

Impact of mass-to-volume ratios on beverage quality in coffee blends

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ABSTRACT

The discrimination of sensory attributes in coffee blends is complex due to the subjective nature of panelist evaluations and the intrinsic chemical heterogeneity of each variety. This study focuses on the influence of blend composition on the sensory evaluation of Robusta coffee, particularly its bitterness and astringency, depending on the proportion used. For specialty and commercial arabica coffees, positive attributes such as flavor and appearance are emphasized. The study also considers the impact of preparation concentrations, specifically the ratio of ground coffee (in grams) to water (in milliliters). We investigate coffee blends composed of different proportions of commercial roasted and ground Arabica coffee (CAC), Robusta coffee (RC), and a genotype of the Arabica specialty coffee (ASC) of the cultivar Yellow Bourbon, processed by both dry and wet methods. The blends were prepared at two concentrations: 7% (70 g ground coffee per 1,000 mL of water) and 10% (100 g ground coffee per 1,000 mL of water). Through predictive statistical modeling, this research investigates the sensory outcomes of coffee blends, considering implications previously associated with chemical variables in the literature. It was found that blends prepared at 10% concentration (m/v) with intermediate proportions of CAC and RC achieved a balance in bitterness and flavor attributes for both dry and wet processed Yellow Bourbon. Including brew concentration in the models improved predictive power substantially, increasing R^2 from approximately 75% to over 90%. Therefore, this concentration can be recommended to ensure a balanced sensory profile without disproportionate influence from any single attribute.

Key words: Arabica coffee; robusta coffee; sensory analysis; mixture models; simplex regression.

1 INTRODUCTION

Food sensory analysis employs a set of techniques to evaluate the degree of acceptance and/or characterization of a product. These evaluations are conducted by a sensory panel, which, in some cases, includes consumers with limited experience (Giacalone; Bredie; Frost, 2013). The results are influenced by each consumer's sensory perception, which reflects stimuli influencing sensations such as intensity, duration, quality, and preference (Mahmud; Shellie; Keast, 2020). Given these variables, sensory analysis is complex, particularly as the human sense of smell can detect between 2,000 and 4,000 odors.

In the case of coffee blends from different varieties, such as Robusta and Arabica, these species differ in the physical and sensory characteristics of the fruit, propagation processes, and flowering periods, among others (Oliveira; Oliveira, 2023). Due to its higher sensory quality, Arabica coffee is more commonly cultivated worldwide compared to Robusta (Cheng, et al., 2016; Shankar et al., 2022; Siridevi et al., 2019; Aswathi et al., 2024), which is known for producing a fuller-bodied beverage, a significant sensory characteristic for many consumers (Paterson; Lima; Taniwaki, 2014).

Adding Robusta coffee in high proportions is not widely accepted by consumers due to its pronounced bitterness, despite its full-bodied nature (Pacetti et al, 2012). In this context, the creation of coffee blends including one or more

Specialty or premium coffees is considered to cater to diverse markets (Vellema et al., 2015).

Consumer preferences for coffee blends are influenced by a balance between bitterness and body, with many markets showing a tendency towards beverages that combine moderate bitterness with a fuller body and aroma complexity (McCain-Keefer; Meals; Drake, 2020). Industry standards and quality protocols, such as those established by the Specialty Coffee Association (SCA), guide the formulation of blends to meet these sensory criteria while ensuring consistency across batches (Specialty Coffee Association - SCA, 2021). Market research further indicates that consumers increasingly favor blends that deliver a balanced sensory profile, reflecting growing demand for premium and specialty coffees alongside traditional robusta blends (Bressani et al., 2021).

Santos et al. (2013) discuss the formulation of two types of blends: Special Blend (SB) and Market Blend (MB). The SB consists of 100% Arabica coffee roasted to varying degrees, while the MB includes five coffee brands, four of which are 100% Arabica and one that contains some Robusta. Notably, the consumption of SB coffee has been associated with a decrease in body fat and increases in energy and nutrient intake (Bakuradze et al., 2014).

Wintgens (2012) emphasizes the importance of prioritizing Arabica coffee in blends that also include Robusta, noting that Robusta is seldom used alone due to significant variability in quality depending on the growing environment.

This can affect various attributes of the coffee, enhancing positive qualities like appearance and likability, while reducing negative qualities such as bitterness and astringency (Geromel et al., 2008; Prakash et al., 2022; Agnoletti et al., 2022).

Given the complexity involved, tasters face limitations when expressing their opinions using a hedonic scale, which spans up to 9 points and includes a neutral category and a bipolar structure representing four positive categories, each labeled according to affective levels of taste. Negative categories are similarly divided by levels of disgust. Commonly, a continuous 0–9-point scale is employed, facilitating the application of a broad range of statistical descriptive methodologies.

Louzada et al. (2017) emphasize that selecting specialists for sensory panels depends not only on their experience but also on their sensory sensitivity. This becomes particularly challenging in consumer experiments, as Costel (2002) cautions against the potential fallacy that experts' opinions necessarily reflect consumer preferences.

In this context, statistical methodologies play a crucial role in aggregating information that enhances the accuracy and precision of sensory evaluations. These methodologies are integral to experimental planning and the development of sophisticated statistical models, aiming to achieve a precise diagnostic of sensory perceptions.

Various statistical methods have been employed in the sensory analysis of coffee, considering environmental factors such as origin, processing type, and genetics. These models are designed to reveal new patterns in consumer attitudes toward the quality of coffee and its derivatives. Ramos et al. (2016) developed a method for assessing the quality of the specialty coffee Yellow Bourbon, grown in the micro-region of Serra da Mantiqueira in Minas Gerais State, Brazil. This method adheres to the standards set by the Specialty Coffee Association (SCA). Using decision trees and the chi-square automatic interaction detection (CHAID) method, Ramos et al. (2016) could distinguish coffee samples that not only met but exceeded a sensory evaluation score of 88 points. This success was particularly linked to coffees grown at altitudes of 1200 meters or higher.

