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# Harnessing fuzzy logic for adaptive and stable selection of upland rice lines

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**Abstract:** *Fuzzy logic enables automated decision-making and classifies genotype suitability across environments. This study assessed the adaptability and stability of upland rice genotypes using fuzzy logic. To do so, eight lines from the Federal University of Goiás, 10 from the Federal University of Lavras, and two commercial cultivars were evaluated for grain yield, plant height, and flowering days in 13 environments in Goiás. The trials used a randomized complete block design with three replications. Adaptability and stability were analyzed using fuzzy controllers, which classified genotypes into four groups: general adaptability, poorly adapted, favorable, and unfavorable environments. The CSD 08004 line exhibited broad adaptability and stability for yield and plant height and was close to general adaptability for flowering days, making it suitable for cultivation in Goiás.*

**Keywords**: *Line recommendation,* Oryza sativa*, genotypes, computer automation*

## INTRODUCTION

Rice (*Oryza sativa* L.) is traditionally cultivated in two systems: upland and lowland. Brazilian production is predominantly composed of the lowland system, accounting for over 90% of total production. Upland rice production has been losing ground to other crops, representing only 7.94% of the total produced in the 2023/2023 harvest (CONAB 2024). The area available for expanding lowland rice production in Brazil is limited due to the high environmental impact and social issues, such as the competition for water resources between industrial and domestic uses. Rice production is concentrated in a single state, Rio Grande do Sul, which accounts for 76.7% of the total volume (MAPA 2021, CONAB 2024). This highlights a significant risk to the domestic supply, as production may vary according to climatic conditions. In this context, there is great interest in the upland rice production system in the Central-West region of Brazil. Expanding upland rice cultivation in the Cerrado region increases the geographical distribution of the crop, contributing to greater food security and minimizing logistical problems (Carvalho et al. 2020).

Genetic improvement with the release of modern cultivars adapted to local environmental conditions in Brazil has been one of the main drivers of increased yield (Costa et al. 2021). One of the key stages in breeding programs is to evaluate and recommend cultivars for cultivation in target regions. Adaptability

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and stability studies help in the recommendation process by assessing the performance of genotypes in response to environmental variations (Carneiro et al. 2020).

The large number of methods for studying adaptability and stability reflects the importance of this topic in plant breeding. However, some methodologies produce specific parameters for adaptability, stability, and mean, along with complementary parameters, which need to be evaluated simultaneously. In turn, alternative approaches can be employed given the complexity of multiple genotypes, parameters, and classifications produced by these methodologies (Silva Júnior et al. 2021).

Computational intelligence is an approach with potential application in plant breeding, as it is already well-established in the field of bioinformatics (Carneiro et al. 2018). Fuzzy logic is an alternative for decision-making automation, as it translates incomplete verbal expressions commonly found in human language into numerical values, enabling conversion into a language decipherable by computers (Silva et al. 2019).

Unlike classical logic, which uses well-defined distinctions to separate sets, fuzzy logic employs the concept that all things (temperature, speed, height, etc.) have degrees of membership. Thus, fuzzy logic models decision-making in an approximate way, reflecting the way humans think, and is applied in various fields (Simões and Shaw 2007).

The use of fuzzy logic in plant breeding, especially in adaptability and stability studies, has been used as a strategy which facilitates breeder decision-making. One of its advantages is the degree of membership or non-membership to the sets defined by the researcher. These membership degrees are obtained through membership functions, which translate quantitative agronomic variables into continuous numerical values ranging from 0 to 1. Fuzzy inference is performed based on linguistic rules, formulated from the breeder's knowledge, allowing a classification that closely resembles human reasoning. As a result, the fuzzy approach not only enables quantifying a genotype's presence in a given set but also ensures the accurate classification of genotypes according to the criteria of the adopted method (Carneiro et al. 2018, Carneiro et al. 2019, Carneiro et al. 2020, Silva Júnior et al. 2021, Cardoso et al. 2021).

In view of the above, the objective of this study was to evaluate the adaptability and stability of agronomic traits of upland rice lines using data from the Value for Cultivation and Use (VCU) trial network of the Upland Rice Breeding Program using fuzzy logic.

