated with  $\mu + 3\sigma$  were assigned a value of 100 (Carneiro et al., 2017).

The other parameter evaluated by the Eberhart and Russell (1966) method ( $\beta_1$ ) was either "less than 1", "equal to 1" or "greater than 1", with Z-shaped ("zmf"), 75% of " $\pi$ "-shaped ("pimf") and S-shaped ("smf") pertinence functions, respectively. The genotypes with pertinence values greater than 50% within the set – that that were "equal to 1" – were classified as having a  $\beta_1$  value that was statistically equal to 1 (Student's t-test). When submitted to the controller, the original  $\beta_1$  values for each genotype were standardized to a scale of -5 to 7 since the limits of this scale are equidistant from 1. This standardization was based on the t-test confidence interval, which was in turn based on the t-distribution. The lower limit of the confidence interval was assigned a value of -2, and the upper limit was assigned a value of 4 (Carneiro et al., 2017).

A fuzzy linguistic variable called the "Sugeno response" was generated for the Sugeno fuzzy controller (Takagi & Sugeno, 1985; Sugeno & Kang, 1988b; Sugeno & Tanaka, 1991; Sugeno & Yasukawa, 1993). This variable ranged from 0 to 100 and was allocated into four specific sets called singletons that were described with the following constant functions: poorly adapted ( $f(x) = 25$ ), unfavourable ( $f(x) = 50$ ), favourable ( $f(x) = 75$ ) and general ( $f(x) = 100$ ) (Carneiro et al., 2017).

Table 1 shows the rules applied to the controllers and adapted to the Eberhart and Russell (1966) method to estimate the parameters ( $\beta_0$ ,  $\beta_1$ , and  $R^2$ ). The coefficient of determination ( $R^2$ ) was not standardized since the scale of this parameter was common for all agronomic characteristics (Carneiro et al., 2017).

**Table 1.** Linguistic fuzzy logic used with the Sugeno fuzzy controllers for the adaptability and stability of genotypes, based on the Eberhart and Russell (1966) method and adapted from Carneiro et al. (2019).

Means	Input		Output
( $\beta_0$ )	$\beta_1$	$R^2$	Sugeno response
Low	Less than 1	Low	Poorly Adapted
Low	Less than 1	High	Poorly Adapted
Low	Equal to 1	Low	Poorly Adapted
Low	Equal to 1	High	Poorly Adapted
Low	Greater than 1	Low	Poorly Adapted
Low	Greater than 1	High	Poorly Adapted
High	Less than 1	Low	Poorly Adapted
High	Less than 1	High	Unfavorable
High	Igual a 1	Low	Poorly Adapted
High	Igual a 1	High	General
High	Greater than 1	Low	Poorly Adapted
High	Greater than 1	High	Unfavorable

$\beta_1$  = Linear regression coefficient for cultivar;  $R^2$  = Coefficient of determination, in %.

The additive mean effects and multiplicative interaction analysis (AMMI) method predicts the genotype responses to an environment by combining the additive components of the main genotype and environmental effects and the multiplicative components for the interactive effects as follows (Duarte & Vencosvsky, 1999):

$$Y_{ij} = \mu + g_i + e_j + \sum_{k=1}^n \lambda_k \gamma_{ik} \alpha_{jk} + \rho_{ij} + \varepsilon_{ij}$$

with  $(g_e)_{ij}$ :  $\sum_{k=1}^n \lambda_k \gamma_{ik} \alpha_{jk} + \rho_{ij}$ ;  $Y_{ij}$  = observed average of the  $i^{\text{th}}$  genotype in the  $j^{\text{th}}$  environment;  $\mu$  = general experimental mean;  $g_i$  = main genotype effects;  $e_j$  = main environment effects;  $g_e$  = multiplicative interaction components;  $\lambda_k$  =  $k^{\text{th}}$  singular value of  $g_e$ ;  $\alpha_{jk}$  = singular vectors associated with  $\lambda_k$ ; and  $\rho_{ij}$  = additional residual.

The effects of the interactive deviations were based on an evaluation of the principal components with multivariate analysis and by the decomposition of the singular values. Components that have significant deviations reflect variation patterns, and components with non-significant deviations reflect “noise” (Cruz et al., 2014a).