Given the same experimental conditions, Liska et al. (2015) analyzed the acceptance of specialty coffees among two distinct consumer groups: trained and untrained. They evaluated Yellow Bourbon and Acaiá coffees from the Serra da Mantiqueira region, cultivated at various altitudes. By employing the boosting method (Skurichina and Duin, 2000) and comparing it with discriminant analysis, the authors found that the accuracy rate for trained consumers in distinguishing Yellow Bourbon from Acaiá beverages was approximately 80.63%.

Recent advancements have demonstrated the potential of machine learning (ML) algorithms in enhancing

sensory prediction and classification in coffee analysis. For instance, Chang et al. (2021) utilized near-infrared spectroscopy combined with support vector machines and deep convolutional neural networks to predict seven flavor categories in specialty coffees, achieving accuracies between 75% and 77%. Similarly, He et al. (2024) developed a binary classifier named PredCoffee, employing various ML models, including graph neural networks, to determine the presence of coffee odor in molecules, with the top-performing model reaching an accuracy exceeding 84%. These studies underscore the efficacy of ML techniques in providing objective and efficient assessments of coffee sensory attributes.

Despite these promising results, the general population often lacks the knowledge and experience needed for coffee tasting, due to economic, cultural, or social factors. This issue is further complicated in the context of blends that combine specialty coffees with other varieties. Elias et al. (2022) noted that industrial blends might include a mix of Arabica and Robusta coffees in varying proportions. Generally, Arabica coffee is known for its fruity and acidic profile, while Robusta tends to be more bitter, contributing to a fuller-bodied beverage.

According to Santos et al. (2020), coffee blending allows for competitive market pricing by combining coffees from various geographic origins and varieties of *Coffea Arabica L.* or *Coffea canephora*. However, this diversity complicates the assessment of coffee quality due to the factors previously discussed.

Statistically, the composition of a blend is defined by the sum of its component proportions. For example, a blend consisting of three components— x_1 , x_2 , and x_3 , representing the proportions of Arabica, Robusta, and commercial coffees respectively—must adhere to the condition that $x_1 + x_2 + x_3 = 1$. Traditional polynomial regression models are unsuitable due to the interdependence of these variables (x_i , $i=1,2$, and 3). Instead, mixture models (Liska et al., 2019), including this constraint, are recommended to ensure more accurate and precise predictions. These models are typically referred to as simplex regression in the literature (Cornell, 2002).

Given the importance of coffee blends in the consumer market and current economic conditions, this study aimed to investigate the sensory characterization of coffee blends composed of different proportions of commercial roasted and ground Arabica coffee (CAC), Robusta coffee (RC), and Arabica specialty coffee (ASC). Specifically, the ASC used corresponds to a genotype of the Yellow Bourbon cultivar, prepared at two concentrations: 7% (70 g of ground coffee per 1,000 mL of water) and 10% (100 g of ground coffee per 1,000 mL of water). To achieve this, simplex regression models were employed

to analyze sensory data focusing on both the acceptability and the sensory profiles of the blends, thereby providing insights into how variety and mass-to-volume ratios impact the overall beverage quality.

2 MATERIAL AND METHODS

In alignment with the study's objectives, we established the blend formulations (Table 1) using coffees of varying quality standards. These include commercial roasted and ground Arabica coffee (CAC), Robusta coffee (RC), and Arabica specialty coffee (ASC). The ASC used was a genotype of the cultivar Yellow Bourbon, processed using dry methods for samples $k = 1$ to 9 and peeled cherry methods for samples $k = 10$ to 18.

The dry process involves drying the whole coffee cherries under the sun with the skin and pulp intact. This

method allows sugars and mucilage to be absorbed into the beans during drying. It often results in a beverage with more body and sweetness (Oliveira et al., 2018; Knopp; Bytof; Selmar, 2006). In contrast, the wet process requires removing the outer skin and pulp of the cherries soon after harvesting. Then, the cherries undergo fermentation and washing to eliminate the mucilage before drying the beans. This method tends to produce coffees with higher clarity, acidity, and cleaner flavor profiles (Lee et al., 2015). We prepared and processed all samples according to the protocols established by the Specialty Coffee Association (SCA).

We conducted two experiments following the outlined specifications. Each sample corresponds to a blend whose proportions are detailed in Table 1.

Figure 1 illustrates how points are distributed for each experiment within the experimental region characterized by the simplex.

Table 1: Description of blend compositions with commercial roasted and ground Arabica coffee (CAC), Arabica specialty coffee (ASC), and Robusta coffee (RC).

Values represent proportions in the blend (unitless; $\sum = 1.000$).							
Experiment 1: Dry-processed Yellow Bourbon				Experiment 2: Wet-processed Yellow Bourbon			
Sample	ASC	CAC	RC	Sample	ASC	CAC	RC
Model code	x_1	x_2	x_3	Model code	x_1	x_2	x_3
1	1.000	0.000	0.000	10	0.340	0.330	0.330
2	0.670	0.330	0.000	11	0.000	0.000	1.000
3	0.340	0.330	0.330	12	0.340	0.000	0.660
4	0.500	0.500	0.000	13	0.000	0.000	0.000
5	0.500	0.000	0.500	14	0.670	0.330	0.000
6	0.340	0.660	0.000	15	0.340	0.660	0.000
7	0.340	0.000	0.660	16	1.000	0.000	0.000
8	0.000	1.000	0.000	17	0.500	0.000	0.500
9	0.000	0.000	1.000	18	0.500	0.500	0.000

Note: Arabica specialty coffee = ASC; Commercial Arabica coffee = CAC; Robusta coffee = RC.