## MATERIAL AND METHODS

The data were obtained from Value for Cultivation and Use (VCU) trials conducted by the Upland Rice Breeding Program of the Federal University of Goiás. The BRS GO Serra Dourada and BRS Sertaneja cultivars were used as controls, and a total of 18 lines were evaluated, with eight lines from the Federal University of Goiás Breeding Program and 10 lines from the Federal University of Lavras Breeding Program.

The trials were conducted in 13 environments to evaluate the plant height and grain yield traits, and in eight environments for the number of days to flowering. The trials were conducted in the municipalities of Anápolis, Goiânia, Porangatu, Rio Verde, Santo Antônio, and Uruaçu, all located in the state of Goiás, Brazil, over four crop seasons from 2017/18 to 2020/21. Each combination of location and year was considered as one environment (Figure 1). The region is predominantly classified as Aw (Tropical with a dry season in winter) according to the Köppen climate classification system, with an average annual rainfall of 1500 mm, and an average monthly temperature which varies from 20.8 ºC in the coldest months to 25.3 ºC in the hottest months (Cardoso et al. 2014).

The experimental design was a randomized complete block with three replications using plots of four rows spaced 0.45 m apart and 4 m in length. The effective area considered was 3 meters of the central rows. Crop management followed the recommended agronomic practices for rice cultivation.

The experimental data were subjected to individual analysis of variance, and if homogeneity of residual variances was detected ($\frac{max(\sigma^2_{\varepsilon i})}{min(\sigma^2_{\varepsilon i})} < 7$) (Pimentel-Gomes 2009), a joint analysis was performed to detect genotype-environment interaction using the Genes software (Cruz 2013), according to model:

