ARTICLE

Probability of risk in recommending white oat cultivars in Brazil

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Abstract: *White oats are considered one of the main winter cereals, due to their diverse purposes and nutritional quality, and accurate recommendation of cultivars is essential to maximize crop yield. The objective of the study was to position white oat genotypes based on estimates of probability of risk in the recommendation. The study was carried out in 23 environments in Brazil between 2014 and 2023, with 44 white oat cultivars. Soil and climate variables were used together with grain yield data to recommend cultivars. Recommendation risk estimates were made. IPR Artemis cultivar showed a higher probability of superior performance for grain yield and FAEM 007 showed greater stability.*

Keywords: *Sustainability, yield, stability*

INTRODUCTION

White oat (*Avena sativa* L.) is one of the most cultivated cereals during the winter season, considered a temperate climate crop. It is a crop characterized by having grains of high nutritional quality and rich in proteins, fibers and lipids intended mainly for human consumption (Hawerroth et al. 2014, Maximino et al. 2021). According to a survey by the National Supply Company, Brazil in 2023 sowed more than 494 thousand hectares, with production exceeding one million tons and yield exceeding 2.1 tons of grains per hectare (CONAB 2023). Brazil is the fifth largest producer of oats in the world along with Canada, Russia, Australia and Poland, being responsible for 48.5% of the total grains produced in South America (FAOSTAT 2022).

White oats are cultivated under different environmental conditions, with more than 57 cultivars registered in Brazil, in the last two decades of research based on agronomic recommendations. Many techniques have already been used to better position cultivars in environments in the most reliable way possible, employing simple and complex methods, based on analysis of variance and decomposition of deviations from linear, non-linear and segmented regression (Carvalho et al. 2016), as well as those based on factorial regressions and reaction norms (Schmidt et al. 2023, Loro et al. 2023), all of these supported by the construction of an environmental index. This, in turn, can be used to stratify environments, estimate stability or predictability, and adaptability to favorable and unfavorable environments (Berlezi et al. 2023, Pradebon et al. 2024).

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Accuracy in cultivar positioning is essential to ensure the best agronomic performance of genotypes. Inadequate positioning of a genotype causes losses for the cultivar breeder and especially for the producer who will use this cultivar. Emerging methodologies have been used to improve the accuracy of genotype positioning, such as methodologies based on Bayesian probability (Dias et al. 2022). This methodology has been efficiently applied in the selection of corn (Loro et al. 2024) and Tahiti acid lime (Malikouski et al. 2024) genotypes.

When contrasting linear, random, mixed and Bayesian models in recommending cultivars, the great effectiveness obtained is evident, as well as favorable results for plant genetic improvement (Schneider et al. 2021, Azevedo et al. 2023). Effectiveness is observed when using linear methods, which include analysis of variance, linear regression, nonlinear regression, bisegmented regression, harmonic mean and the best linear unbiased prediction, as well as methods based on multivariate analysis Additive Main Effects and Multiplicative Interaction Analysis (AMMI), Genotype and Genotypes by Environments Interaction (GGE), and probabilistic methods such as the Bayesian approach.

The Bayesian approach can be applied to recommend global and specific cultivars in the target population of environments. Concepts developed by Dias et al. (2022) define that Bayesian probability models can assist in the selection of favorable, stable cultivars with satisfactory performance in contrasting environments. In addition, this methodology offers the advantage of presenting specific information, enabling the identification of high-performance and plastic genotypes in specific improvement regions. The joint use of complementary methodologies maximizes the reliability of genotype positioning. This minimizes wasted time and financial resources, increases the reliability of choosing the environment and cultivars, and minimizes the inflations of coefficients focused on the interactions genotypes x environments and genotypes x environments x agricultural years, in addition to enhancing crop grain yield (Chaves et al. 2024).

Based on the agricultural, social and economic importance of white oats in Brazil and given the availability of few genotypes, it is important to define which genetic constitutions were superior over the decades and which environments are strategic for the white oat production chain. In this context, the objective of this work was to position white oat genotypes based on risk probability estimates in the recommendation.