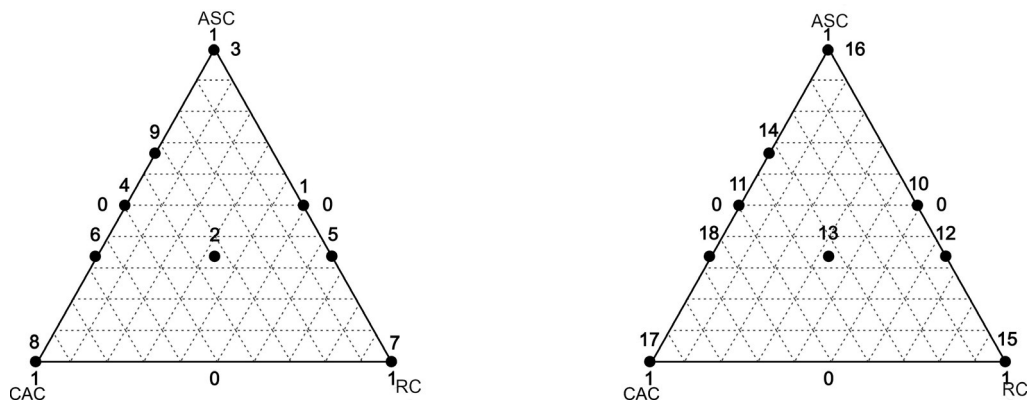


Figure 1: Experimental design points distributed within the simplex region for two processing methods. Panel (a) shows the dry process, and panel (b) the wet process. This distribution illustrates the blend composition space explored in the study.

Figure 1 initially presents the interpretation associated with each vertex. The pure components—Arabica Specialty Coffee (ASC), produced in the Serra da Mantiqueira microregion over two harvests (2009/2010 and 2010/2011) in farms located at altitudes above 1200 meters; Robusta Coffee (RC); and Commercially Roasted and Ground Arabica Coffee (CAC)—are identified by unit values at the vertices. These points correspond to pure coffee samples, without the addition of any other components. The edges connecting the vertices represent binary mixtures, where the third component is absent (value of zero).

We conducted each experiment in separate sessions spaced 24 hours apart due to the extensive number of evaluations. The panel of evaluators included five qualified tasters recognized for their ability to discern samples in sensory experiments.

Each panelist evaluated the samples in a randomized order, with four repetitions, and without any information about their origin, processing method, or blend composition. For beverage preparation, the team used filtered, potable water free of contaminants and without added sugar. They standardized the temperature at approximately 65°C for all samples. The coffees were served in 50 mL disposable cups, each containing 20 mL of the evaluated blends (Table 1).

We identified outliers and evaluated the sensory panel following the statistical procedure proposed by Cirillo et al. (2019), which assessed the panel's discriminatory power in differentiating pure blends and coffees. The research team visually determined the roasting degree using the standardized color classification discs from the SCAA/Agtron Roast Color Classification System.

We evaluated the blends for qualitative characteristics of the beverage (final score, bitterness, and flavor) on a 0-10 scale. We fitted the data using a quadratic Equation 1 ($\hat{y}_k$, $k = 1, 2$, and 3).

$$\hat{y}_k = \sum_{i=1}^3 \hat{\beta}_i x_i + \sum_{i<j} \hat{\beta}_{ij} x_i x_j ; k = 1, 2 \text{ e } 3. \quad (1)$$

We chose two beverage concentrations based on the experiment formulations (Table 1): 7% (70 g ground coffee to 1,000 mL water) and 10% (100 g ground coffee to 1,000 mL water). We used unsweetened drinking water at 93 °C for both concentrations. The extraction method involved filtration for 4 minutes. We followed hygiene standards set by the ethics committee under CAAE protocol 14959413.1.0000.5148 in all procedures.

We considered beverage concentration as a process variable. To improve understanding of the model estimation, we reformulated the original quadratic Equation 1 as Equation 2.

$$Q(\beta, x) = \sum_{i=1}^3 \hat{\beta}_i x_i + \sum_{i<j} \hat{\beta}_{ij} x_i x_j, \quad (2)$$

We defined an exclusive model for the process variable, following the procedure outlined by Bello and Vieira (2011). In this study, we adopted the linear Equation 3.

$$Q(\alpha, z) = \alpha_0 + \alpha_1 z \quad (3)$$

Where: z represents the concentrations of the formulations specified at 7 and 10% (w/v).

First, models (2) and (3) were merged. In this step, we replaced the notation β for the mixture model parameters with γ , where $i = 1, 2, 3$ indicates terms that replace $\alpha_0 \beta_i$. This combination eliminates the intercept specific to the process variables when estimating the additive combined model (4), as shown in Equation (4).

$$C(\gamma, x, z) = \sum_{i=1}^q \gamma_i^0 x_i + \sum_{i<j} \sum_{i=1}^q \gamma_{ij}^0 x_i x_j. \quad (4)$$

Based on this notation, and considering that the β s are functions of the process variables (z), Equation (4) resulted in a quadratic model combined with three components and a process variable. Consequently, we fitted equation 5 for each sensory attribute of every experiment using the least squares method.

$$\hat{y}_k(\gamma, x, z) = \beta_1(z)x_1 + \beta_2(z)x_2 + \beta_3(z)x_1 + \beta_{12}(z)x_1 x_2 + \beta_{13}(z)x_1 x_3 + \beta_{23}(z)x_2 x_3 + \varepsilon_m \quad (5)$$

Where: m is the number of experimental points, and ε_m represents the random error.

We conducted the statistical analysis using these specifications. First, we compared the quadratic model (2) to the model including the process variable (5), using the coefficient of determination as a reference. Then, we calculated specification limits, defined as the mean $\pm$ one standard deviation. Plotting these limits in the experimental region allowed us to identify the most representative blends for each attribute.

To carry out this study, we used the R software (Core Team, 2025), within which we developed custom scripts and employed the mixexp package proposed by Willden (2016).

3 RESULTS

The results presented in Table 2 represent the estimates of the coefficient of determination (R^2) for the quadratic regression model, which was adjusted for the variables flavor, bitterness, and score. These estimates were obtained considering both the presence (Equation 5) and absence (Equation 2) of the process variable, denoted by the beverage concentrations prepared at 7 and 10% (m/v). These experiments were conducted using dry- and wet-processed Yellow Bourbon specialty coffee, as described in Table 1.

Table 2: Coefficients of determination (R^2 Adjusted, %) of the quadratic model for the presence and absence of the process variable as a function of coffee beverage concentrations at 7% and 10% (m/v).