$$Y_{ijk} = \mu + B/E_{jk} + G_i + E_k + GE_{jk} + \varepsilon_{ijk}$$

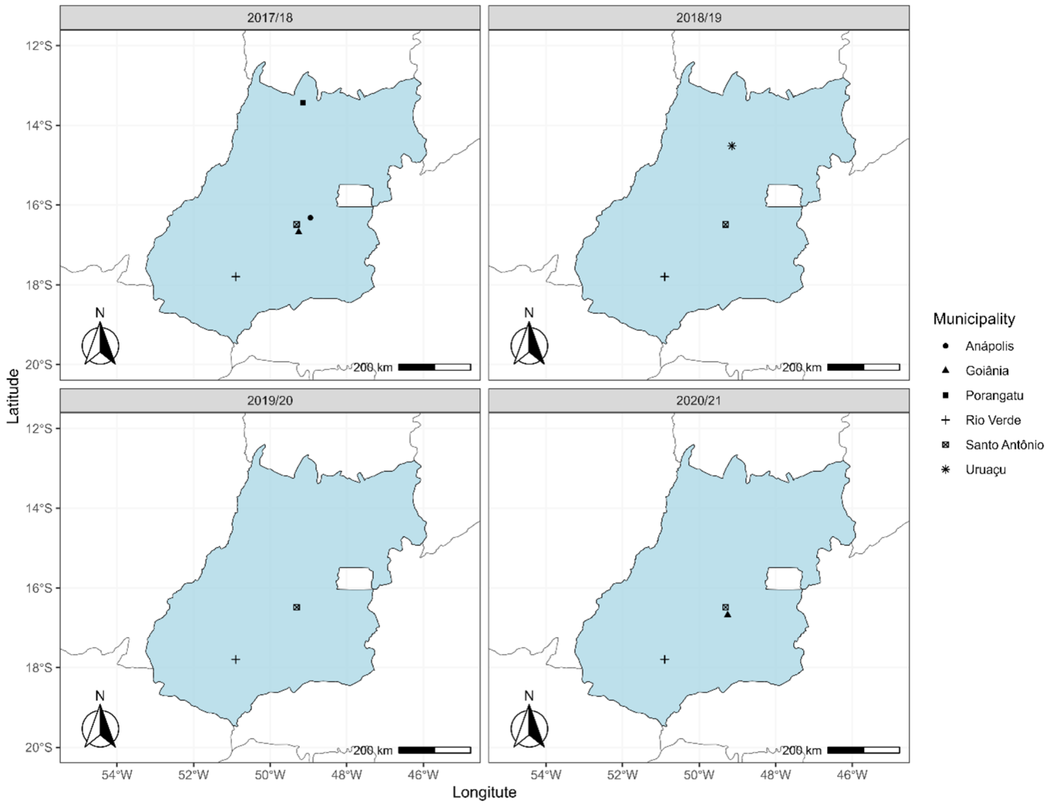


***Figure 1.*** Geographic distribution of VCU trial sites across four cropping seasons.

In which: $Y_{ijk}$ is the observation for genotype *i* in block *l* in environment *k*; $\mu$ is the overall mean of the experiments; $B/E_{jk}$ is the random effect of block *l* within environment *k*; $G_i$ is the fixed effect of genotype *i*; $E_k$ is the random effect of environment *k*; $GE_{jk}$ is the random interaction effect between genotype *i* and environment *k*; and $\varepsilon_{ijk}$ is the random error associated with observation $Y_{ijk}$.

For traits that did not meet the homogeneity of variances assumption, degrees of freedom were adjusted according to the model by Cochran (1954). Means were grouped using the Scott-Knott (1974) method at a 5% significance level.

Selective accuracy ($\hat{r}_{\hat{g}g}$) was estimated according to the model proposed by Resende and Duarte (2007) to assess the experimental precision of each trial. This estimate is obtained by the formula: $\hat{r}_{\hat{g}g} = (1 - \frac{1}{F})^{1/2}$, where *F* is the F-value obtained from the experiments. $\hat{r}_{\hat{g}g}$ can be classified as very high ($\hat{r}_{\hat{g}g} \geq 0.90$), high ($0.70 \leq \hat{r}_{\hat{g}g} < 0.90$), moderate ($0.50 \leq \hat{r}_{\hat{g}g} < 0.70$) and low ($\hat{r}_{\hat{g}g} < 0.50$).

Fuzzy logic analysis was performed using fuzzy controllers developed by Carneiro et al. (2020). Next, membership functions were defined for each agronomic trait based on agronomic performance parameters such as mean ($\beta_0$), regression coefficient ($\beta_1 = 1$), coefficient of determination ($R^2$), and superiority measures ($P_{if}$ and $P_{id}$). The linguistic rules for fuzzy inference were established based on the classical methods. Genotypes with $\beta_0 > \overline{\beta_0}$, $\beta_1 = 1$ and $R^2 > 80\%$ were considered as general adaptability in the ER controller. General adaptability was then indicated by low $P_{if}$ and $P_{id}$ values in the hybrid controller, combining with $\beta_1 = 1$ and $R^2 > 80\%$. Fuzzy inference combined these parameters to calculate the degrees of membership for four adaptability and stability groups: general adaptability (GA), poorly adapted (PA), favorable environment (FAV), and unfavorable environment (UNF). The final classification was based on the highest membership degree obtained by each genotype, allowing for a nuanced and continuous evaluation of genotype performance across diverse environments.

The controller analysis was performed using the R software version 4.4.1 (R Core Team 2024). The input into the controllers for the plant height and days to flowering traits was performed using data derived from subtracting a value greater than the observed value in the plot with the highest value. Thus, genotypes with lower means presented higher input means in the fuzzy controllers with the aim of classifying the genotypes with lower means for plant height and days to flowering as the most adapted.

## RESULTS AND DISCUSSION

A significant effect was observed for plant height (PH) regarding the effects of genotypes, environments, and genotype × environment (G × E) interaction (Table 1). The presence of G × E interaction was expected since the genotypes come from different breeding programs, and there is broad variation between locations and years (Table 1). The significant genotype effects contributed to 7.98% of the variation in the sum of squares. Environmental effects accounted for 54.3%, followed by the G × E interaction effects at 15.4%, highlighting the importance of environmental effects and the interaction in the evaluation of lines and cultivars. The coefficient of variation (CV) was 7.07%, considered low. The selective accuracy ($\hat{r}_{\hat{g}g}$) was 0.92, indicating genotypic variation and consequently good data quality for comparing lines.

Significant effects for the days to flowering (DF) trait were found for genotypes, environments, and the G × E interaction (Table 1). Environmental effects were the most important, contributing 76.7% of the effects, followed by G × E interaction (7.7%) and genotypes (5.35%). The strong influence of the environment on days to flowering in upland rice was also reported by Terra et al. (2015), where the environment accounted for 95.6% of the variability, and only 3.5% was attributed to genotypes. The $\hat{r}_{\hat{g}g}$ of 0.89 indicates good experimental quality for comparing lines.