The biplot graph that represents this interaction uses AMMI1, where the x-axis represents the main effects of the mean yields for the genotypes in the various environments and the y-axis represents the scores of the first interaction axis (Hongyu, García-Peña, Araújo, & Santos Dias, 2014).

All analyses were performed with the Genes software (Cruz, 2016). The Sugeno fuzzy logic and fuzzy controllers were analysed using MATLAB software and implemented with the integration routine of the Genes software (Cruz, 2016).

## Results and discussion

An interaction of the genotype with the environment (G x A) was detected, which provided evidence of phenotypic and consequently genotypic yield responses to environmental variation (Table 2). This interaction justified the study of the genotypic adaptability and stability within a given environment.

**Table 2.** Mean square significance and coefficients of experimental variation (percentage) for the nine traits in 12 cotton genotypes during the 2013/14, 2014/15, 2015/16, and 2016/17 crop seasons.

VS	DF	Mean squares
		Yield (kg ha <sup>-1</sup> )
Block/Environment	6	150786.68
Genotypes	11	1550103.94**
Environments	3	47800085.49**
Genotypes x Environments	33	902470.83**
IPCA 1	13	1538025.7**
IPCA 2	11	646768.8*
IPCA 3	9	296972.3 <sup>ns</sup>
Residuals	88	294720.7
CV (%)		23.63
Means		2,258.84
(MQMR <sub>1</sub> )/MQMR <sub>2</sub>		4.08

\*\*, \* Significant at 1 and 5% probability, respectively, according to the F test; VS = Variation source; DF = Degrees of freedom; CV = Coefficient of variation; MQMR<sub>1</sub>/MQMR<sub>2</sub> = Ratio of the largest mean square to the smallest.

The homogeneity of the residual mean square (RMS) was less than seven, which met the homogeneity criterion needed for joint analysis. The mean yield of 2,258 kg ha<sup>-1</sup> was higher than the 1,046 kg ha<sup>-1</sup> found by Alves, Sousa Cavalcante, Oliveira-Júnior, Ferraz, and Siqueira (2019) for cotton from BRS-Rubi seeds.

The coefficient of variation (CV) for the yield was 23.63%. Reis et al. (2017) found a higher yield CV (46%) when conducting correlation and path analysis in cotton genotypes. According to Santos, Moreira, Farias, and Freire (1998), the values between 12.20 and 28.54% are considered average and therefore were acceptable for this characteristic, which was strongly influenced by environmental factors.

The low yields in environment 2 (2014/2015 crop) (Table 3) can be partially explained by attacks by *Alabama argillacea* at approximately 110 days after emergence during boll formation and development. These attacks reduced the leaf area, photoassimilates and nutrient allocation to the fruit (Zhao, Reddy, Kakani, Koti, & Gao, 2005; Snider, Oosterhuis, Skulman, & Kawakami, 2009; Yeates, Constable, & McCumstie, 2010).

Another factor that contributed to the low performance in environment 2 was the limited rainfall (679 mm), which was lower than the 740 mm needed to fully complete the crop cycle (Sobrinho, Fernandes, Beltrão, Soares, & Neto, 2007).

**Table 3.** Mean seed cotton yield (kg ha<sup>-1</sup>) of 12 cotton genotypes from four crops in Uberlandia, Minas Gerais State, Brazil.

Genotype	2013/2014 crop	2014/2015 crop	2015/2016 crop	2016/2017 crop
UFUJP-01	2,501.66 Ac	131.26 Ba	2,157.08 Aa	2,628.56 Ac
UFUJP-02	3,478.12 Ab	687.08 Ca	3,135.62 Aa	2,069.73 Bc
UFUJP-05	1,972.50 Ad	647.71 Ba	2,266.04 Aa	2,496.26 Ac
UFUJP-08	2,681.25 Ac	409.38 Ba	2,743.96 Aa	2,295.79 Ac
UFUJP-09	3,630.00 Ab	381.04 Ca	2,342.91 Ba	2,778.33 Bc
UFUJP-10	2,983.33 Ac	332.76 Ba	2,969.17 Aa	2,231.53 Ac
UFUJP-11	2,841.87 Ac	1,050.62 Ba	2,572.08 Aa	2,350.44 Ac
UFUJP-13	1,687.50 Bd	486.88 Ca	2,664.79 Aa	2,499.31 Ac
UFUJP-16	3,229.16 Ac	616.87 Ba	2,642.50 Aa	2,969.48 Ac
UFUJP-17	3,689.58 Ab	449.37 Ca	2,529.79 Ba	3,310.48 Ab
BRS-Rubi	4,670.00 Aa	387.92 Ca	2,300.00 Ba	4,275.93 Aa
BRS-Topázio	4,665.00 Aa	1,303.33 Ca	2,401.46 Ba	2,946.81 Bc