Processing	Variable Processing	Flavor (R^2 Adjusted, %)	Bitterness (R^2 Adjusted, %)	Score (R^2 Adjusted, %)
Dry	Present	0.8986	0.9748	0.8707
Wet	Present	0.8783	0.9623	0.9260
Dry	Absent	0.9637	0.9704	0.9633
Wet	Absent	0.9626	0.9573	0.9844

Note: "Presence" and "Absence" refer to the inclusion or removal of a specific processing variable, as described in the methods section. R^2 = coefficient of determination adjusted of the quadratic regression model.

All evaluated sensory attributes yielded estimated values of the coefficient of determination. Thus, there is statistical evidence to assert that the quadratic model exhibited high predictive power, particularly when considering the process variable.

Consequently, intervals defined by mean $\pm$ one standard deviation were derived, using values predicted by this model as specification limits to delineate the experimental region. Identification of components best characterizing

the blends was achieved through tasters' responses to the evaluated attributes. Table 3 presents these intervals, aiming to underscore the accuracy and precision of the predicted values employed in generating graphs and defining the limited experimental regions. This aids in elucidating the relationship with known chemical variables' results documented in the literature, aligning with flavor and bitterness attributes.

Table 3: Predicted values (mean + 1 SD) from quadratic models for dry- and wet-processed Yellow Bourbon coffees.

Attribute	Wet processing (Mean $\pm$ SD)	Dry processing (Mean $\pm$ SD)
Score	5.09 $\pm$ 1.06	4.23 $\pm$ 1.40
Bitterness	5.39 $\pm$ 1.23	5.36 $\pm$ 1.51
Flavor	4.76 $\pm$ 1.20	4.51 $\pm$ 1.33

Note: Values represent model-based predictions for each sensory attribute; SD = standard deviation derived from the quadratic model residuals.

The intervals presented in Table 3, along with the blends formulated at concentrations of 7% (m/v) and 10% (m/v) for the first experiment (Table 1), depicted in Figure 2, revealed that blends with high proportions of ASC tended to yield higher scores for the flavor attribute.

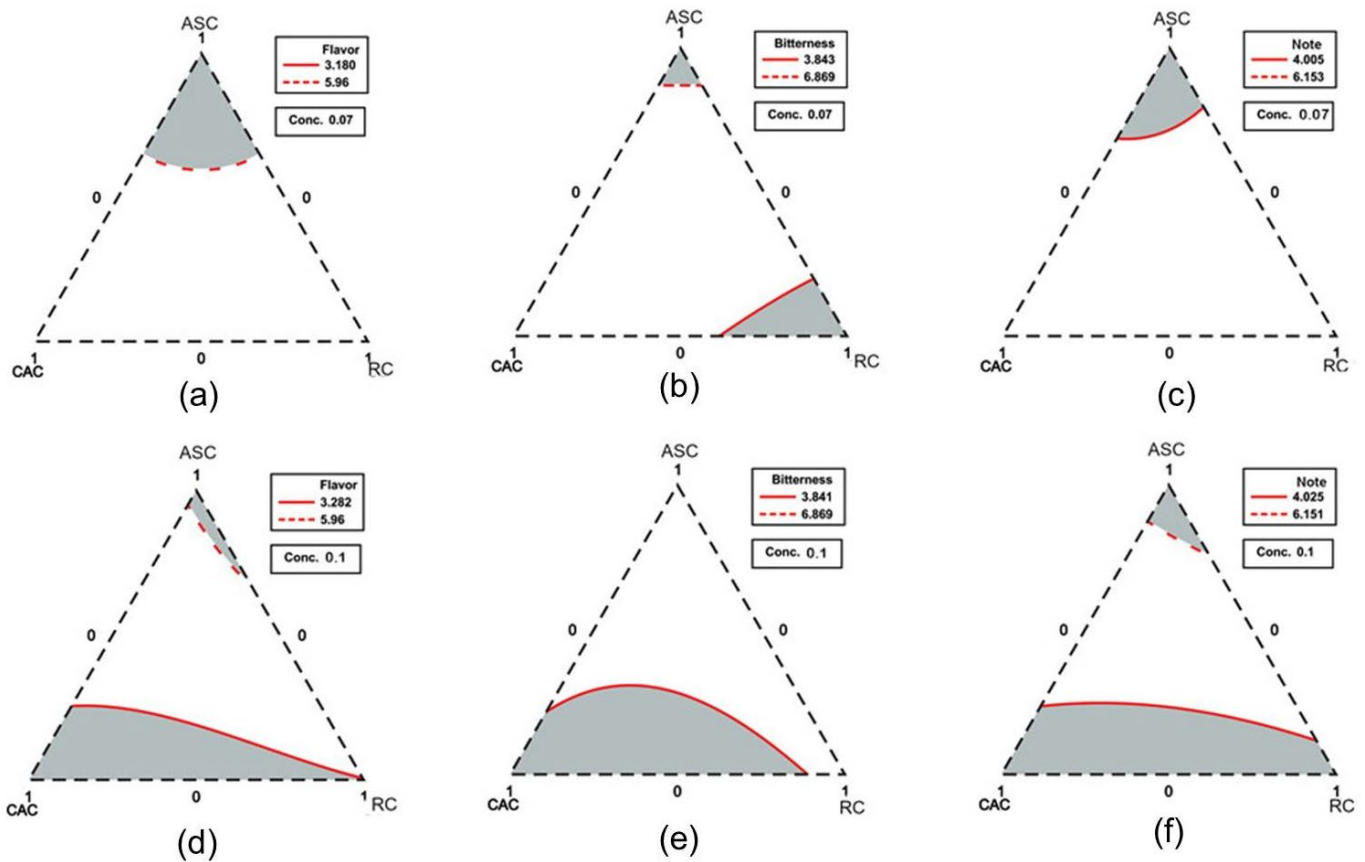
**Figure 2:** Predicted sensory responses of dry-processed Yellow Bourbon coffee at two brew concentrations (0.07 and 0.1 m/v). (a, d) Flavor response surface, (b, e) Bitterness response surface, (c, f) Overall sensory score response surface. Panels (a), (b), and (c) correspond to 0.07 m/v concentration, while (d), (e), and (f) correspond to 0.1 m/v concentration.