Similar to the other variables, grain yield (GY) showed significant effects for genotypes, environments, and the G × E interaction (Table 1). Environmental effects were the most important, contributing 40.3%, followed by the G × E interaction (19.6%) and genotype effects (5.1%). The identification of G × E interaction in quantitative traits is frequently reported in rice studies (Carneiro et al. 2018, Silva Júnior et al. 2021). The CV was 23.64%, higher than the aforementioned studies (13.10%, 10.77%, and 19.20%), but the $\hat{r}_{\hat{g}g}$ value was high at 0.75, providing a good balance between the genotypic and environmental coefficients of variation.

Next, the Eberhart and Russell (ER) controller classified seven lines as having general adaptability and stability (GA) for plant height (PH) (Table 2), meaning lines that can be recommended for all cultivation environments. This classification is due to the controller only classifying the lines which have a higher mean than the overall mean as having GA ($\beta_1$ equal to 1, and $R^2$ greater than 80%); i.e. high mean (adaptability) and high predictability (stability). Only one line (CSD 10004) was classified as having adaptability and stability for favorable environments (FAV). No lines were classified as having adaptability and stability for unfavorable environments (UNF), and most lines were classified as poorly adapted (PA).

The hybrid controller similarly classified the genotypes, with six lines classified as having GA for Plant Height (PH) (Table 2), all of which were in common with the ER controller. This classification is due to the low $P_{if}$ and $P_{id}$ of the modified method of Lin and Binns (1988)'s values combined with $\beta_1$ = 1 and $R^2$ > 80% of the ER method, in the same

***Table 1.*** Summary of the joint analysis of variance for the plant height (PH), days to flowering (DF), and grain yield (GY) variables in upland rice lines and cultivars

| **Traits** | **PH** | | **DF** | | **GY** | |
|---|---|---|---|---|---|---|
| **Sources of variation** | **df** | **MS** | **df** | **MS** | **df** | **MS** |
| Genotype (G) | 19 | 519.37** | 19 | 58.66** | 19 | 2086591.36** |
| Environment (E) | 12 | 5595.35** | 7 | 2284.77** | 12 | 26027821.74** |
| G x E | 228 | 83.51** | 133 | 12.08** | 228 (164) | 923105.65** |
| Block/Environment | 26 | 145.38 | 16 | 8.55 | 26 | 1459113.04 |
| Residual | 494 | 48.23 | 304 | 6.53 | 494 (346) | 673906.33 |
| Mean | | 98.24 | | 78.25 | | 3473 |
| CV (%) | | 7.07 | | 3.26 | | 23.64 |
| $\hat{r}_{\hat{g}g}$ | | 0.92 | | 0.89 | | 0.75 |

$\hat{r}_{\hat{g}g}$ (selective accuracy). Degrees of freedom (df) in parentheses were adjusted using the Cochran (1954) method.

***Tabela 2.*** Fuzzy controller inputs and outputs for adaptability and stability for plant height (PH) in upland rice lines and cultivars