MATERIAL AND METHODS

The study was carried out in 23 environments in Brazil between 2014 and 2023 (Figure 1S, Table 1). In each environment, 44 cultivars of white oat were cultivated (Table 2): FAEM Albasul, FAEM Barbarasul, FAEM Brisasul, FAEM 006, FAEM 007, FAEM Carlasul, FAEM Chiarasul, Louise (FAPA4), FAPA5, FAPA6, URS Guapa, IAC 007, IPR Afrodite, IPR Andrômeda, IPR Artêmis, UFRGS 14 Amiga, UFRGS 19, UPF 15, UPF 16, UPF 18, UPFA Gaudéria, UPFA Ouro, UPFA 20 Teixeirinha, UPFA 22 Temprana, UPFA Fuerza, UPFPS Farroupilha, URS 21, URS 22 Londrina, URS Altaneira, URS Altiva, URS Brava, URS Torena, URS Corona, URS Estampa, URS Fapa Slava, URS Guará, URS Guria, URS Monarca, URS Olada, URS Penca, URS Poente, URS Tarimba and URS Taura.

The experiments were carried out using the protocol of the Brazilian Oat Research Commission. With 23 environments and 10 years, 44 genotypes, trials were laid out as incomplete block designs, with three replications (one replication in each block). The experimental units were composed of five sowing rows measuring five meters in length, spaced 0.17 meters apart, totaling 4.25 m^2. The absolute population density used for this test network was 300 viable seeds per square meter, and basal fertilization and cultural practices were defined in accordance with the standards of the Brazilian Oat Research Commission.

The target variable for the estimates was grain yield per hectare (kg ha^{-1}), corrected to 13% moisture. In order to better understand the variability between cultivation environments, information related to soil characteristics of each environment was used, from which the following parameters were inferred: organic carbon in the soil (g kg^{-1}), total nitrogen accumulated in the soil (g kg^{-1}), cation exchange capacity ($cmol_c$ kg^{-1}) and clay content (g $100g^{-1}$); these data were obtained through the Soil Grid platform. The meteorological data (from 2014 to 2023) used were: mean air temperature (Tmean, ºC), minimum air temperature (Tmin, ºC), maximum air temperature (Tmax, ºC) and average monthly precipitation (mm), obtained through the NASA Power platform (Nasa Power 2024), as well as the geographic information altitude, longitude and latitude, obtained from the Google Earth platform (Google Earth 2024), expressed in order to better understand the results obtained.

Table 1. White oat growing environments in Brazil, geographic coordinates, soil type, climate and altitude

Environment	State	Latitude	Longitude	Altitude	Soil type	Climate
Três Passos	RS	-27°26'51" S	-53°54'51" W	420	Oxisol	*Cfa*
Tibagi	PR	-24°39'10" S	-50°15'25" W	800	Inceptisols and Oxisols	*Cfa*
São Carlos	SP	-21°57'00" S	-47°53'27" W	856	Oxisols	*Cwa*
Santa Tereza	PR	-24°50'42" S	-53°29'42" W	215	Ultisols	*Cfa*
Ponta Grossa	PR	-25°00'45" S	-50°09'05" W	956	Oxisol	*Cfb*
Pinhão	PR	-25°70'73" S	-51°63'34" W	1.088	Ultisol	*Cfa*
Pelotas	RS	-31°02'00" S	-52°30'00" W	13	Ultisol and Entisol	*Cfa*
Pato Branco	PR	-26°13'43" S	-52°40'14" W	721	Oxisol	*Cfa*
Passo Fundo	RS	-28°13'39" S	-52°24'33" W	687	Oxisol	*Cfa*
Maua da Serra	PR	-23°54'05" S	-51°13'46" W	720	Oxisol	*Cfb*
Maracaju	MS	-26°36'50" S	-55°10'04" W	384	Ultisol	*Cfa*
Londrina	PR	-23°11'37" S	-51°11'03" W	700	Oxisol	*Cfa*
Lages	SC	-27°48'58" S	-50°19'58" W	770	Ultisol	*Cfb*
Itaqui	RS	-29°07'10" S	-56°32'52" W	76	Alfisol	*Cfa*
Itabera	SP	-23°51'43" S	-49°08'14" W	740	Alfisol	*Cfa*
Guarapoava	PR	-25°23'36" S	-51°27'19" W	1.095	Oxisol	*Cfb*
Eldorado	RS	-30°05'22" S	-51°39'08" W	22	Ultisol	*Cfa*
Castro	PR	-24°47'32" S	-50°00'42" W	996	Inceptisol	*Cfb*
Cascavel	PR	-24°57'20" S	-53°27'19" W	682	Oxisol	*Cfa*
Capao Bonito	SP	-24°00'00" S	-48°22'00" W	702	Oxisol	*Cfb*
Campos Novos	SC	-27°24'00" S	-51°13'30" W	925	Oxisol	*Cfb*
Augusto Pestana	RS	-28°26'32" S	-54°00'12" W	385	Ultisol	*Cfb*
Arapotti	PR	-24°08'29" S	-49°49'45" W	800	Oxisol	*Cfb*