Table 4: Parameter estimates of the quadratic model with and without the inclusion of the process variable concentration (z) for naturally processed blends.

With process variables						
	Flavor		Bitterness		Note	
	Estimates	Pr(> t)	Estimates	Pr(> t)	Estimates	Pr(> t)
z:x1	78.804	2.48e-05	33.549	0.0004	76.790	5.95e-05
z:x2	36.141	0.0107	89.236	2.69e-08	29.130	0.0421
z:x3	45.368	0.002	60.371	2.15e-06	41.244	0.0079
z:x1: x2	-47.356	0.344	23.003	0.433	-45.354	0.39557
z:x2: x3	-83.905	0.511	-8.875	0.905	-56.218	0.67919
z:x1: x3	2.577	0.961	28.332	0.370	2.392	0.96616
No process variables						
	Flavor		Bitterness		Note	
	Estimates	Pr(> t)	Estimates	Pr(> t)	Estimates	Pr(> t)
x1	7.0641	7.88e-08	2.769	0.0011	6.908	5.86e-08
x2	3.144	0.0002	7.758	6.01e-08	2.593	0.00086
x3	3.921	4.21e-05	5.253	4.48e-06	3.656	5.11e-05
x1: x2	-4.094	0.125	1.947	0.4764	-3.995	0.1172
x2: x3	-5.368	0.418	-2.624	0.7074	-3.421	0.5851
x1: x3	-0.353	0.896	2.957	0.3184	-0.364	0.8883

The results presented in Table 4 show the parameter estimates and significance probabilities for two scenarios: with and without the effects of the process variable concentration (z), set at levels of 0.07 and 0.10 (w/v).

Considering the naturally processed coffees, we observed significant results ($\text{Pr}(>|t|) < 0.05$) in both scenarios for the pure components (x_1 , x_2 , x_3) and their interactions with concentration (z). We emphasize that the statistical significance of the parameter estimates demonstrates their important contribution to the model's predictive power.

Regarding interaction effects, we highlight the sign of the estimates: negative values indicate antagonistic effects, while positive values suggest synergistic effects. Regardless of the presence or absence of the process variable (z), the interactions among components were mostly antagonistic. In other words, the effects of the interactions were smaller than the sum of the pure component effects.

Concerning model fit quality, Figures 3 to 8 display Q-Q plots of the residuals along with confidence bands. Residuals within these bands indicate an adequate fit. Therefore, there was no need to include higher-order terms in the model or to conduct additional lack-of-fit tests.

Considering dry-processed specialty coffees, the results depicted in Figure 9 pertain to blends formulated at 7% (m/v) and 10% (m/v). In general, the variables flavor and score were similar under conditions of low concentrations when compared to the same concentrations in wet-processed coffees.

Higher differentiation occurred for high proportions, with lower scores for the flavor and score attributes, particularly involving blends composed of intermediate proportions of ASC. Analogously, this characteristic was also remarkable for the attribute bitterness, with higher scores observed for wet-processed specialty coffees.

The results presented in Table 5 refer to pulped natural processed coffees. When we included the process variable defined by concentration (7% and 10% w/v), we observed significant results for the pure components ($\text{Pr}(>|t|) < 0.05$).

Analyzing the signs of the interaction estimates, we found synergistic effects in all cases. This means the effects of interactions on the evaluated sensory responses exceed the sum of the pure component effects.

In this context, the statistical modeling of pulped natural processed coffees differs from that of naturally processed coffees.

Regarding model fit quality, Figures 10 to 15 demonstrate that the model fits well and does not require higher-order terms.

4 DISCUSSION

According to Cordoba Castro et al. (2020), the attribute final scores reflect a balance between aroma, acidity, bitterness, body, flavor, and sweetness. Thus, given the low scores for the attribute bitterness (Figure 2), there is evidence that tasters characterized blends with high proportions of ASC, although aroma and body were not evaluated in this study.

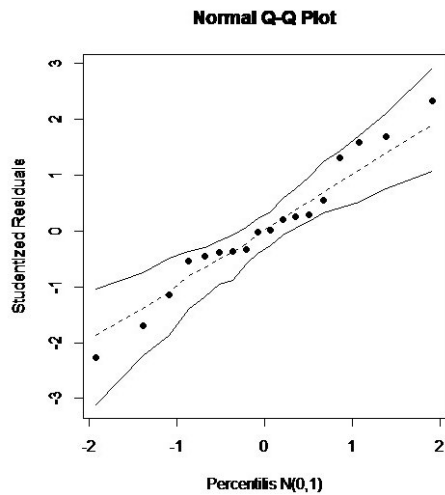


Figure 3: Q-Q plot of residuals including the process variable (z) for naturally processed coffees regarding flavor.

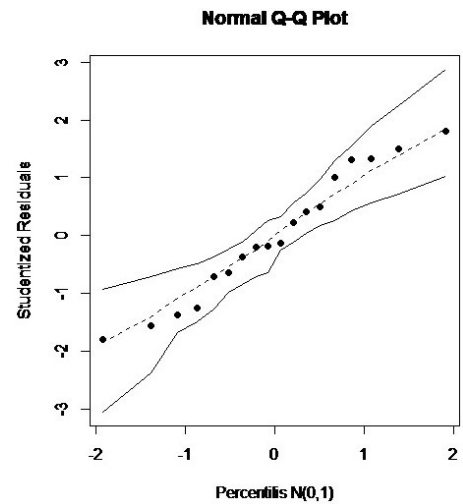


Figure 6: Q-Q plot of residuals for naturally processed coffees considering flavor only.