Means followed by the same uppercase letters within a row and lowercase letters within a column indicate a statistically homogenous group according to the Scott-Knott at 0.05%, Environment 1 = 2013/14 crop, Environment 2 = 2014/15 crop, Environment 3 = 2015/16 crop, and Environment 4 = 2016/17 crop.

The AMMI1 method also confirmed the inferior yields in environment 2, as shown by the greater graphical distance among the genotypes. Despite the unfavourable conditions in environment 2, the cultivars UFUJP-11 and BRS-Topázio still produced higher than average yields.

Environment 1 (2013/2014 crop) produced the greatest yields. The temperature and precipitation were ideal during this crop cycle. The precipitation was greater than the minimum needed for the crop and was well distributed, with a gradual increase in rainfall from budding to boll formation, which is a period when the crop is more susceptible to yield-limiting water stress (Borém & Freire, 2014).

Environment 4 (2016/2017 crop) contributed the least to the G x A interaction and obtained the second highest average yield. Although the rainfall was evenly distributed throughout this period, the accumulations only reached 555 mm, which is 20% lower than that recommended for this crop and caused lower yields. The water stress induces plants to prioritize the growth of larger bolls, which leads to the shedding of reproductive structures and lower rates of photosynthesis. Another determining factor for the yield was a degree-day accumulation (1,622°) that was lower than the minimum (1,970° day<sup>-1</sup>) needed for the crop cycle (Loka, Oosterhuis, & Ritchie, 2011).

The Lin and Binns (1988) method for determining adaptability and stability decomposes the parameter estimates into the general  $P_i$  and the  $P_i$  from the favourable and unfavourable environments, which are then used to distinguish the genotypes affected by the environmental oscillations. Table 3 shows that the genotypes with the highest average yields (BRS-Rubi, BRS-Topázio, and UFUJP-17) were also classified as having general and predictable adaptability, according to the  $P_i$  parameter (Table 4).

**Table 4.** Estimates of the phenotypic stability parameters ( $P_i$ ) for the seed cotton yield in the favourable environments ( $P_i+$ ) and unfavourable environments ( $P_i-$ ) as calculated with the nonparametric method of Lin and Binns (1988) that was adapted by Carneiro (Cruz, Carneiro, & Regazzi, 2014b).

Genotype	Mean	$P_i$ general	$P_i(+)$	$P_i(-)$
BRS-Rubi	2,908.46	192031.75	116377.73	418993.84
BRS-Topázio	2,829.15	288197.60	384263.46	.
UFUJP-17	2,494.81	373697.72	376722.35	364623.84
UFUJP-16	2,364.51	562150.19	670995.70	235613.67
UFUJP-09	2,283.07	600426.24	658797.49	425312.50
UFUJP-02	2,342.64	833453.73	1047977.63	189882.03
UFUJP-11	2,203.76	928872.16	1227852.49	31931.17
UFUJP-10	2,129.20	999267.03	1175353.94	471006.30
UFUJP-08	2,032.60	1103578.64	1338245.09	399579.26
UFUJP-01	1,842.88	1238007.36	1421717.17	686877.95
UFUJP-05	1,845.63	1453719.13	1866651.12	214923.16
UFUJP-13	1,829.41	1626806.52	2057976.93	333295.30

The BRS-Rubi, BRS-Topázio, and UFUJP-17 genotypes were more stable and responded well to favourable environments. In unfavourable environments, the UFUJP-11 and UFUJP-02 genotypes were the most stable, which indicated that these may be promising genotypes in environments with adverse edaphoclimatic conditions.