Cfa: Subtropical climate, with hot summers; Cfb: Temperate climate with mild summer; Cwa: Subtropical climate with dry winters and hot summers.

The data matrix obtained was organized jointly using the agricultural year variation factor, cultivation environment, cultivar used, block and the grain yield variable, being subjected to descriptive analyses to understand the upper and lower limits, as well as the coefficients of variation obtained in each test, after extracting the outliers when necessary. Descriptive analyses were also carried out using central tendency statistics for soil and climate variables, which were expressed in a heatmap. Based on the available data matrix, estimates of the risk of recommending cultivars in multi-environment trials were carried out, using the model that combines agricultural years, regions of recommendation and cultivation environments proposed by Dias et al. (2022):

$$Yjqp = \mu + l(k) + r(qk) + bp(qk) + g(j) + gl(jk) + \varepsilon jkqp$$

Where: $Yjqp$: corresponds to the phenotypic effect of the j-th genotype, allocated in the p-th block, in the q-th years; μ: is the overall mean; lk: effect of the k-th environments; rqk: interaction between the q-th year and the k-th environments; $bpqk$: effect of the p-th block in interaction between q-th year and the environments; gj: effect of the j-th genotype; $gljk$: interaction between the j-th genotype and the k-th environments; $\varepsilon jkqp$: experimental error associated whith the j-th genotype, k-th environments, q-th year, and p-th block.

The field data were determined as a priori information, after which it was subjected to Markov Chain Monte Carlo (MCMC) algorithms, and several re-samplings were carried out, obtaining several chains with more than a million comparisons. Under these conditions, a known *a priori* information matrix, random effects for the genotypes, 1000000 iterations and a burn-in of 100000 were considered. Based on this model, it was possible to obtain the decomposition of the effects of variances, stratified by the effects of environment (l), effects of the agricultural year (m), effects of the cultivar (g), and effects of the interactions g x l and g x m, highlighting the variance (var), standard deviation (sd), error attributed to the Naive algorithm (naive.se), the higher probability density (HPD) and confidence intervals between 5% (HPD 0.05) and 95% (HPD 0.95). The diagnosis of Markov chains was obtained based on the parameters maximum, minimum and mean probability, standard deviation of the probability, Akaike information criterion (WAIC), convergence function and effective sample size. In these precepts, up to four chains were estimated, and the most representative and correlated with the a *priori* data were used for the estimates. Afterwards, the distribution of the effects of each variance component, HPD by cultivar, the general, marginal and conditional probability, performance and stability of genotypes were estimated. All analyses were carried out in R software using the packages *metan* (Olivoto and Lúcio

Table 2. Description of cultivars used with information from breeders, cycle and recommended cultivation region