| Lines | Input | | | | | Output | |
|---|---|---|---|---|---|---|---|
| | $\beta_0$ (cm) | $\beta_1$ | $R^2$ (%) | $P_{if}$ | $P_{id}$ | ER | Hybrid |
| BRSGO S. Dourada | 92.93 a | 0.968 | 78.06 | 12.269 | 16.654 | PA | PA |
| BRS Sertaneja | 96.52 b | 0.922 | 86.94 | 44.961 | 37.719 | GA | GA |
| CSD 09001 | 101.1 c | 1.338* | 74.09 | 56.126 | 139.207 | PA | PA |
| CSD 09005 | 101.53 c | 1.189 | 88.08 | 109.344 | 107.312 | PA | PA |
| CSD 09006 | 101.22 c | 0.925 | 80.78 | 138.863 | 81.960 | PA | PA |
| CSD 09009 | 98.04 b | 0.857 | 68.97 | 68.908 | 71.890 | PA | PA |
| CSD 10002 | 108.89 d | 0.776 | 46.02 | 347.725 | 210.107 | PA | PA |
| CSD 10004 | 97.59 b | 1.265* | 90.61 | 29.736 | 72.608 | FAV | FAV |
| CSD 10005 | 96.48 b | 0.855 | 84.25 | 65.255 | 32.970 | GA | GA |
| CSD 08004 | 96.17 b | 1.106 | 81.35 | 37.096 | 42.367 | GA | GA |
| CMG ERF 221-7 | 98.78 b | 1.442* | 95.61 | 59.633 | 84.774 | PA | FAV |
| MULTILINHA | 97.55 b | 0.819 | 89.03 | 82.649 | 34.651 | GA | UNF |
| CMG ERF 221-29 | 95.14 a | 1.203 | 90.72 | 20.985 | 35.755 | GA | GA |
| CMG 2119 | 93.37 a | 0.945 | 78.47 | 29.691 | 12.789 | PA | PA |
| CMG 2085 | 97.19 b | 0.770 | 77.66 | 84.365 | 28.438 | PA | PA |
| CMG ERF 221-4 | 94.64 a | 0.873 | 76.55 | 50.713 | 13.767 | PA | PA |
| CMG F6 LAM 20-2 | 102.62 d | 0.863 | 75.64 | 163.736 | 91.440 | PA | PA |
| CMG ERF 85-14 | 98.03 b | 0.992 | 82.76 | 47.936 | 62.134 | GA | GA |
| CMG ERF 221-16 | 96.89 b | 0.899 | 88.99 | 68.709 | 34.991 | GA | GA |
| CMG ERF 85-6 | 100.12 c | 0.964 | 69.33 | 81.590 | 98.057 | PA | PA |

$P_{if}$, measure of the adaptability and stability of genotype behavior in favorable environments; $P_{id}$, measure of the adaptability and stability of genotype behavior in unfavorable environments; $\beta_0$, intercept of the regression model, representing the mean performance of the genotype across environments. $\beta_1$, regression coefficient; and $R^2$, coefficient of determination. Coefficients $\beta_0$ followed by different letters are significant according to the Scott-Knott mean clustering test. Coefficients $\beta_1$ followed by * are significant at the 5% level according to the t-test, considering the null hypothesis that $\beta_1$=1. PA (Poorly adapted), GA (General Adaptability), FAV (Favorable), UNF (Unfavorable).

lines. Two lines were classified as FAV (CSD 10004 and CMG ERF 221-7), and one line was classified as UNF (MULTILINHA). All other lines were classified as PA. The hybrid controller is more informative due to simultaneously evaluating two complementary methodologies, allowing for a better classification of the genotypic response to environmental variations (Silva Júnior et al. 2021).

All lines classified by the controllers as having general adaptability and stability had heights ranging between 95.14 cm and 97.55 cm. Shorter lines are desirable because this trait is correlated with lodging, which causes yield losses and makes mechanical harvesting difficult or even unfeasible (Gitti et al. 2011, Arf et al. 2012). Another positive aspect of reduced plant height is that plants conserve energy during vegetative growth and divert more carbohydrates towards grain production, thus directly affecting the harvest index (Costa et al. 2021). However, very short plants tend to be less competitive with weeds, so plants between 90 cm and 100 cm are considered desirable (Breseghello et al. 2011).

In turn, the ER controller only classified one line for grain yield (GY), CSD 08004, as having general adaptability and stability (GA) (Table 3). These lines showed high means ($\beta_1$ equal to 1), and high $R^2$. All other lines were classified as poorly adapted (PA), as they did not meet any of the criteria of the Eberhart and Russell (1966) method for being recommended for a group of environments. One line was classified as FAV, CMG ERF 221-16, which occurs because the line presents a high mean ($\beta_0$), $\beta_1$ > 1 and $R^2$ > 80%.

The hybrid controller classified the same line, CSD 08004 as having GA for GY (Table 3). This classification is due to the line showing low $P_{if}$ and $P_{id}$, a regression coefficient of $\beta_1$qual to 1, and a high coefficient of determination. Similar to the ER method, the hybrid controller classified CMG ERF 221-16 as FAV. This classification results from the low $P_{if}$ value combined with an intermediate $P_{id}$ value of the modified method of Lin & Binns, associate with $\beta_1$ > 1 and $R^2$ > 80% of the ER method. These results are similar to those found in studies by Carneiro et al. (2020) and Silva Júnior et al. (2021), which also reported similar classifications between the hybrid and ER controllers using grain yield data for common bean. Again, all other lines were classified as PA.