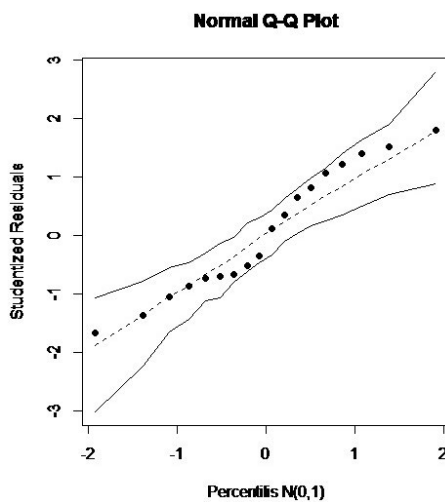


Figure 4: Q-Q plot of residuals including the process variable (z) for naturally processed coffees regarding bitterness.

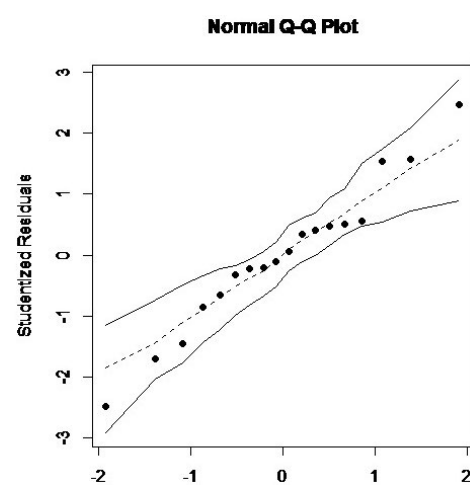


Figure 7: Q-Q plot of residuals for naturally processed coffees considering bitterness only.

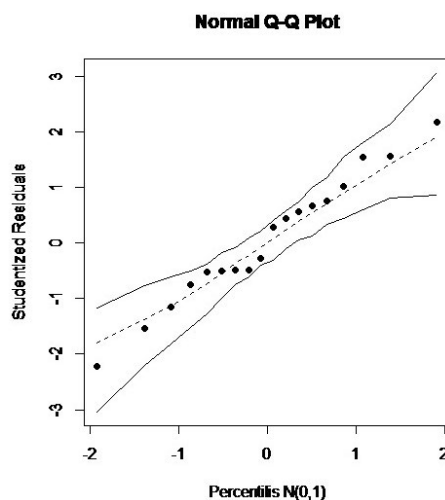


Figure 5: Q-Q plot of residuals including the process variable (z) for naturally processed coffees regarding overall score.

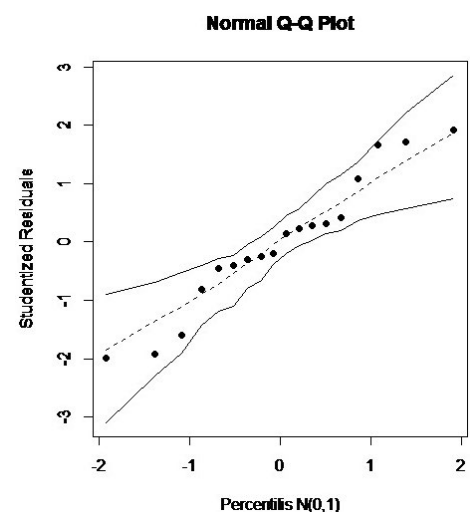


Figure 8: Q-Q plot of residuals for naturally processed coffees considering overall score only.

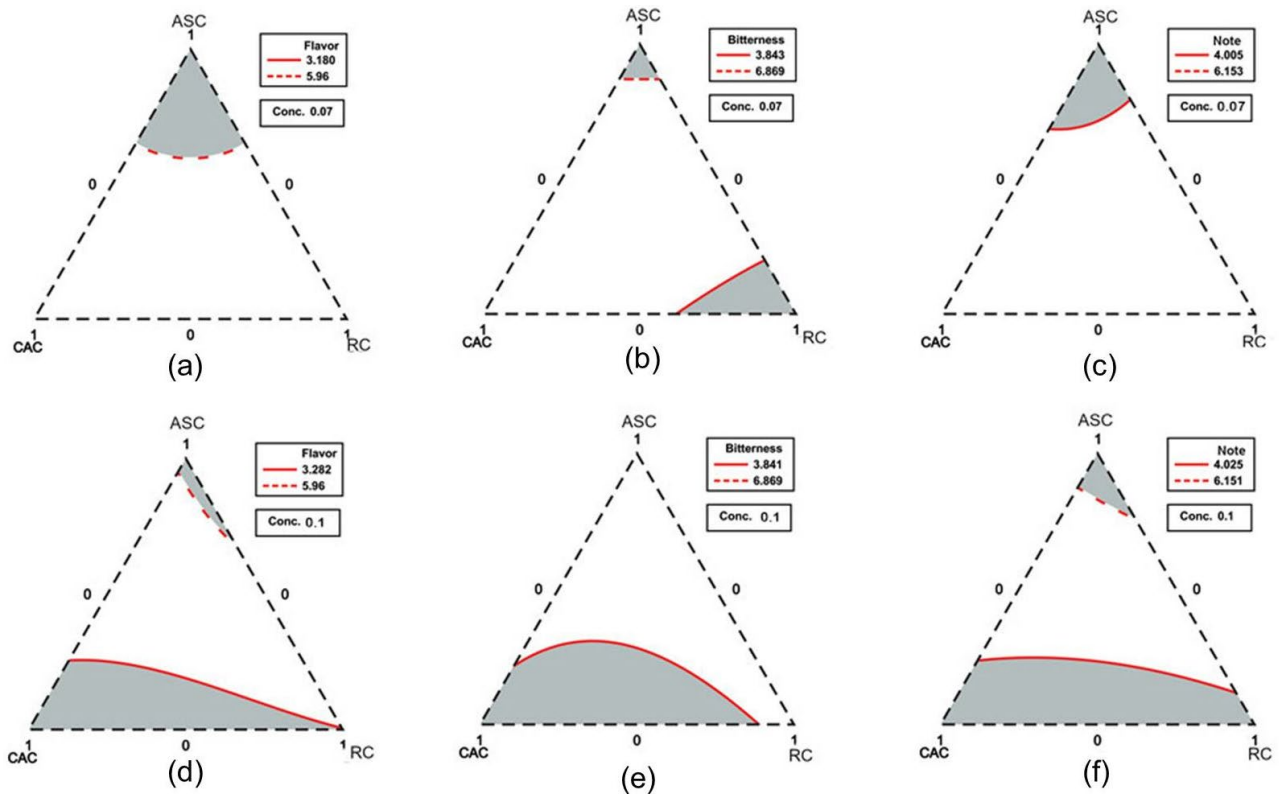


Figure 9: Predicted responses for flavor and bitterness attributes for Yellow Bourbon coffee before processing at two brew concentrations (0.07 and 0.1 m/v). (a, d) Flavor response surface, (b, e) Bitterness response surface, (c, f) Overall sensory score response surface. Panels (a), (b), and (c) correspond to 0.07 m/v concentration, while (d), (e), and (f) correspond to 0.1 m/v concentration.