Cultivars	Days cycle	Breeder	Recommendation
(G1) FAEM Albasul	124	UFPel	RS, PR, SC, and SP
(G2) FAEM Barbarasul	125	UFPel	RS
(G3) FAEM Brisasul	126	UFPel	RS
(G4) FAEM 006	121	UFPel	RS
(G5) FAEM 007	123	UFPel	RS
(G6) FAEM Carlasul	126	UFPel	RS
(G7) FAEM Chiarasul	124	UFPel	RS
(G8) Louise (FAPA 4)	-	FAPA	RS, PR, SC, and SP
(G9) Fapa 5	-	FAPA	RS, PR, SC, and SP
(G10) Fapa 6	-	FAPA	RS, PR, SC, and SP
(G11) URS Guapa	124	UFRGS	RS, PR, SC, and SP
(G12) IAC 007	120	IAC	RS
(G13) IPR Afrodite	129	IAPAR	RS, PR, SC, and SP
(G14) IPR Andromeda	121	IAPAR	RS, PR, SC, and SP
(G15) IPR Artemis	117	IAPAR	RS, PR, SC, and SP
(G16) UFRGS 14 (Amiga)	99	UFRGS	RS
(G17) UFRGS 19	-	UFRGS	RS
(G18) UPF 15	134	UPF	RS
(G19) UPF 16	99	UPF	RS
(G20) UPF 18	134	UPF	RS
(G21) UPFA Gauderia	124	UPF	RS, PR, SC, and SP
(G22) UPFA Ouro	129	UPF	RS, PR, SC, and SP
(G23) UPFA 20	-	UPF	-
(G24) Teixeirinha	131	UPF	RS, PR, SC, and SP
(G25) UPFA 22 Temprana	131	UPF	RS, PR, SC, and SP
(G26) UPFA Fuerza	121	UPF	RS, PR, and SP
(G27) UPFPS Farroupilha	121	UPF	RS, PR, SC, and SP
(G28) URS 21	125	UFRGS	RS
(G29) URS 22 Londrina	122	UFRGS	RS
(G30) URS Altanera	-	UFRGS	RS
(G31) URS Altiva	130	UFRGS	RS, PR, and SP
(G32) URS Brava	120	UFRGS	RS, PR, and SP
(G33) URS Torena	124	UFRGS	RS, PR
(G34) URS Corona	123	UFRGS	RS, SC, PR
(G35) URS Estampa	126	UFRGS	RS, PR
(G36) URS Fapa Slava	125	FAPA/UFRGS	RS, PR and SP
(G37) URS Guará	124	UFRGS	PR and RS
(G38) URS Guria	123	UFRGS	PR and RS
(G39) URS Monarca	116	UFRGS	PR, RS, and SC
(G40) URS Olada	-	UFRGS	PR, RS, and SC
(G41) URS Penca	126	UFRGS	PR and RS
(G42) URS Poente	-	UFRGS	RS, PR and SC
(G43) URS Tarimba	121	UFRGS	RS, PR, and SC
(G44) URS Taura	122	UFRGS	RS, PR, SC, and SP

Abbreviations: FAPA: Agricultural Research Foundation; IAC: Campinas Agronomic Institute; IAPAR: Paraná Rural Development Institute; UFRGS: Federal University of Rio Grande do Sul; UFPel: Federal University of Pelotas; UPF: University of Passo Fundo. Recommended States: RS: Rio Grande do Sul; PR: Paraná; SC: Santa Catarina; SP: São Paulo.

2020), *EnvRtype* (Costa Neto et al. 2021), *SoilType*, *rnaturalearth* (South et al. 2017), *ggplot2* (Wickham 2016) and *ProbBreed* (R Core Team 2015, Chaves et al. 2024).

RESULTS AND DISCUSSION

White oats have the characteristic of adapting to different types of soil. Acidity does not become a limiting factor for plant growth. The reference pH for optimal crop development is around 5.0 to 6.0, being responsive to 2.0 to 3.0% of organic nitrogen in the soil (Santos and Lima 2020). High fertility was observed in Cascavel - PR, Guarapuava - PR Pinhão - PR and Santa Tereza - PR. Considering all the environments studied, the state of Paraná has all high fertility environments (Figure 2S).

For the development of the white oat crop, it is essential that meteorological conditions are favorable, especially precipitation and air temperature. Variations in temperature and precipitation were observed between different growing environments (Figure 3S). The ideal temperature is between 20 °C and 25 °C, the lower basal temperature of oats is 4 ºC and the upper basal temperature is 30 ºC, that is, temperatures outside this range are harmful to the development of the crop, resulting in a decrease in yield and quality of the grains produced. In this context, from May to October there were maximum air temperatures of up to 33 °C and minimum temperatures of 7 °C, revealing large amplitudes that could lead to a reduction in crop performance. Between June and July, air temperatures often approached the lower and upper limits. For September and October, which coincide with the physiological maturity of the crop, some environments were challenging, such as São Carlos – SP and Capão Bonito – SP, mainly in relation to maximum air temperatures.