***Table 3.*** Fuzzy controller inputs and outputs for adaptability and stability for grain yield (GY) in upland rice lines and cultivars

| Lines | Input | | | | | Output | |
|---|---|---|---|---|---|---|---|
| | $\beta_0$ (kg ha$^{-1}$) | $\beta_1$ | $R^2$ (%) | $P_{if}$ | $P_{id}$ | ER | Hybrid |
| BRSGO S. Dourada | 3113.3 b | 1.073 | 81.24 | 999205.4 | 803459.7 | PA | PA |
| BRS Sertaneja | 3190.6 b | 0.956 | 84.09 | 961176.1 | 588508.0 | PA | PA |
| CSD 09001 | 3280.9 b | 0.847 | 52.97 | 986887.7 | 567415.6 | PA | PA |
| CSD 09005 | 3158.6 b | 1.116 | 66.57 | 1096309.5 | 847040.6 | PA | PA |
| CSD 09006 | 3253.7 b | 0.846 | 58.07 | 1248683.5 | 423497.3 | PA | PA |
| CSD 09009 | 3407.7 b | 0.767 | 66.48 | 928331.4 | 265585.6 | PA | PA |
| CSD 10002 | 3159.9 b | 0.825 | 55.94 | 1296198.4 | 580493.6 | PA | PA |
| CSD 10004 | 3715.4 a | 0.994 | 71.07 | 386726.0 | 196713.7 | PA | PA |
| CSD 10005 | 3462.3 a | 0.837 | 60.56 | 640241.9 | 331642.4 | PA | PA |
| CSD 08004 | 3569.7 a | 1.107 | 81.67 | 363338.9 | 444330.6 | GA | GA |
| CMG ERF 221-7 | 3920.7 a | 1.063 | 74.13 | 109426.8 | 140620.2 | PA | PA |
| MULTILINHA | 3692.3 a | 0.910 | 59.99 | 275178.3 | 322784.1 | PA | PA |
| CMG ERF 221-29 | 3585.5 a | 1.090 | 71.21 | 413777.9 | 415980.4 | PA | PA |
| CMG 2119 | 3314.8 b | 1.100 | 83.13 | 615473.8 | 637910.9 | PA | PA |
| CMG 2085 | 3460.1 a | 1.092 | 67.80 | 819962.1 | 386457.0 | PA | PA |
| CMG ERF 221-4 | 3640.4 a | 1.098 | 58.39 | 365325.5 | 537930.8 | PA | PA |
| CMG F6 LAM 20-2 | 3489.1 a | 1.011 | 58.35 | 752675.6 | 460429.1 | PA | PA |
| CMG ERF 85-14 | 3725.1 a | 1.172 | 78.05 | 403345.3 | 311787.0 | PA | PA |
| CMG ERF 221-16 | 3712.2 a | 1.355* | 86.35 | 137196.9 | 448895.9 | FAV | FAV |
| CMG ERF 85-6 | 3605.7 a | 0.740 | 49.78 | 589141.8 | 271655.8 | PA | PA |

$P_{if}$, measure of the adaptability and stability of genotype behavior in favorable environments; $P_{id}$, measure of the adaptability and stability of genotype behavior in unfavorable environments; $\beta_0$, intercept of the regression model, representing the mean performance of the genotype across environments. $\beta_1$, regression coefficient; and $R^2$, coefficient of determination. Coefficients $\beta_0$ followed by different letters are significant according to the Scott-Knott mean clustering test. Coefficients $\beta_1$ followed by * are significant at the 5% level according to the t-test, considering the null hypothesis that $\beta_1$=1. PA (Poorly adapted), GA (General Adaptability), FAV (Favorable), UNF (Unfavorable).