Table 5: Parameter estimates of the quadratic model with and without the process variable concentration (z) for pulped natural processed blends.

With process variables						
	Flavor		Bitterness		Note	
	Beta	Pr(> t)	Beta	Pr(> t)	Beta	Pr(> t)
z:x ₁	74.626	0.0001	50.821	6.99e-05	77.576	1.67e-05
z:x ₂	32.525	0.0357	83.579	5.04e-07	36.927	0.00681
z:x ₃	39.817	0.0144	54.062	4.69e-05	44.303	0.00226
z:x ₁ :x ₂	-0.425	0.9939	-0.638	0.986	14.326	0.75825
z:x ₂ :x ₃	0.701	0.9961	30.581	0.738	26.208	0.82687
z:x ₁ :x ₃	26.201	0.6664	8.492	0.823	7.846	0.87495
No process variables						
	Flavor		Bitterness		Note	
	Beta	Pr(> t)	Beta	Pr(> t)	Beta	Pr(> t)
x ₁	6.6343	3.11e-07	4.252	0.0001	6.8509	2.99e-09
x ₂	2.9302	0.0007	7.268	9.1e-07	3.3317	8.03e-06
x ₃	3.5759	0.0001	4.435	0.0001	3.9192	1.74e-06
x ₁ :x ₂	0.0593	0.9824	0.267	0.9345	1.1154	0.548
x ₂ :x ₃	0.7936	0.9092	2.064	0.8057	2.9952	0.531
x ₁ :x ₃	1.8202	0.5333	1.670	0.6338	0.2368	0.905

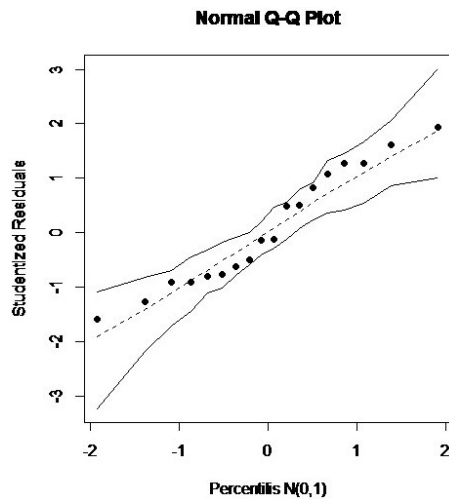


Figure 10: Q-Q plot of residuals including the process variable (z) for pulped natural processed coffees regarding flavor.

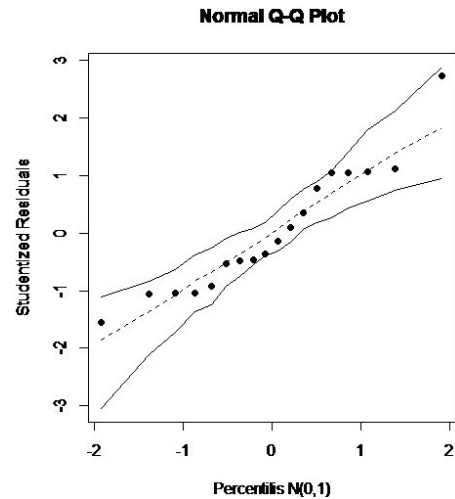


Figure 13: Q-Q plot of residuals for pulped natural processed coffees considering flavor only.

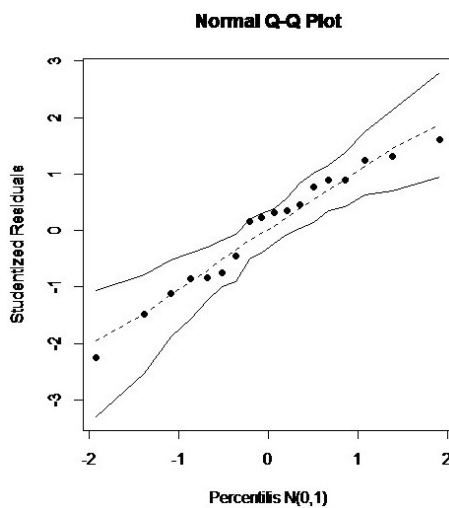


Figure 11: Q-Q plot of residuals including the process variable (z) for pulped natural processed coffees regarding bitterness.

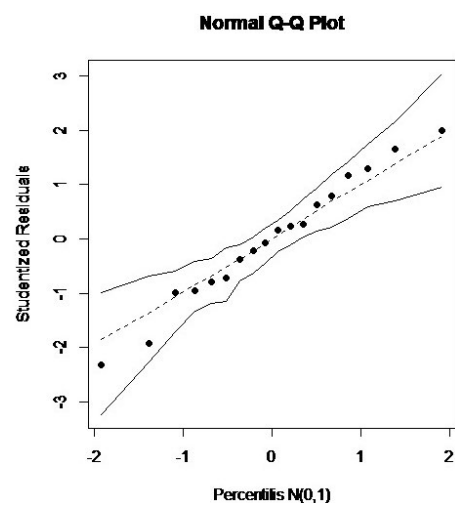


Figure 14: Q-Q plot of residuals for pulped natural processed coffees considering bitterness only.