Based on the general *a posteriori* diagnosis, the variance and diagnostic probability components were estimated for the 44 oat cultivars grown in 23 environments (Table 3). The phenotypic magnitude is related to the effects of the growing environment, with a fraction resulting from genetic variation. Thus, by obtaining a relationship between phenotypic variance and genotypic variance, it becomes possible to demonstrate that for grain yield the environmental effect had a contribution of 13.73%, genotypic effect had a contribution of 13.20%, with 12.50% for the effects of the interaction between genotypes and environments. The year effect had the largest contribution to the total variance, with 33.80%. According to Loro et al. (2022), higher minimum air temperature and lower average temperature and relative air humidity improve the production performance of white oat genotypes, that is, a fact that justifies the greater contribution of the year to the expression of grain yield of white oats, due to the great meteorological variability. The triple interaction of genotypes x environments x years resulted in a contribution of 20%, while the residual component reveals only 6.70%.

The probability diagnosis provides a model fit; the maximum probability was 0.55 and the minimum was 0.00, with an average of 0.49. The standard deviation of the probability was also 0.49, indicating significance in the variability of

Table 3. Decomposition of the effects of variances and diagnosis of probabilities

Decomposition of variance effects						
Effects	**Variances**	**Component Contribution Percentage**	**Standard Deviation**	**Error**	**HPD_0.05**	**HPD_0.95**
EE	2.07	13.73	6.86	1.08	1.21	3.34
GE	1.99	13.20	5.35	8.47	1.27	2.98
G x E	1.88	12.47	1.00	1.59	1.40	4.17
Year	5.10	33.84	2.44	3.85	2.41	9.56
G x E x Year	3.02	20.03	6.10	9.64	9.74	1.95
Residual	1.01	6.70	1.45	2.30	1.01	2.15
Diagnosis of probabilities						
Maximum probability				0.55		
Minimum probability				0.00		
Average probability				0.49		
Probability standard Deviation				0.49		
Number of effective Parameters				47.57		
Akaike information criterion Widely applicable				255906.14		

EE – Environmental effect; GE – Genotype effect; G x E – Genotype-environment interaction; G x E x Year – Genotype, environment and year interaction.

predicted probabilities. The number of effective parameters was 47.57, with Akaike's criterion (WAIC) of 255906.14 being used to confirm the statistical models.

A posteriori information is generated through the actual distribution of a priori information. The prediction of four chains (1, 2, 3 and 4) was observed. Bayesian models are used to analyze individual differences between study subjects, where each subject may have a unique set of parameters that characterize their responses. A value of ^R close to 1 indicates strong convergence of the parameters. This indicates the effectiveness of the model in replicating the data distribution. The density of the generated data follows the trend of the real density, thus indicating the effectiveness of the model in replicating the distribution of the data that is observed, through the generated data (Figure S4).

In the analysis of Bayesian chains, it was possible through the six density graphs (Figure S4) to represent the predictions of the dependent variable grain yield in graph (a), which shows a normal distribution centered approximately around zero, graph (b), which represented the distribution of data from one (environment), with a tendency for positive values to right and also with a large part of values concentrated close to zero, graph (c) g (genotype), from which an asymmetric normal distribution was inferred, with values centered on zero or close to zero in the four chains, graph (d), which is the gl interaction between genotype × environment, graph (e) m (year), which represented an asymmetric normal distribution, with values centered on zero or close to zero in the four chains, and graph (f) gm, which represents the interaction between (genotype) and (year), presents values located exactly on the zero line or values very close to zero.

In the Bayesian chain analysis, the formation of six histograms was observed (Figure S5), which represent the distribution of genetic effects in relation to different components. Histogram (a) shows the distribution of sampled_y (grain yield), which shows us a normal distribution, centered approximately around zero. In histogram (b), the distribution of g (genotype) is observed, also appearing normal, close to zero, and can obtain a variance of -1000 to 1000. Histogram (c), which contains the distribution of values for the environments, shows an asymmetric distribution, concentrating values close to zero, but with a tendency of some values indicating high positive values to the right, which refer to one (year).