The line classified as having GA by both controllers, CSD 08004, had a mean yield of 3,569.7 kg ha$^{-1}$ (Table 3). The productive stability of this line may offer greater resilience to climatic variations. Its performance exceeded the national and Goiás state averages, which were 2,587 kg ha$^{-1}$ and 1,595 kgha$^{-1}$, respectively (CONAB 2024), and compared to the BRSGO Serra Dourada and BRS Sertanejo cultivars, indicating the genetic potential of these lines in the region. Higher yield per cultivated area favors economic viability of the crop, as well as increasing grain supply without the need to expand agricultural areas. This is crucial in a climate change scenario in which the availability of agricultural land and water resources becomes increasingly limited (Ramirez-Villegas et al. 2018). Increased yield reduces production costs per unit, directly impacting the availability and price of food in the market.

The ER controller classified eight lines as having general adaptability and stability for days to flowering (DF) (Table 4). These lines had low means, $\beta_1$ equal to 1, and high $R^2$. According to the Eberhart and Russell (1966) method, these lines exhibit stable and predictable behavior in both favorable and unfavorable environments. All other lines were classified as poorly adapted.

The fuzzy hybrid controller classified seven lines as having general adaptability and stability (Table 4). This similar classification is due to the low $P_{if}$ and $P_{id}$ values of the lines. $P_{if}$ and $P_{id}$ values are associated with the lines' performance, meaning that lines with lower values had similar performance to the best-performing line in as many favorable and unfavorable environments as possible. The lines classified as GA by both controllers have DF averages ranging from 75.2 to 78 days, with the lowest averages being the CMG ERF 85-6 and CMG ERF 85-14 lines (Table 4). These lines demonstrate great genetic potential for precocity, with values lower than those found by Tomé et al. (2025) in crosses with the objective of precocity associated with high yield. Unlike the ER controller, the hybrid controller classified the CMG 2119 line as having specific adaptability and stability for favorable environments. This classification is due to the line having a low $P_{if}$ value and a high $P_{id}$ value, combined with $\beta_1$ > 1 and a high $R^2$.

Rainfall distribution in the Brazilian Cerrado region (where most upland rice is cultivated) is irregular, with the occurrence of dry spells during the rainy season. These periods are unpredictable and compromise the plant's productive potential (Guimarães et al. 2016). DF is closely associated with responses to environmental stresses, such as drought and temperature variations. Early-maturing cultivars in regions where rainfall is inconsistent can complete their cycle before water stress occurs, increasing their chances of survival and yield (Khotasena et al. 2022). Year-to-year variations in abiotic stress can lead to reduced investment by farmers in inputs, resulting in larger yields gaps (Saito et al. 2018).

The increased competitiveness of upland rice faces several challenges, such as improving yield alongside early maturity, lodging resistance, and good response to chemical fertilization. These are essential traits for inclusion in crop rotation and succession systems (Furtini et al. 2020). The use of early-maturing cultivars allows for greater flexibility in managing agricultural areas, enabling to insert rice into crop rotation systems as it can be grown in a shorter period, freeing the area for subsequent crops. This is particularly relevant for regions with short planting windows (Meirelles et al. 2019).

Since the main objective of the breeding program is to select productive lines, only one was classified as having GA, CSD 08004. The lines were classified as having general adaptability and stability for PH by both controllers. The line for DF was not classified as having general adaptability and stability; however, it is worth noting that the CSD 08004 line had a membership value of 42% in the ER controller, combined with $\beta_1$ = 1 and $R^2$ above 80%, indicating predictable behavior and an intermediate mean among the evaluated genotypes.

The use of fuzzy logic not only provided categorical classification of genotypes, but also quantitative values representing the degree of membership to each adaptability and stability class. These membership degrees, calculated by membership functions and linguistic rules, enable identifying genotypes with intermediate or borderline behavior, cases that would likely be overlooked by traditional methods. For instance, although the CSD 08004 line was not classified as having GA for days to flowering by the ER controller, it presented a 42% membership value in this group, combined with $\beta_1$ = 1 and $R^2$ > 80%, indicating predictable behavior. This nuance highlights the potential of fuzzy logic to support more refined and flexible decision-making.