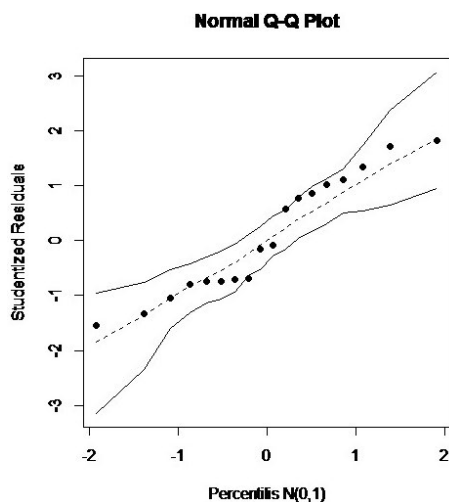


Figure 12: Q-Q plot of residuals including the process variable (z) for pulped natural processed coffees regarding overall score.

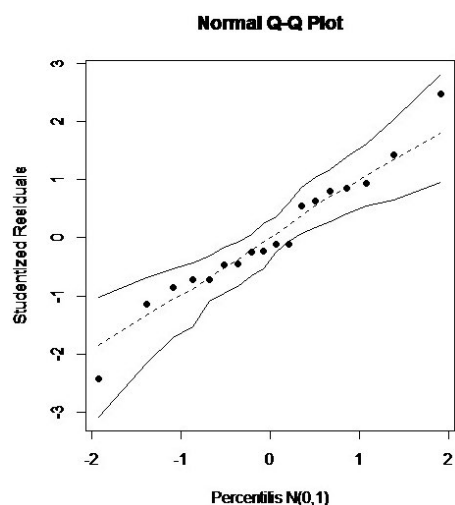


Figure 15: Q-Q plot of residuals for pulped natural processed coffees considering overall score only.

The results align with the aforementioned observation when the concentration was increased to 10% (w/v). However, the highest scores were identified within a smaller interval amplitude, corresponding to blends composed of high ASC proportions and moderate RC proportions.

Cheng et al. (2016) highlighted the influence of certain chemical components and mentioned that caffeine imparts strength, body, and bitterness, while trigonelline contributes to overall aromatic perception and bitterness, including the effects of chlorogenic acids, which are present in drinks with greater acidity and astringency. Thus, by comparing the results illustrated in Figures 2 and 3, it is possible to infer the effects of concentrations formulated at 7% (m/v) and 10% (m/v) that most characterize these components. It is worth noting that the influence of roasting can alter the amounts of these components present in the beverage (Bhumiratana; Adhikariand; Chambers, 2011; Chambers, et al. 2016; Adhikari; Chambers; Koppel, 2018).

The intensity of these characteristics can vary depending on the degree of roast attained by the beans. Richard and Chambers (2020) explored the characterization of flavor compounds released during the grinding of roasted coffee. The results suggested that variations in volatile compounds released during grinding can be attributed to factors such as origin, species variety, and roasting conditions, as reported by Akiyama et al. (2005).

The development of coffee's characteristic color and flavor during roasting is well documented in the literature and is attributed to various chemical reactions, including the Maillard reaction, caramelization, and pyrolysis, which collectively generate over 1,000 different aroma compounds (Hameed et al., 2018; Pires et al., 2024). It is important to clarify that these descriptions are based solely on existing studies and were not experimentally investigated in the present work, as the roasting degree was fixed and not varied in our experiments.

We acknowledge several limitations in our study. Firstly, the roasting profile remained constant, which may have restricted the range of sensory variations captured. Secondly, some sensory attributes, such as aroma and body, were not measured, potentially overlooking important aspects of coffee quality. Thirdly, the sensory panel size was relatively small, which may affect the generalizability of the results.

To address these gaps, future research should validate the present findings using larger and more diverse sensory panels, as well as additional coffee cultivars, to enhance the generalizability of the results. Moreover, exploring different roasting degrees will be important to comprehensively assess their impact on sensory characteristics. Expanding sensory evaluations to include additional attributes, such as aroma and body, would also contribute to a deeper understanding of coffee quality and consumer preferences. Larger and more diverse panels would also strengthen the robustness of findings and improve reproducibility.

The positioning of the samples in the graphs with these characteristics shows that sample 3 falls within this interval region. The lowest responses of the attribute bitterness for low concentrations were identified in blends with well-differentiated compositions, namely, high proportions of ASC and RC. For higher concentrations, responses related to bitterness were more evident in blends characterized by higher CAC and RC proportions. Finally, the final score at both concentrations exhibited a similar effect on the responses regarding the flavor attribute, consistent with the statement by Hecimovic et al. (2011), that arabica coffee is generally preferred by most consumers over Robusta due to its lower bitterness and favorable flavor. These characteristics are contributed by carbohydrates, which account for more than 50% of the coffee bean dry weight.

Given these results, some reports in the literature justify statistical modeling. Regarding the validation of sensory results, particularly the attribute bitterness, Cristovam et al. (2000) suggest that the differentiation between blend samples primarily occurs due to the degree of roasting rather than solely the presence of Robusta coffee in the blend.

Filho et al. (2011) observed higher bitterness in Robusta coffee beverages compared to Arabica coffee beverages in blends with higher Robusta concentrations, while Malaquias, Celestino, and Xavier (2018) recommend using blends with up to 50% Robusta mixed with Arabica coffee. Ferreira et al. (2016) pointed out that heterogeneity among observations may result from uncontrollable factors such as genetics, fatigue, unwillingness to complete all tests, and differences in consumers' abilities, as well as external causes including natural and chemical factors like variations in chemical composition due to genetic variability between cultivars, which influence the sensory quality of coffees.

5 CONCLUSIONS

Statistical modeling effectively evaluated 7% and 10% (m/v) blend concentrations. Including beverage concentration as a process variable improved the model's predictive power (R^2) of sensory attributes from about 70–75% to over 90%. The 10% concentration enhanced bitterness and flavor in dry-processed blends and promoted balance in wet-processed blends. These findings confirm the interaction between beverage concentration and blend composition, supporting mixture–process regression models as valuable tools for optimizing coffee blending and sensory performance.

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