Table 4. Conditional probability of environments and cultivars

Environments	**Probability** (%)	**Factor** (%)
(E1) Três Passos	15.44	(G8) Fapa 4 (18.04)
(E2) Tibagi	18.46	(G8) Fapa 4 (15.44)
(E3) São Carlos	11.61	(G8) Fapa 4 (22.22)
(E4) Santa Tereza	18.85	(G8) Fapa 4 (23.17)
(E5) Ponta Grossa	16.46	(G8) Fapa 4 (17.21)
(E6) Pinhão	4.41	-
(E7) Pelotas	15.38	(G8) Fapa 4 (17.64)
(E8) Pato Branco	14.71	(G44) URS Taura (23.52); (G35) URS Estampa (23.52)
(E9) Passo Fundo	14.86	(G8) Fapa 4 (18.75)
(E10) Maua da Serra	15.79	(G8) Fapa 4 (17.64)
(E11) Maracaju	15.58	(G44) Torena (25.00)
(E12) Londrina	15.79	(G8) Fapa 4 (16.91)
(E13) Lages	13.95	(G8) Fapa 4 (18.18)
(E14) Itaqui	12.68	(G35) URS Estampa (25.42)
(E15) Itabera	16.96	(G8) Fapa 4 (15.92)
(E16) Guarapoava	14.16	(G8) Fapa 4 (19.67)
(E17) Eldorado	15.56	(G8) Fapa 4 (17.91)
(E18) Castro	13.93	(G8) Fapa 4 (20.00)
(E19) Cascavel	13.85	(G35) URS Estampa (28.12)
(E20) Capão Bonito	14.40	(G8) Fapa 4 (19.35)
(E21) Campos Novos	10.66	(G34) URS Corona (25.00)
(E22) Augusto Pestana	15.21	(G8) Fapa 4 (17.55)
(E23) Arapotti	13.58	(G8) Fapa 4 (18.80)

Note in histogram (d) the interaction between two components gl (interaction genotype × environment), where the distribution is extremely concentrated at zero, indicating that the values are at zero or very close to zero. In histogram (e), we obtain the values of m (year), with a normal distribution close to zero, which may show a variance from -1500 to 2000, varying in greater proportion to the negative left side. Finally, histogram (f), with the interaction between gm genotype and year, presents its distribution centered on zero or with values very close to zero.

According to the conditional probability between environments and cultivars (Table 4), it was observed that in the Pinhão-PR (E6) environment, no cultivar was recommended. However, in the Pato Branco-PR environment (E8), the cultivars URS Taura (G44) and URS Estampa (G35) both showed a conditional probability of 23.52%. FAPA 4 (G8) showed a higher probability in 16 environments, which indicates that this cultivar has potential for recommendation in the most diverse oat-producing environments in Brazil. The percentage indicates the variation of cultivars within each environment, showing the difference in response and adaptation in the environments. Understanding the genetic and environmental effects on the expression of oat production traits is essential to increase the response to selection of well-adapted, high-yielding cultivars (Mazurkievicz et al. 2019).

Cultivars IPR Artêmis (G15), URS Penca (G41), URS 22 Londrina (G29), URS Monarca (G39), UPFA 22 Temprana (G25), URS Torena (G33) and URS Altiva (G31) showed a higher probability (> 75%) of marginal superior performance compared to the others, highlighting the importance of carefully selecting cultivars to maximize performance (Figure 1). These findings corroborate those observed by Rother et al. (2019), who report that grain yield is controlled by a high number of genes and this characteristic is highly influenced by the environment, justifying the discrepancy in grain yield between different environments and growing seasons.