AMMI showed that the principal components PC1 and PC2 were significant (Table 5) and explained a high degree of the proportional patterns of the sum of squares of the interaction. The first two components captured 91% of the  $SS_{G \times A}$  and 73% of the degrees of freedom of the interaction, with 27% of the SQ associated with noise. For the noise associated SS values, there was a nearly 70% increase the accuracy and prediction of the results (Gauch, 1998).

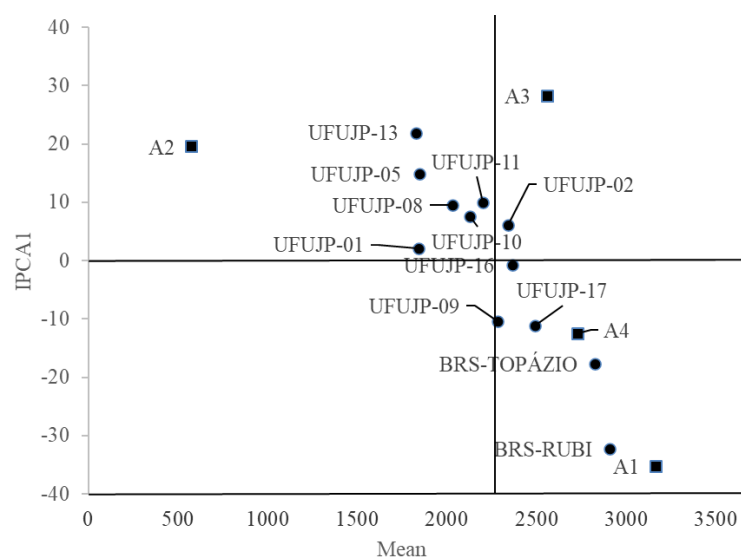
**Table 5.** Percentage  $SS_{G \times A}$  interaction on each main axis of the AMMI analysis for four environments and twelve genotypes.

Principal component	Explanation (%)	Accumulated explanation (%)
PC1**	67.1	67.1
PC2*	23.9	91.0
PC3 <sup>ns</sup>	9.0	100.0

\*, \*\*. Significant according to the F test at the 0.05 and 0.01 levels, respectively. <sup>ns</sup>= not significant according to the F test. Principal component= Main axis.

Nevertheless, the AMMI1 model was chosen because CP1 explained much of the  $SS_{G \times A}$ , reaching nearly 70%, and because it avoided noise that could affect the model representation. According to Duarte and Vencovsky (1999), the first component values near 70% concentrated much of the differentiation in the mean genotype values caused by environmental oscillations. Maleia et al. (2017) studied the adaptability and stability of cotton using the AMMI analysis and found values below those of the present study, with 80% of the interactions in the first two main axes.

The most stable and well-adapted genotypes (Figure 2) were found close to the intersection of the axes (IPCA1), indicating that they contributed little to the interaction (Duarte & Vencovsky, 1999). Thus, according to this parameter, the most stable genotypes were UFUJP-01, UFUJP-02, UFUJP-08, UFUJP-09, UFUJP-11, UFUJP-16, and UFUJP-17.



**Figure 2.** AMMI1 biplot of the principal effects of the interaction and productivity of seed cotton ( $\text{kg ha}^{-1}$ ) for the 12 coloured-fibre cotton genotypes. A1 = environment 1 (2013/2014 crop), A2 = environment 2 (2014/2015 crop), A3 = environment 3 (2015/2016 crop), A4 = environment 4 (2016/2017 crop).

However, for the purposes of recommendation, the genotypes that are more stable should express higher productivity. The superior performance of UFUJP-02, UFUJP-16, UFUJP-17 suggests that they should be recommended and should provide greater adaptability, stability and yield.

In general, the most stable genotypes (UFUJP-01, UFUJP-08, UFUJP-09, UFUJP-11) generated yields that were below the group average. This shows that higher yields may have been associated with specific favourable adaptations. For example, the commercial genotypes (BRS-Rubi and BRS-Topázio) were more productive and interacted positively with environment 1 (2013/2014 crop), which caused them to produce the highest average yields and generally ideal crop conditions.