***Table 4.*** Fuzzy controller inputs and outputs for adaptability and stability for days to flowering (DF) in upland rice lines and cultivars

| Lines | Input | | | | | Output | |
|---|---|---|---|---|---|---|---|
| | **$\beta_0$ (days)** | **$\beta_1$** | **$R^2$ (%)** | **$P_{if}$** | **$P_{id}$** | ER | Hybrid |
| BRSGO S. Dourada | 77.9 b | 0.862 | 75.05 | 18.76 | 4.38 | PA | PA |
| BRS Sertaneja | 79.6 d | 1.075 | 96.69 | 16.85 | 18.10 | PA | PA |
| CSD 09001 | 79.2 c | 1.006 | 84.82 | 19.42 | 12.54 | PA | PA |
| CSD 09005 | 80.6 d | 0.905 | 79.22 | 30.19 | 23.26 | PA | PA |
| CSD 09006 | 78.0 b | 1.007 | 94.54 | 10.90 | 6.46 | GA | GA |
| CSD 09009 | 78.3 c | 0.981 | 88.41 | 14.04 | 15.19 | PA | PA |
| CSD 10002 | 79.5 d | 0.918 | 93.89 | 22.32 | 13.69 | PA | PA |
| CSD 10004 | 77.9 b | 0.981 | 92.03 | 11.71 | 8.81 | GA | GA |
| CSD 10005 | 77.4 b | 1.044 | 95.06 | 6.96 | 11.50 | GA | PA |
| CSD 08004 | 78.6 c | 1.129 | 96.72 | 10.14 | 16.08 | PA | PA |
| CMG ERF 221-7 | 80.1 d | 1.096 | 92.78 | 20.14 | 19.74 | PA | PA |
| MULTILINHA | 76.5 a | 0.830 | 94.18 | 8.94 | 2.81 | GA | GA |
| CMG ERF 221-29 | 80.1 d | 0.927 | 87.81 | 22.75 | 22.25 | PA | PA |
| CMG 2119 | 78.7 c | 1.195* | 97.90 | 8.38 | 17.58 | PA | FAV |
| CMG 2085 | 77.3 b | 0.988 | 93.01 | 10.63 | 6.67 | GA | GA |
| CMG ERF 221-4 | 78.7 c | 1.076 | 95.41 | 12.31 | 12.69 | PA | PA |
| CMG F6 LAM 20-2 | 76.3 a | 1.020 | 92.64 | 7.07 | 2.54 | GA | GA |
| CMG ERF 85-14 | 75.2 a | 1.077 | 94.61 | 0.81 | 6.13 | GA | GA |
| CMG ERF 221-16 | 79.8 d | 0.869 | 90.45 | 25.92 | 13.36 | PA | PA |
| CMG ERF 85-6 | 75.2 a | 1.014 | 92.00 | 2.40 | 0.53 | GA | GA |

$P_{if}$, measure of the adaptability and stability of genotype behavior in favorable environments; $P_{id}$, measure of the adaptability and stability of genotype behavior in unfavorable environments; $\beta_0$, intercept of the regression model, representing the mean performance of the genotype across environments. $\beta_1$, regression coefficient; and $R^2$, coefficient of determination. Coefficients $\beta_0$ followed by different letters are significant according to the Scott-Knott mean clustering test. Coefficients $\beta_1$ followed by * are significant at the 5% level according to the t-test, considering the null hypothesis that $\beta_1$=1. PA (Poorly adapted), GA (General Adaptability), FAV (Favorable), UNF (Unfavorable).

Silva Júnior et al. (2021) emphasize the importance of membership parameters, as they can be used as a tool for selecting genotypes relevant to a specific class of environments. These parameters help identify genotypes with better adaptation and performance for a set of specific environments, contributing to select suitable genotypes for different growing conditions.

Moreover, integrating two complementary methodologies within the hybrid controller enabled a more robust and informative classification. The alignment of results between the classical and fuzzy methods reinforces the reliability of the approach while offering additional interpretation layers. Because fuzzy inference is based on linguistic rules that mimic human reasoning, the resulting classifications are more intuitive for breeders, aligning with how genotype performance is interpreted in the field.

## CONCLUSION

The CSD 08004 line exhibits broad adaptability and stability for the state of Goiás in terms of plant height and grain yield, surpassing the control cultivars and thus being recommended for cultivation in the state of Goiás.

## DATA AVAILABILITY

The datasets generated and/or analyzed during this research are available from the corresponding author upon request.

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