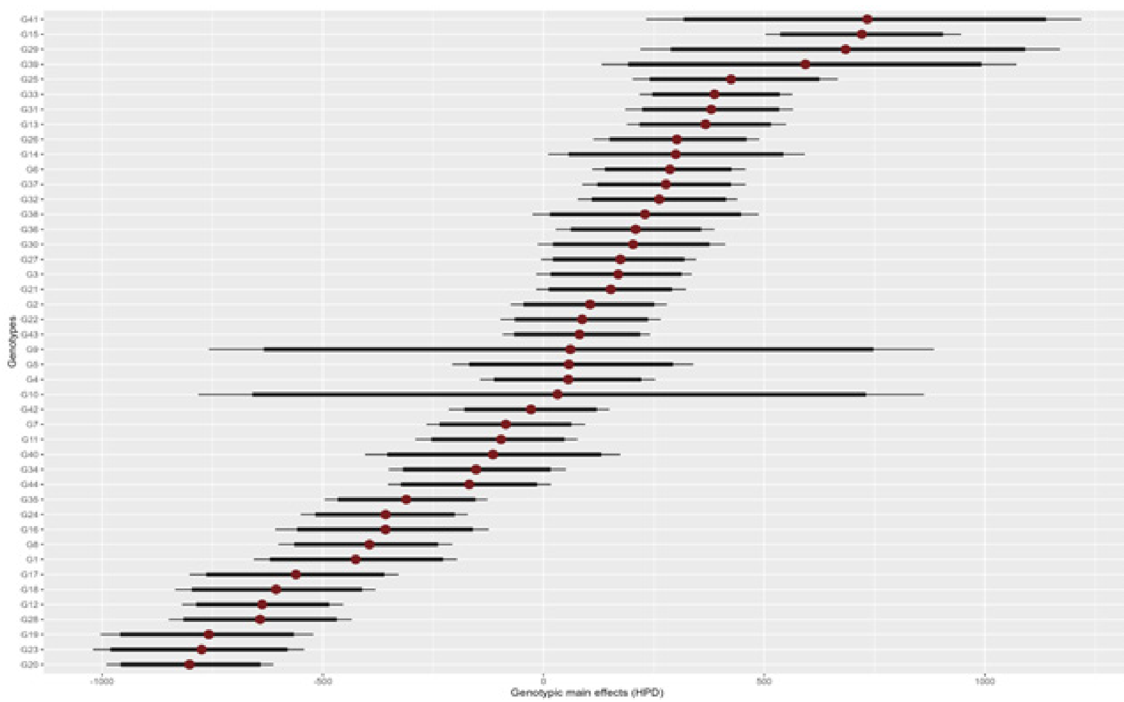

Figure 1. Main genotypic effects (HPD), with estimated confidence interval for each genotype tested. Main Genotypic Effects of Each Cultivar (G41) URS Penca, (G15) IPR Artêmis, (G29) URS 22 Londrina, (G39) URS Monarca, (G25) UPFA 22 Temprana, (G33) URS Torena, (G31) URS Altiva, (G13) IPR Afrodite, (G26) UPFA Fuerza, (G14) IPR Andrômeda, (G6) FAEM Carlasul, (G37) URS Guará, (G32) URS Brava, (G38) URS Guria, (G36) URS Fapa Slava, (G30) URS Altaneira, (G27) UPFPS Farroupilha, (G3) FAEM Brisasul, (G21) UPFA Gaudéria, (G2) FAEM Barbarasul, (G22) UPFA Ouro, (G43) URS Tarimba, (G9) FAPA5, (G5) FAEM 007, (G4) FAEM 006, (G10) FAPA6, (G42) URS Poente, (G7) FAEM Chiarasul, (G11) URS Guapa, (G40) URS Olada, (G34) URS Corona, (G44) URS Taura, (G35) URS Estampa, (G24) Teixeirinha, (G16) UFRGS 14 Amiga, (G8) Louise (FAPA4), (G1) FAEM Albasul, (G17) UFRGS 19, (G18) UPF 15, (G12) IAC 007, (G28) URS 21, (G19) UPF 16, (G23) UPFA 20 Teixeirinha, (G20) UPF 18.