The stability of environment 4 (2016/2017 crop) resulted in greater responsivity and predictability. Thus, recommendations for this environment can be made with greater confidence given that the yield was determined mainly by genotypic effects, and there was a lower  $G \times A$  interaction. Environment 2 (2014/2015 crop) was the most unstable and produced the lowest yields due to lower rainfall and biotic stress.

The fuzzy controller-based computational intelligence approach, which was based on the method of Eberhart and Russell (1966) (Table 6), showed that the genotypes UFUJP-02, UFUJP-09, UFUJP-16, UFUJP-17, and BRS-Topaz were widely adaptable and highly stable. This was especially true for the UFUJP-16, UFUJP-17, and BRS-Topazio genotypes, which also recorded higher yields than the other tested genotypes.

**Table 6.** Standardized inputs and behavioural classifications as general, poorly adapted, favourable and unfavourable for the 12 genotypes analysed with a fuzzy controller based on the method of Eberhart and Russell (1966).

Genotype	Mean	$\beta_1$	R <sup>2</sup>	Pertinence	Output
UFUJP-01	1,842.88	0.8634	96.6614	0.8114	Poorly adapted
UFUJP-02	2,342.64	0.8762	82.0617	0.5747	Wide adaptability
UFUJP-05	1,845.63	-2.5157	80.7667	0.6571	Poorly adapted
UFUJP-08	2,032.60	0.2089	92.8704	0.6878	Poorly adapted
UFUJP-09	2,283.07	2.7405	96.9471	0.5222	Wide adaptability
UFUJP-10	2,129.20	1.3059	90.6026	0.6130	Poorly adapted
UFUJP-11	2,203.76	-2.1781	96.9527	0.5498	Poorly adapted
UFUJP-13	1,829.41	-2.2088	61.859	0.5672	Poorly adapted
UFUJP-16	2,364.51	1.296	99.5205	0.5932	Wide adaptability
UFUJP-17	2,494.81	3.3554	97.2347	0.6918	Wide adaptability
BRS-Rubi	2,908.46	6.7949	85.5862	0.9210	Favorable adaptability
BRS-Topázio	2,829.15	1.4614	74.0192	0.8650	Wide adaptability

$\beta_1$  = Linear regression coefficient for cultivar; R<sup>2</sup> = Coefficient of determination, in %.

As the interpretation of the parameters requires the ability to compare multiple variables, the experience of the breeder, who often deals with a large amount of information, is often well-suited to complex problems. Fuzzy logic based on approximations and uncertainties uses prior knowledge, eliminates subjectivity in the interpretation of and recommendations for parameters based on their behaviour, presents a single output, and may even opt for recommendations specific to each environment of interest, depending on the relevance of the fuzzy output (Cruz & Nascimento, 2018).

Among the widely adaptable genotypes, BRS-Topaz had the highest relevance (0.8650) and therefore had the greatest potential for recommendation in any of these environments. UFUJP-11 was classified as poorly adapted, with a pertinence of 0.5498, but the fact that it had close pertinence also made it highly relevant for specific adaptability to unfavourable environments (0.45), corroborating the method of Lin and Binns (1988), who classified UFUJP-11 as adaptable to harsh environments, which could hinder their classification by the traditional method. However, the fuzzy method was effective in eliminating the bias of incorrect interpretations.

This method also showed that the genotypes that achieved wide adaptability were similar to those indicated by the AMMI and Lin and Binns methods, thereby demonstrating the reliability of the fuzzy logic approach. However, computational intelligence classified 50% of the genotypes as poorly adapted, which was 17% higher than those of the AMMI1 method.

This difference could be explained by the fuzzy methodology that simulates human psychology (i.e., It has the ability to make decisions based on pre-established factors and make recommendations using the concepts of experts (Cruz & Nascimento, 2018).

The BRS-Rubi genotype showed favourable adaptability, meaning that it should have high yields under ideal conditions. This result was corroborated by the AMMI method, which showed specific adaptability to environment 1, and by the nonparametric Lin and Binns (1988) method, which classified it as the best adapted to favourable environments.

## Conclusion

The linguistic fuzzy logic implemented in the Sugeno fuzzy controllers has great potential for selecting cotton genotypes for adaptability and stability.

The UFUJP-16 and UFUPJ-17 genotypes showed promising yields within the tested environments.

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