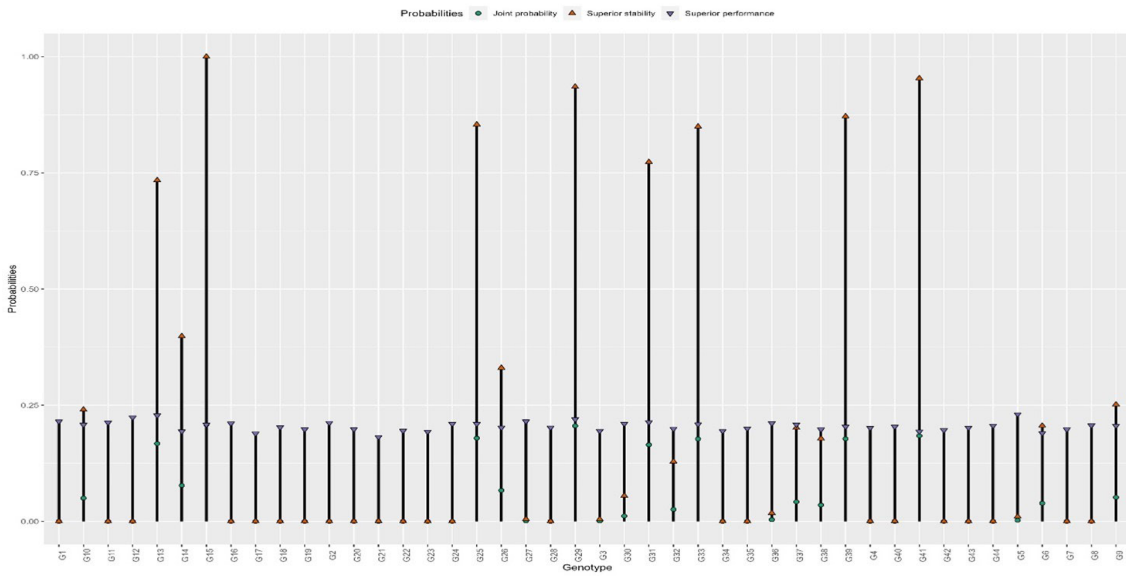

Figure 2. Joint probability for superior grain yield performance, marginal and joint stability based on posterior distributions. Joint Probability of Superior Performance and Superior Stability of Cultivars (G1) FAEM Albasul, (G10) FAPA6, (G11) URS Guapa, (G12) IAC 007, (G13) IPR Afrodite, (G14) IPR Andrômeda, (G15) IPR Artêmis, (G16) UFRGS 14 Amiga, (G17) UFRGS 19, (G18) UPF 15, (G19) UPF 16, (G2) FAEM Barbarasul, (G20) UPF 18, (G21) UPFA Gaudéria, (G22) UPFA Ouro, (G23) UPFA 20 Teixeirinha, (G24) Teixeirinha (G25) UPFA 22 Temprana, (G26) UPFA Fuerza, (G27) UPFPS Farroupilha, (G28) URS 21, (G29) URS 22 Londrina, (G3) FAEM Brisasul, (G30) URS Altaneira, (G31) URS Altiva, (G32) URS Brava, (G33) URS Torena, (G34) URS Corona, (G35) URS Estampa, (G36) URS Fapa Slava, (G37) URS Guará, (G38) URS Guria, (G39) URS Monarca, (G4) FAEM 006, (G40) URS Olada, (G41) URS Penca, (G42) URS Poente, (G43) URS Tarimba, (G44) URS Taura, (G5) FAEM 007, (G6) FAEM Carlasul, (G7) FAEM Chiarasul, (G8) Louise (FAPA4), (G9) FAPA5.

The height of the bars gradually increases from right to left, showing the difference between the cultivars (Figure 2), so the cultivars with the best stability are FAEM 007 (G5) and IPR Afrodite (G13). The cultivars with the highest joint probability were IPR Artêmis (G15), UPFA 22 Temprana (G25), URS 22 Londrina (G29), URS Altiva (G31), URS Torena (G33), URS Monarca (G39) and URS Penca (G41). Loro et al. (2022), when evaluating 26 white oat genotypes in 20 environments, found that the IPR Artêmis cultivar showed high performance in a large number of environments. This indicates that these cultivars were the most stable and best performing. However, all cultivars had a combined probability of less than 25%, that is, they all have less than a 25% probability of being among the cultivars with the highest performance and stability.

Risk probability analysis when recommending white oat cultivars has become important. With modern agriculture and to keep up with all the advances in technology, this component becomes essential to help make decisions with better information. Assessing the risks associated with different types of factors allows producers to have greater assurance that they choose cultivars that are responsive to their environment, aiming at the productivity and sustainability of the system. The adoption of risk analysis methods contributes to agricultural resilience, mitigating losses and promoting more efficient use of available resources, which is important for the continued development of agriculture in Brazil.

CONCLUSION

FAPA 4 cultivar showed the highest conditional probability of success in 16 environments. IPR Artemis cultivar showed the highest probability of superior performance. FAEM 007 and IPR Afrodite cultivars are the most stable.

These genetic bases will be responsible for building future blocks of crosses to build lines with potential for high genetic response and stability for grain yield in Brazil.

DATA AVAILABILITY

The datasets generated and/or analyzed in this study are available from the corresponding author upon reasonable request.

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